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Table of Contents

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Na Liu

16 September 2024, Leuven

Disclaimer:
In writing this thesis, I choose to openly embrace the new way of working by using ChatGPT as an augmentation tool, inspired by Ethan Mollick's concept of human-AI "cyborg"[1] and adhering to KU Leuven's guidelines on the use of generative AI[2] (in the absence of such guidelines at IMT at the time of thesis submission) as well as academic discussions on the topic[3][4][5]

I have used ChatGPT for two purposes throughout all chapters of the thesis: First, as a language assistant to review and improve the writing style and clarity of texts I wrote myself; second, as a search tool for brainstorming, refining outlines, and adding details.

In using ChatGPT, I always carefully review and edit any AI-generated content to ensure accuracy to avoid plagiarism and fabrication. All content and references are manually verified and cross-checked.

The constant dialogue with ChatGPT not only enhanced my productivity but also transformed what can often be a lonely research process into a dynamic, engaging exchange of ideas. While every final argument, insight, and conclusion in this thesis remains my own, I am grateful for the way this human-AI partnership enriched my academic journey.

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[1] Mollick, E., & Euchner, J. (2023). The Transformative Potential of Generative AI: A Conversation with Ethan Mollick. *Research-Technology Management*, *66*(4), 11-16.

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Prologue

In 2019, years already since Artificial Intelligence (AI) had become a major buzzword, I embarked on my master's degree in Business Analytics at Esade Business School. Living by the mantra "data is the new oil", I was particularly drawn to the intersection of technology and people, especially within the gig economy. Witnessing its rapid growth and the opportunities it provided, especially for those facing high unemployment and fierce competition, was eye-opening. Inspired by stories of individuals finding success and freedom on gig economy platforms such as Uber, TaskRabbit, Fiverr, Upwork, Freelancer, etc., I found traditional employment structures unappealing, and the gig economy's promise of autonomy was enticing. However, deeper investigation revealed a darker side: many workers were trapped in precarious conditions, vulnerable to platforms that prioritize profit over people, using the guise of flexible work to evade responsibilities.

Despite these disturbing realizations, my perspective shifted as Algorithmic Management (AM), which originated from the gig economy, began influencing traditional organizations. Rooted in a cultural background of techno-optimism, I remained curious and hopeful about AM's potential to positively transform conventional workplaces and ventured into a further exploration into how technology could be harnessed for good.

My doctoral research began with two positivist studies focused on AM in traditional work settings, challenging the pessimistic view of AM. These studies showed that while AM could sustain job engagement and autonomy under certain conditions—like close leader relationships and fair system design—it rarely enhanced them. We struggled for a long time to understand the limited significant role of the moderators and the seemingly destined negative-to-neutral impact that AM has on workplace wellbeing. Since AM has not yet been widely applied (or recognized) by employees in standard work settings, large-scale self-reported quantitative studies were challenging, as we experienced in the first two papers. All these aforementioned factors combined pushed us to study AM more critically and creatively.

In my third paper, we shifted paradigms, adopting a rather critical stance and an abductive approach to explore the phenomenon more innovatively through a theatrical talk. This methodological shift was crucial for studying a future that is still taking shape. The findings from the third paper revealed deeper underlying issues with AM and workplace wellbeing and challenged me to fundamentally question the notion of wellbeing at work. Why are we pursuing it, and at what cost? While I do not yet have a definitive answer, we are moving toward a direction to find one.

Looking back, I realize how transformative and fulfilling this journey has been. From the initial exploration of the gig economy to focusing on AM, from taking a quantitative positivist stance to an interpretivist one, from studying current phenomenon (i.e., study what exists and take a more diagnostic approach) to envisioning a future of work (i.e., study what does not exist yet, thereby taking a more proactive, prescriptive approach), my research evolved together with my identity as a researcher. One of the most significant challenges encountered during this research was the difficulty in collecting meaningful data on AM. Employees mostly perceived AM as an abstract concept, disconnected from their daily work experiences, even though it was subtly influencing various aspects of their professional lives in ways that are more omnipresent than they would imagine. This disconnection implies a broader and burning issue: the need for greater awareness and understanding of AM among employees and the public. Without this foundational understanding, discussions about the role of AM in the workplace remain limited, hindering meaningful engagement with the technology that increasingly shapes work environments.

Furthermore, AM is not merely a technological tool but an encompassing system that intersects with organizational behavior, ethics, and human resources. Capturing the full scope of its impact required a multi-paradigmatic and cross-disciplinary approach, which was initially daunting. We sought to involve not only quantitative analyses of employee engagement and job autonomy but also a transition to qualitative methods that could better capture the ethical and humanistic concerns. I hope that as a reader, you find this exploration to offer somewhat valuable insights into the complex relationship between technology, work, and humanity, although I am aware that what we have uncovered is merely the tip of the iceberg. Nevertheless, I remain optimistic that with careful thought and innovative approaches, technology can truly serve the greater good—though it will require far more foundational work than we initially anticipated.

The future of work, shaped by AM, holds both promise and peril. As this thesis concludes, it marks the beginning of a broader exploration into the future of work, technology, and human dignity and autonomy. It is my hope that this research starts the effort to foster a more thoughtful and ethical dialogue about how these technologies should be integrated into our work lives.

Vita

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Journal Publications

Conference Presentations

1. Liu, N., De Winne, S., Dries, N., De Coster, M. (2024). Rage Against the Machine: Sensemaking Amid Algorithmic Technologies. Presented at the 40th European Group for Organizational Studies, Milan, Italy, 04 Jul 2024-06 Jul 2024.
2. Liu, N., De Winne, S., De Cooman, R. (2023). Uncovering the Mechanism between Algorithmic Management and Job Engagement: A Social Exchange Perspective. Presented at the 83rd Annual Meeting of the Academy of Management, Boston, 04 Aug 2023-08 Aug 2023.
3. Liu, N., Lattanzi, N., De Winne, S., De Cooman, R. (2023). Uncovering the Mechanism between Algorithmic Management and Job Engagement: A Social Exchange Perspective. Presented at the 2nd EIASM workshop on people analytics & algorithmic management (PAAM), Leeds, 21 Jun 2023-22 Jun 2023.
4. Liu, N., Lattanzi, N., De Winne, S., De Cooman, R. (2023). Exploring the Relationship between Algorithmic Management and Job Autonomy: Identifying Boundary Conditions. Presented at the 2nd EIASM workshop on people analytics & algorithmic management (PAAM), Leeds, 21 Jun 2023-22 Jun 2023.
5. Liu, N., De Winne, S., De Cooman, R., Lattanzi, N. (2022). Algorithmic HR Management and Job Engagement: A Perspective from Social Exchange Theory. Presented at the Dutch HRM Conference, Enschede, The Netherlands, 09 Nov 2022-11 Nov 2022.

Abstract

This thesis explores the relationship between Algorithmic Management (AM) and employee well-being in standard work environments. AM, which refers to the use of algorithms to assume managerial functions traditionally handled by humans, is an emerging phenomenon that promises efficiency and objectivity. However, its impact on well-being is still under heated debate, particularly regarding when and why AM leads to positive or negative well-being outcomes for employees.

This research seeks to address this debate by examining AM from different perspectives. Specifically, a multi-paradigmatic approach is employed to study when AM enhances or erodes engagement, autonomy, and overall well-being, as well as why these outcomes occur. Drawing on both positivist and interpretivist approaches, this thesis integrates quantitative and qualitative methods to investigate the mechanisms, boundary conditions, as well as sensemaking processes that shape the AM-well-being relationship.

First, in line with a positivist perspective, we use quantitative surveys to explore how AM relates to employee engagement, mediated by social and economic exchanges. The findings of the first study suggest AM shifts work interactions from social to economic, often correlating with lower engagement. A close leader's moderating role is highlighted, showing that strong interpersonal relationships can buffer these negative effects. The second study addresses job autonomy, revealing that AM's association with reduced autonomy is influenced by factors like systemic justice and individual proactivity, with high justice and proactivity mitigating the loss the job autonomy.

The final study adopts an interpretivist approach, using qualitative methods to explore how employees make sense of and respond to AM in environments marked by uncertainty and complexity. It shows that employees actively reinterpret or resist AM's influence on their well-being and emphasizes employees' political potential to reshape workplace dynamics in an AM context.

The thesis concludes that AM poses challenges to employee well-being in standard work settings, despite efficiency gains. To balance these aspects, organizations should implement AM systems that prioritize genuine interpersonal relationships, justice, and autonomy. This

research provides a nuanced understanding of AM's dual nature and practical insights for its ethical use at work.

Abbreviations

AM: Algorithmic Management

AI: Artificial Intelligence

AVE: Average Variance Extracted

CFA: Confirmatory Factor Analyses

CR: Composite Reliability

HRM: Human Resource Management

SEM: Structural Equation Modeling

SET: Social Exchange Theory

STS: Sociotechnical Systems

STST: Sociotechnical Systems Theory

List of Figures

List of Tables

"Success in creating effective AI, could be the biggest event in the history of our civilization. Or the worst."

Stephen Hawking

Introduction

"Success in creating effective AI could be the biggest event in the history of our civilization. Or the worst." Stephen Hawking's words capture the profound duality that defines the rise of artificial intelligence (AI). As AI continues to develop and permeate various aspects of society, its potential to transform the workplace is both eagerly anticipated and deeply feared (Bullock et al., 2024; Floridi & Cowls, 2022; Fosso Wamba et al., 2021; Makridakis, 2017). This duality is reflected in algorithmic management (AM), a system that uses algorithms—potentially including AI—to perform managerial tasks and is increasingly altering the landscape of employee management (Jarrahi, 2019; Libbertz, 2024; Meijerink et al., 2021; Orhan et al., 2022).

Algorithmic Management (AM)

In the literature, AM originates from the gig economy (i.e., "an emerging labor market wherein organizations engage independent workers for short-term contracts ('gigs') to create virtual jobs, often by connecting workers to customers via a platform-enabled digital marketplace" (Jabagi et al., 2019, pp. 192–193) and has been defined in a variety of ways. It generally refers to the use of algorithms to assume managerial functions traditionally handled by humans (Duggan et al., 2020; Kellogg et al., 2019; Lee, 2018; Rosenblat, 2018; Wesche & Sonderegger, 2019). Lee et al. (2015) first coined the term, defining it as the use of software algorithms to manage tasks like assigning, optimizing, and evaluating human jobs. This definition highlights the automation of managerial functions such as task allocation and performance evaluation. Another key feature of AM is the predictive modeling driven by data, which transforms labor norms by optimizing work processes based on algorithmic evaluations (Newlands, 2021; Shestakofsky, 2017). Duggan et al. (2020) emphasize this system of control, where algorithms take over labor-related decisions, thus limiting human involvement in managing the workforce. Mateescu and Nguyen (2019) further expand on this by describing AM as a set of technological tools that remotely manage workforces, using data collection and surveillance to enable automated or semi-automated decision-making. Similarly, Kellogg et al. (2020) focus on how AM reshapes organizational control through automated control systems that are more encompassing, instantaneous, interactive, and opaque. Furthermore, Kellogg et al. (2020) also highlight that empirical research indicates that AM is predominantly reshaping organizational control through three control mechanisms—(partial) automation of direction (e.g., determining what needs to be done, in what order, and within what time frame), evaluation (e.g., reviewing workers' activities to correct mistakes, assess performance, and identify underperforming employees), and discipline (e.g., punishing or rewarding workers to elicit cooperation and enforce compliance).

Building on these three control mechanisms, Parent-Rocheleau and Parker (2021) identified six key functions of AM: monitoring, goal setting, performance management, scheduling, compensation, and job termination. Monitoring algorithms track and report employee activities, while goal-setting algorithms assign tasks and set performance targets (Kellogg et al., 2019; Robert et al., 2020). Performance management algorithms assess employee performance, provide feedback, and influence compensation (Duggan et al., 2020). Scheduling algorithms optimize work schedules, and algorithms also automate pay calculations and termination decisions (Tambe et al., 2019).

This thesis adopts an overarching conceptualization of AM that integrates its varying aspects, emphasizing its role as a system of data-driven automation that transforms managerial practices. AM's increasing penetration into both gig economies and traditional organizational settings raises pressing questions about the future of work, including the role of human oversight (Amershi et al., 2019), the ethical implications of algorithmic decision-making (Bankins & Formosa, 2023), and the broader impact on workplace dynamics and employee well-being (Niaz et al., 2020). Furthermore, the contextual nuances are highlighted in each study to reflect the multidimensional nature of AM. Specifically, in Paper 1 and Paper 2, we explore AM's role in reshaping engagement and autonomy in a workplace setting by using a definition focused on AM's capacity to manage the workforce through direction, evaluation, and discipline. In Paper 3, we adopt a critical management perspective, drawing on definitions that emphasize the surveillance and data collection aspects of AM, to analyze how workers respond to and resist these AM practices.

Existing literature presents mixed findings regarding AM's impact on the workplace. On the positive side, AM offers potential benefits in terms of efficiency and productivity. Proponents argue that AM can streamline workflows, reduce ambiguity, and enhance decision-making through real-time feedback and performance metrics (Kellogg et al., 2020). For workers, this can translate into a more structured and predictable work environment, where clear instructions and objective performance reviews reduce uncertainty and help employees focus on task completion (Parent-Rocheleau & Parker, 2021). Furthermore, health-oriented AM technologies, such as wearable technologies, are designed to prevent exhaustion and promote a healthier work-life balance, contributing to overall well-being (Alhejaili & Alomainy, 2023).

On the negative side, however, AM systems often prioritize efficiency and control over human values, leading to what has been termed "Digital Taylorism," where workers are treated as mere inputs to be optimized (Dupuis, 2024; Rosenblat & Stark, 2016; Wood et al., 2019). The lack of transparency in how algorithms make decisions about scheduling, performance reviews, and even job termination can lead to significant stress and anxiety among workers (Bujold et al., 2022). The constant monitoring and tracking of workers' activities erodes privacy, creating a workplace environment of hyper-surveillance that undermines trust and fosters feelings of exploitation (Leicht-Deobald et al., 2019; Wiener et al., 2021). Additionally, the reduced human interaction in AM diminishes opportunities for interpersonal connection and support, further eroding emotional well-being (Lee, 2018; Jabagi et al., 2019).

AM and Well-being

Given the importance of wellbeing as a key determinant of worker satisfaction and productivity at individual, enterprise, and society levels (Schulte & Vainio, 2010), as well as the contrasting findings of AM on workers' experience, understanding AM's broader implications for well-being is essential. This thesis aims to take a thorough and critical approach to examining workplace well-being by considering both the *managerialist perspective*, which views well-being as mutually beneficial to both employers and employees, and the *critical management perspective*, which challenges the underlying power dynamics and control mechanisms.

From a *managerialist perspective*, well-being is framed as a tool to optimize worker productivity and organizational efficiency (Lau & May, 1998). This perspective focuses on creating workplace conditions that promote employee happiness, health, and strong social connections (Grant et al., 2007; Warr, 2007), with the primary objective of driving organizational success (Peccei & Van De Voorde, 2019). As such, the managerialist approach often presents a win-win narrative, positing that algorithmic technologies can benefit both organizations and employees by improving employee well-being while providing data-driven support for management decisions (Peccei, 2004; Peccei & Van De Voorde, 2019). Advocates argue that these AM technologies increase efficiency, optimize processes, and offer precise tools for assessing and enhancing employee performance and well-being (Peccei & Van De Voorde, 2019; Van De Voorde et al., 2012). Examining employee engagement (Paper 1) and autonomy (Paper 2) within the context of AM is essential, as it directly impacts both individual well-being and organizational performance (Peccei & Van De Voorde, 2019).

The *critical management perspective*, by contrast, takes a more skeptical stance on the well-being claims made by the managerialists and highlights the potential for managerial well-being programs to serve as mechanisms of control, rather than genuine efforts to improve workers' quality of life, or, "humanistic organizing" (Town et al., 2024). The critical management perspective emphasizes the power dynamics inherent in employer-employee relationships (Aloisi & De Stefano, 2022; Jarrahi et al., 2021), where worker well-being is managed and controlled through technologies designed primarily to serve organizational interests (Heffernan and Dundon, 2016; Kellogg et al., 2020). Critical management scholars argue that the increased surveillance and control facilitated by AM systems undermine worker autonomy and contribute to a sense of alienation (Ashforth, 1989), as workers are often excluded from decision-making processes that affect their well-being, as these decisions are delegated to algorithms that prioritize efficiency over human values (Lee, 2018). As Kellogg et al. (2020) argue, this intensification of control through algorithmic systems underscores a broader tension between technological efficiency and the preservation of worker autonomy and dignity. Furthermore, well-being programs driven by AM can shift responsibility for well-being onto workers while masking deeper systemic issues like excessive workloads or poor management (Mohlmann & Zalmanson, 2017). This perspective critiques the superficiality of well-being initiatives that focus on surface level of happiness, health, and social relationships, while neglecting the structural problems affecting workers' mental and physical health (Egede et al., 2024). Furthermore, by framing well-being in terms of productivity, the managerialist approach risks reducing emotional and social connections to mere tools for boosting performance, rather than acknowledging them as fundamental human needs (Town et al., 2024).

Despite the relevance of the topic, there is a noticeable scarcity of empirical research that directly examines the relationship between AM and key aspects of workplace well-being, such as employee engagement and job autonomy, within standard organizational environments. In line with the origin of AM in the gig economy, research on AM and well-being has primarily focused on this context, where workers on short-term contracts engage with organizations through digital platforms. Studies in the gig economy context often emphasize its controlling and restrictive aspects, leading to negative outcomes like reduced job satisfaction and autonomy (Newman et al., 2020). In contrast, the effects of AM in traditional organizations remain underexplored, particularly in terms of how AM can be designed to balance efficiency with preserving employee well-being (Gagné et al., 2022; Malik et al., 2022). In standard work settings, AM interacts with existing power dynamics and reshapes roles, relationships, and information flows, necessitating a re-evaluation of its effects (Jarrahi et al., 2021; Von Krogh, 2018).

The few empirical studies of AM in standard work settings are marked by inconsistencies and contradictions, highlighting the need for deeper investigation into the mechanisms and a dualistic perspective to explore the boundary conditions shaping this relationship (Braganza et al., 2021a; Braganza et al., 2021b; Hughes et al., 2019; Parent-Rocheleau et al., 2023; Malik et al., 2022;). To elaborate, while some studies suggest that AM can positively influence engagement by providing clear structures and goals (Braganza et al., 2021a; Malik et al., 2023), others highlight the potential for disengagement, as AM can shift work interactions from social exchanges to purely transactional ones, thereby diminishing the emotional and relational aspects that foster engagement (Hughes et al., 2019; Parent-Rocheleau et al., 2023). This tension reflects the need to identify the mediating mechanisms that drive these outcomes, as well as specific conditions under which AM enhances or hinders engagement.

Meanwhile, a growing body of literature challenges the deterministic view, suggesting that the interaction between employees and AM systems are rather dynamic than linear, and, that AM can, under certain conditions, enhance autonomy and other well-being indicators. Work design scholars (Parent-Rocheleau & Parker, 2021) and sociotechnical systems theorists (Makarius et al., 2020) argue that AM's impact on autonomy varies based on the system's design and implementation, as well as individual and organizational factors (Meijerink & Bondarouk, 2021; Noponen et al., 2023). Additionally, the concept of algo-activism (Kellogg et al., 2020) highlights workers' ability to actively resist algorithmic control, demonstrating that they are not merely passive recipients of decisions made by AM systems.

A Multi-Paradigmatic Approach

The complexity of AM in standard work settings necessitate a more robust theoretical framework, as well as a multi-paradigmatic approach, to understand how AM either disrupts or integrates into the broader organizational ecosystem, and how it shapes employee engagement, job autonomy, and genuine well-being. This thesis thus adopts a multi-paradigmatic approach, combining positivist and interpretivist paradigms to provide a comprehensive understanding of AM's impact (Creswell & Creswell, 2018). This approach aligns with the insights from scholars such as Alvesson & Sandberg (2013), Braun & Clarke (2013), and Morgan & Smircich (1980), who emphasize the importance of selecting research methods that are deeply rooted in philosophical assumptions about the nature of reality and knowledge.

The positivist paradigm underpins the quantitative studies within this thesis, utilizing large-scale surveys and statistical analyses to identify general patterns in the relationship between AM and employee engagement and autonomy. This approach is crucial for testing theories such as Social Exchange Theory (in Paper 1) and Sociotechnical Systems Theory (in Paper 2) in diverse organizational contexts, ensuring the findings are generalizable across different settings (Creswell & Creswell, 2018). Scholars like Morgan & Smircich (1980) and Cunliffe (2010) highlight that such empirical approaches are particularly effective when the social world is viewed as a concrete structure, lending itself to objective measurement and the identification of deterministic relationships.

However, to fully understand the subjective experiences and meanings that employees associate with AM, as well as the dynamic interaction between individuals and AM systems, the interpretivist paradigm is employed in the third paper. Supported by Morgan & Smircich (1980), this paradigm emphasizes the value of qualitative methods in uncovering the complex, contextualized experiences often overlooked by quantitative research. Cunliffe (2010) extends this argument, noting that qualitative research is essential when the social world is seen as dynamic and processual, where individuals actively construct their realities. By using methods such as moderated focus groups and theatrical performances, this approach explores how employees make sense of and navigate the implications of AM in their work lives.

Integrating these paradigms allows the thesis to offer both generalizable findings and deep, context-specific insights, contributing to a more nuanced and comprehensive understanding of AM in standard work settings. This multi-paradigmatic approach enhances the robustness of the findings, aligning with Alvesson & Sandberg's (2013) call for problematization, which challenges existing assumptions and enriches the theoretical discourse surrounding AM. Furthermore, as Morgan & Smircich (1980) and Cunliffe (2010) advocate, this approach avoids the reduction of research to mere methodology by ensuring that the methods used are contextually appropriate and reflective of the broader theoretical and philosophical underpinnings of the research.

Objective and Contribution

This thesis is positioned at the heart of this pivotal topic of AM and well-being at work, addressing the pressing question: Does AM truly enhance workplace well-being, or does it introduce new, unforeseen risks that threaten to undermine the very principles of humanistic management? As organizations grapple with the potential of AM to improve employee engagement (Paper 1), preserve or enhance job autonomy (Paper 2), and make employees healthier and happier with stronger social relationships (Paper 3), it is imperative to understand when AM enhances or hinders engagement, autonomy, and overall well-being, and why these outcomes occur.

This thesis aims to provide a thorough and nuanced analysis of AM's implications for the future of work through the application of both quantitative and qualitative research methodologies. The primary objective of this thesis is to contribute to the ongoing debate on the role of AM in shaping workers' well-being in standard work settings (e.g., Budhwar et al., 2022; Pan & Froese, 2023), and, whether AM can be aligned with humanistic values (Town et al., 2024)—emphasizing employee engagement, autonomy, and overall well-being.

The first paper is theoretically underpinned by Social Exchange Theory and underscores the role of social and economic exchanges, influenced by leadership's social distance, in shaping employee engagement under AM. This suggests that leaders play a critical, albeit limited role in ensuring that AM does not disintegrate the social fabric of the workplace. The second paper focuses on the significance of systemic justice and individual proactivity as socio-technical moderators in the relationship between AM and job autonomy. Drawing on Sociotechnical Systems Theory, we highlight that fair and transparent AM systems can help preserve employee autonomy, a critical component of work design and an important factor for employee well-being at work. The third paper adds a critical dimension by exploring how employees make sense of and react to AM-empowered well-being technologies. Our findings reveal that employees are not passive recipients of AM but actively resist and reinterpret its implications, particularly when it comes to invasive AM technologies that affect their personal and emotional lives. Our findings contribute to sensemaking theory. Figure 0-1 serves as a visual guide for this thesis and encapsulates these findings by illustrating the interconnected processes that influence the well-being outcomes of AM in the workplace and organizations. This thesis emphasizes the need for a balanced approach that considers both the technological capabilities of AM and the human elements crucial to a thriving work environment in the age of AM.

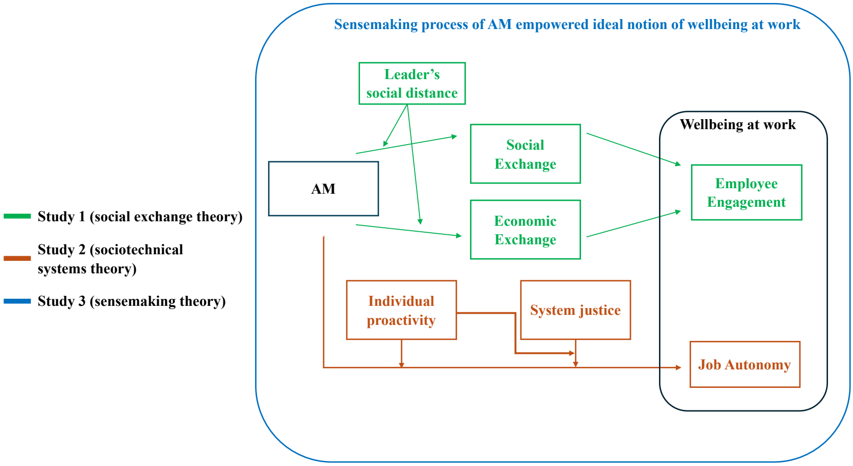

Figure 0-1 Overarching theoretical framework

By engaging in a critical examination of the traditional theoretical frameworks that are being increasingly challenged by the disruptive influence of AM, this research seeks not only to contribute substantively to the ongoing discourse on AM and well-being at work within the fields of organizational behavior and human resource management but also to provide a scholarly foundation upon which actionable insights can be developed. These insights are intended to inform the human-centered implementation of AM technologies, with the ultimate goal of ensuring that such innovations are aligned with the principles of humanistic organizing and workplace flourishing (Town et al., 2024), thereby fostering genuine well-being at work in the context of AM (Lee, 2018;

Robert et al., 2020).

The remainder of this thesis will unfold with a detailed presentation of each paper, concluding in an epilogue that reflects on the findings and their broader implications.

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Paper 1: Unraveling the Relationship between Algorithmic Management, Leader's Social Distance, and Employee Engagement: An Exchange Perspective[6]

Abstract

Understanding the relationship between algorithmic management (AM) and employee engagement is crucial in modern workplaces. Drawing on social exchange theory, we investigated the mechanism underlying this relationship. Two studies were conducted: Study 1 (N=304) explored the mediating roles of social and economic exchange relationships using a cross-sectional field study; Study 2 (N=410) replicated the findings, tested causality, and examined the moderating role of leader's social distance using an experimental vignette design. Results show that social and economic exchanges mediate the AM-employee engagement relationship. AM negatively correlates with social exchange and positively correlates with economic exchange, reducing employee engagement. Leader's social distance interacts with AM, influencing exchange relationships. In a low-AM scenario, social exchange is higher with a close leader compared to a distant one, while economic exchange remains unchanged. Conversely, in a high-AM scenario, economic exchange is lower with a close leader, but social exchange remains consistent. The results emphasize the importance of a close leader in promoting social exchange in low AM environments and reducing economic exchange in high AM environments, ultimately enhancing employee engagement. Implications for HR research and practice are discussed.

Keywords: Algorithmic Management, Exchange Relationships, Employee Engagement, Leader's Social Distance, Mixed Method Design

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[6]This paper has been presented at three conferences (the Dutch HRM Network conference in Enschede, in 2022; the 2nd EIASM workshop on people analytics and algorithmic management in Leeds, in 2023 and the Academy of Management Meeting in Boston, in 2023). The paper received a 'revise and resubmit' decision at the International Journal of Human Resource Management just before submitting the thesis.

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Introduction

Technology is reshaping our professional environments, and algorithmic management (AM) stands at the forefront of this transformation. AM encompasses a suite of automated control mechanisms that mimic traditional leadership directive behaviors, such as monitoring, goal setting, performance management, scheduling, algorithmic compensation, and even job termination (Lee et al., 2015; Meijerink et al., 2021; Parent-Rocheleau and Parker, 2022), tasks traditionally reserved for line management (Cheng & Hackett, 2021; Vrontis et al., 2022). It is considered one of the most transformative HR-related technologies because it shifts power dynamics between workers and technology, from the traditional view of 'technology as a tool' to 'technology as a boss' (Kellogg et al., 2020; Parent-Rocheleau and Parker, 2022).

The prevalence of AM underscores the growing importance of managing the digitalization process of HRM to thrive in the fourth industrial revolution (Ashford et al., 2018; Malik et al., 2020). Implementing AM is not merely about adopting new technologies but fundamentally reimagining how organizations and the workforce are managed in response to technological advancements. As companies navigate the complexities of AM implementation in achieving organizational productivity goals and HRM effectiveness (e.g., Jarrahi et al., 2021; Kellogg et al., 2020; Schildt, 2017) while enhancing employee-centric outcomes such as employee well-being (e.g., Jabagi, et al., 2019; Meijerink & Bondarouk, 2021), the strategic integration of AI in HRM becomes imperative (Malik et al., 2022). This underscores the need for organizations to consider not only the potential benefits of AM in HR ("what AI can do for HR"), but also to proactively address human-centric concerns such as the impact of AM on employee well-being, by placing people and the work they do at the center of business practice ("what HR can do for AI") (Cooke et al., 2022).

Among human-centric outcomes, employee engagement in AM systems is particularly crucial for organizations. Prior research highlights its importance as a vital motivational factor for individual well-being and organizational productivity (Parent-Rocheleau et al., 2023; Parent-Rocheleau & Parker, 2021). Despite its relevance, empirical research that directly links AM with employee engagement in standard organizational contexts is scarce. Moreover, there exists a limited theoretical basis for understanding how AM disrupts or integrates into the broader ecosystem of a standard organization and the mechanisms that link AM with employee engagement. The few existing studies on this topic show inconsistent results. Some suggest a positive impact on engagement (Malik et al., 2023; Braganza et al., 2021a), while others indicate negative effects (Hughes et al., 2019; Parent-Rocheleau et al., 2023; Braganza et al., 2021b). These gaps underscore the need for a thorough examination of the underlying mechanisms in the relationship between AM and employee engagement, as well as an exploration of potential boundary conditions. Such evaluations can provide insights into *how* AM fosters employee engagement, and *when* it does or does not.

Responding to this call and in line with social exchange theory (SET), we focus on the mediating role of exchange relationships (capturing the employer-employee relationship) and the moderating role of leader's social distance (capturing the manager-employee relationship) between AM and employee engagement. SET serves as a foundational theory for understanding both exchange relationships and employee engagement, as it emphasizes trust and the exchange of value based on established norms and negotiation among employees, managers, and employers (Cropanzano & Mitchell, 2005). Social exchanges are primarily driven by trust, mutual commitment, and open-ended obligations, where the parties invest in and build long-term relationships beyond immediate gains. In contrast, economic exchanges are transactional, driven by explicit agreements and quid-pro-quo interactions based on short-term gains and specific rewards or outputs (Blau, 1964). The introduction of AM leads to a significant shift in the execution of HR tasks from human managers to algorithms. This shift disrupts established norms of reciprocity and negotiation, primarily developed from interpersonal interactions, which could potentially erode trust (Araujo et al., 2020) and alter the nature of the exchange relationships—AM environments lean toward transactional relationships, as seen in app-based work where pay is based on output rather than time, while the lack of emphasis on mutual trust and commitment undermines the social exchange relationships and further reinforces this transactional nature (Duggan et al., 2020; Jabagi et al., 2019).

Our study makes several contributions to existing literature. First, it clarifies the link between AM and employee engagement by uncovering mediating mechanisms through social and economic exchanges, offering a nuanced and theory-driven understanding of the relationship and expanding the relevance of SET in the context of AM. Second, we clarify the inconsistent findings in existing literature by pinpointing a leader's social distance as a critical moderator. In doing so, we answer the call for more research on social and human aspects in an AM system (Parent-Rocheleau, 2024). Third, our study expands the domain of AM research to standard working settings (von Krogh, 2018; Jarrahi et al., 2021). Fourth, the study integrates literature on SET, leader's distance, and AM. In doing so, we contribute to a more comprehensive understanding of the AM phenomenon and detect future research avenues that explore the intersection of transformative technology, organizational behavior, and human resource management. Finally, our results guide organizations in making strategic choices regarding AM implementation to achieve high levels of employee engagement.

Theory and hypothesis development

Early research primarily focused on AM in the context of the gig economy, characterized as a labor market where organizations hire independent workers for short-term contracts through digital platforms (Jabagi et al., 2019). Recent studies, however, depict AM as a technological phenomenon applicable across diverse work environments (Kellogg et al., 2019). The increasing proliferation of AM practices in standard organizational contexts (Jarrahi et al., 2021; Wood, 2021) raises a critical need for a deeper understanding of how AM impacts employer-employee relationships and well-being of employees within standard organizations.

In standard work settings, AM emerges at the intersection of employers, line managers, workers, and algorithms (Jarrahi et al., 2021). Meijerink et al. (2021) define it as the utilization of software algorithms using digital data to enhance HR-related decisions or automate HRM activities. We follow this definition in our paper, emphasizing the role of algorithms in automating a line manager's HRM activities, while recognizing the line manager's role in providing individual consideration, empathy, and communication.

Social Exchange Theory (SET) and its application in AM

The main tenet of SET is that "relationships evolve over time into trusting, loyal, and mutual commitments" through negotiated rules and norms as guidelines (Cropanzano & Mitchell, 2005, p.875). In an employer-employee relationship, exchanges can involve both socioemotional and economic factors (Cropanzano & Mitchell, 2005; Shore et al., 2006), which can operate relatively independently.

Depending on the type of exchange, employees choose to invest varying levels of cognitive, emotional, and physical resources as a way to respond to an organization's actions (Saks, 2006; Robinson et al., 2004). Specifically, social exchange centers on trust, long-term investment, and open-ended commitments, emphasizing socioemotional aspects. Economic exchange, in turn, is impersonal, focusing on interactions with an emphasis on tangible elements like pay and benefits (Cropanzano & Mitchell, 2005). As such, SET provides a robust theoretical foundation explaining why employees decide to increase or decrease their engagement levels in their jobs.

Previous research has identified three key control mechanisms of AM within standard work settings (Kellogg et al., 2020): algorithmic direction, evaluation, and discipline. Additionally, Parent-Rocheleau & Parker's (2021) model consolidates six managerial functions and HRM activities where algorithms are utilized. In our study, we aim to unify these contributions into a coherent framework. Thus, algorithmic direction includes goal-setting and scheduling, algorithmic evaluation comprises monitoring and performance management, and algorithmic discipline involves compensation and job termination. We contend that considering the managerial tasks assigned to algorithms (Kellogg et al., 2020; Parent-Rocheleau & Parker, 2021), AM in standard organizations can threaten the rules and norms in the organization and can disrupt the traditional interpersonal interactions that are fundamental to SET. Social and economic exchanges are distinct dimensions of exchange relationships, rather than mutually exclusive. Employees may simultaneously perceive both economic benefits and social benefits from their organization, but the relative emphasis may shift based on the intensity of AM. As such, we expect AM to diminish perceived *social exchange relationships* by reducing opportunities for trust, reciprocity, and socioemotional support and increase perceived *economic exchange* by emphasizing transactional, performance-based interactions.

Algorithmic direction provides precise instructions about tasks, their order and deadlines, which reduces ambiguity and enhances predictability in work processes (Karunakaran, 2018). This can be perceived as a structured *economic exchange* where tasks are completed for financial compensation (Shore et al., 2006). However, the specificity of tasks provided by algorithmic direction limits personalization or flexibility. Employees value interactions, feedback, and recognition (Shore & Shore, 1995, cited in Shore et al., 2006). When tasks are assigned or scheduled by algorithms, the interpersonal aspect of work, which fosters *social exchange relationships*, increasingly diminishes (Turner, 2017). Algorithmic evaluation assesses and predicts employees' productivity using data-derived metrics (Rosenblat & Stark, 2016). This ties compensation directly to measurable output, strengthening the economic exchange (Shore et al., 2006). However, it often prioritizes quantitative metrics, potentially undervaluing human nuances, dignity, and virtuous work life (e.g., Lamers, 2020). Relying solely on quantitative data for error correction and performance assessment can lead to detachment and dehumanization (Prassl, 2018), eroding the workplace's social aspect. Algorithmic discipline incentivizes cooperation and compliance through rewards and punishments (Irani, 2015; Shapiro, 2018), highlighting the efficiency and economic implications of employees' actions (Jabagi et al., 2019). However, it often lacks contextual understanding and a human touch (Rosenblat & Stark, 2016), diminishing essential trust factors like mutual understanding and reciprocity (Wilson & Eckel, 2011). This reduces the social aspect of exchange relationships.

Algorithmic systems transform HR tasks by replacing the empathetic, adaptive qualities of human managers with rigid, rule-based processes. This mechanization disrupts the trust and reciprocity critical to social exchanges (Araujo et al., 2020). By prioritizing efficiency and surveillance, AM fosters a transactional approach where workers are monitored and evaluated based on performance metrics, amplifying perceptions of hyper-surveillance and diminishing the socioemotional connections essential for engagement (Duggan et al., 2020; Jabagi et al., 2019). Additionally, the opacity of algorithmic decision-making processes further alienates workers, as they cannot negotiate or contest decisions in the same way they would with a human manager.

We expect these relationships to be stronger in accordance with the extent to which individuals perceive the presence of AM practices in their work environment, i.e. perceived intensity of AM. In summary, we propose the following:

Hypothesis 1: The perceived intensity of AM has a negative relationship with employees' perceived social exchange relationship.

Hypothesis 2: The perceived intensity of AM has a positive relationship with employees' perceived economic exchange relationship.

Employee Engagement

Studying employee engagement in the context of AM is crucial as it directly relates to both individual well-being and organizational outcomes (Peccei & Van De Voorde, 2019). Employee engagement encompasses three dimensions: vigor, dedication, and absorption (Demerouti et al., 2001; Schaufeli & Bakker, 2004). Vigor refers to energy, determination, persistence, and mental strength; dedication to enthusiasm, inspiration, pride, and willingness to face challenges; and absorption to focus and mental involvement.

When employees perceive that their organization values social exchange, they tend to reciprocate with supportive behaviors beneficial to the organization (Eisenberger et al., 1990). This mutual investment enhances employees' sense of connection and trust, creating conditions that naturally encourage them to be more engaged and motivated to go beyond basic job requirements. Numerous fundamental studies have demonstrated that robust social exchange relationships are linked to enhanced employee engagement (e.g., Wayne et al., 1997; Shore et al., 2006). Consequently, we propose the following:

Hypothesis 3: Employees' perceived social exchange relationships have a positive relationship with employee engagement.

While research investigating the connection between economic exchange relationships and employee engagement is limited, we rely on the literature on psychological contracts to inform our hypotheses (Tomprou & Lee, 2022). Psychological contracts, viewed within the framework of SET, resemble exchange relationships (Rousseau, 1995; Cropanzano & Mitchell, 2005). Transactional psychological contracts, akin to economic exchanges, focus on short-term financial gains and material outcomes, with limited mutual involvement (Robinson et al., 1994; Rousseau & McLean Parks, 1993). Research suggests that transactional psychological contracts often result in negative outcomes, such as reduced engagement and commitment (Grimmer & Oddy, 2007; Rousseau, 1995). Diminishing transactional aspects in psychological contracts can benefit organizations, as employees with transactional contracts exhibit lower commitment to objectives (Millward & Hopkins, 1998; Grimmer & Oddy, 2007). Applying this logic to economic exchange, we propose:

Hypothesis 4: Employees' perceived economic exchange relationships have a negative relationship with employee engagement.

Line Manager's Social Distance as a Moderator

In an AM system, human line managers are often overlooked despite their crucial role in HRM implementation (Gilbert et al., 2011). Beyond implementation, these managers can adapt HR practices to their leadership style and workplace environment, contributing to variation in HR processes across organizations (Vermeeren, 2014; Kehoe & Han, 2020). This is particularly true in AM work environments, given that the presence of a human manager is essential for compensating for the potential limitations of a partly or purely automated work environment. In practice, pure automation, where algorithms entirely take over managerial functions, appears to be rare. Even when technically feasible, human managers still uphold a crucial role in the managerial circuit, particularly for the interpersonal and empathetic aspect, an area that researchers have called for further investigation into (Duggan et al., 2020; Angrave et al., 2016).

A line manager's social distance is a key factor that could influence the relationship between AM and exchange relationships. This distance, indicating the level of intimacy and social contact between leaders and their followers (Antonakis & Atwater, 2002), affects trust development (Shamir, 1995). In an AM system, a socially close line manager, being approachable and relatable, fosters trust through personalized and confidence-building communication via direct interactions with employees (Yagil, 1998), thus compensating for the inherent lack of employee-centeredness in the AM work environment. Conversely, a socially distant line manager does not compensate for, or might even further exacerbate the perceived impersonality of AM due to larger spans of control and a lack of empathy with followers and demonstration of individual consideration (Shamir, 1995; Antonakis & Atwater, 2002). While both are rooted in SET, the social distance between a line manager and employee differs significantly from the exchange relationships between the employer and employee. Exchange relationships emphasize the interaction between the employee and the employer, highlighting exchanges of tangible and intangible resources. By contrast, the social distance of a leader focuses on the emotional and psychological closeness between leader and followers, in our case, the line manager and the employee. Thus, while employees may perceive the relationship with the employer as transactional, they may still perceive their line manager as socially close, or vice versa.

In a partially automated work environment (Wood, 2021), employees receive algorithmic direction from the AM system, while feedback and decisions regarding payment and termination are typically provided by human managers. The supervision of human managers remains prominent, limiting workers' ability to override automated instructions (Wood, 2021). A socially close line manager interprets digital directives within a human context, offering personalized guidance and buffering potential alienation. Conversely, a socially distant leader may reinforce digital instructions, accentuating the impersonal nature of automation. In a fully automated work environment (Wood, 2021), employees receive direction, evaluation, and discipline directly from the AM system. Despite this, managers remain essential. For instance, Amazon warehouse managers serve as intermediaries in the AM process, offering human interaction and personalized guidance that algorithms alone cannot provide (Gent, 2018). A socially close leader offers contextual insights and constructive feedback, building trust. Conversely, a socially distant leader solely relies on algorithms, risking distrust by lacking personal engagement (Duggan et al., 2020).

Hypothesis 5a: The relationship between the intensity of AM and the perceived social exchange relationship is moderated by a leader's social distance, such that the relationship is less negative in the presence of a socially close leader, compared to a socially distant leader.

Hypothesis 5b: The relationship between the intensity of AM and the perceived economic exchange relationship is moderated by a leader's social distance, such that the relationship is less positive in the presence of a socially close leader, compared to a socially distant leader.

We focus on the indirect relationship between AM and employee engagement due to the complex interplay of the exchange relationships and the leader's social distance within AM, as evidenced by inconsistent findings (e.g., Braganza et al., 2021a; Braganza et al., 2021b). This approach of refraining from formulating hypotheses on direct relationships aligns with a recent study on AM and employee engagement (Parent-Rocheleau et al., 2023), with a focus on exploring the indirect effect of AM on employee engagement through social and economic exchanges.

Hypothesis 6: Social exchange serves as a mediator in the indirect relationship between the perceived intensity of AM and employee engagement.

Hypothesis 7: Economic exchange serves as a mediator in the indirect relationship between the perceived intensity of AM and employee engagement.

By delving into the explanatory mechanisms and boundary conditions, our study captures the multifaceted nature of the AM work environment, as illustrated in Figure 0-1.

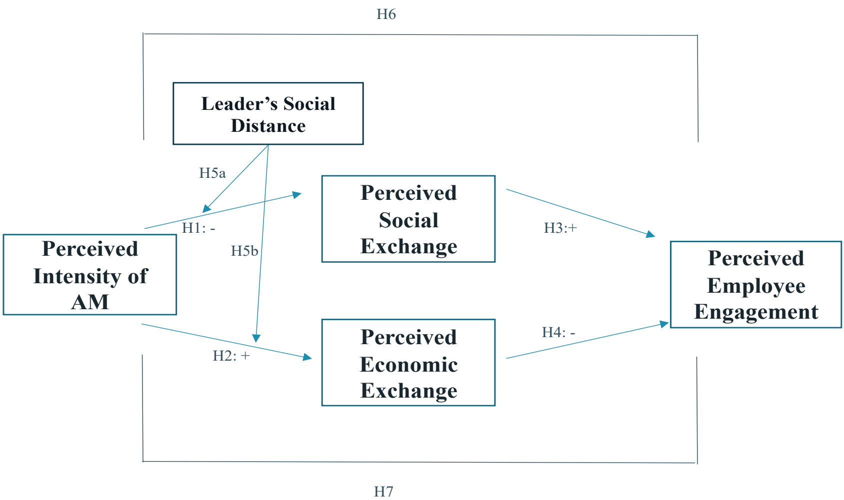

Figure 0-1 Conceptual model

Study 1: Methods

Study 1 Survey Study

Participant Characteristics and Procedure:

Data were collected over a ten-month period, from August 2022 to April 2023, using convenience sampling. The sample comprised 304 full-time workers recruited from online social platforms. Participants were required to have professional proficiency in English and be employed in a standard organization. The survey link was distributed on LinkedIn and Facebook, with researchers and two master's students sharing it in various groups to ensure diverse representation across professions and locations.

The diverse sample included participants from various continents: 54% from Europe, 28% from Asia, 11% from Anglo-America and Oceania, 5% from Africa, and 2% from Latin America. Across sectors, participants were distributed as follows: 1% agriculture and reclamation, 13% industry and construction, 14% service to companies, 13% IT, 10% education, 9% R&D and consulting, 7% retail, and 33% other service sector categories.

Respondents averaged 32.7 years old (s.d. = 9.7 years, N = 274 due to missing data), with 43% reporting 1-3 years of work experience. Among them, 40% were male, 44% lacked programming experience, and 81% held a bachelor's degree or equivalent. Professional employees made up 45% of the sample, while general management comprised 24%.

Participants received an information letter and consent form detailing the study's purpose, structure, and data handling procedures. Only those who provided consent were permitted to take the survey. The study obtained approval from the university's Social and Societal Ethics Committee.

The survey questionnaire consisted of items on employee engagement, algorithmic management, social and economic exchange, and demographic information. We pre-tested the survey with five experts from academia and industry and a pilot study involving 32 participants from the researchers' network. Additionally, an attention check question was included to filter out participants who were not paying adequate attention to the survey.

Measures

All the multi-item scales and the definition of AM used in this survey study can be found in the Appendix.

Algorithmic management. Due to the absence of a validated scale for measuring AM during the data collection period, a 12-item scale was developed based on the conceptual work of Parent-Rocheleau & Parker (2022) and Kellogg et al. (2020). The scale aims to assess the intensity of AM in the workplace, encompassing six key functions that reflect the three control mechanisms: monitoring, goal-setting, performance management, scheduling, compensation, and job termination. The responses were on a six-point scale (1 = No, 2 = I don't know or I'm not sure, 3 = Yes, rarely, 4 = Yes, sometimes, 5 = Yes, often, 6 = Yes, always.).

In this study, the "intensity" of AM is operationalized as the cumulative presence of AM practices in the workplace. We created a formative index to quantify the intensity of experienced AM practices, by summing participants’ responses to each item related to the intensity of AM (0 for “no” and “I don’t know”; 1 for “yes”). The resulting index ranged from 0 to 12, with 0 indicating the absence of AM practices at work and 12 representing the presence of all 12 AM practices.

The formative index was developed due to its recognition that each item pertaining to AM signifies an alternate method of accomplishing the same objective and serves as a “cause” of the construct (Jiang et al., 2012). This perspective is supported by established literature, which suggests that AM practices can vary widely and may not necessarily reflect a single underlying latent variable (Kellogg et al., 2020; Parent-Rocheleau & Parker, 2021; Wood, 2021). By treating each item as a separate causal indicator, the formative index captures the diverse dimensions and nuances of AM experiences and is less likely to introduce downward bias (resulting in underestimating the construct’s intensity) than Cronbach’s α (McNeish, 2018). More detailed descriptive statistics on this measure are available in the supplementary material.

Employee engagement. The employee engagement scale (UWES-9) (Schaufeli et al., 2006) was used in the survey with a 5-point scale ranging from 1 (strongly disagree) to 5 (strongly agree). The coefficient α was .88. We consider job engagement as a single construct due to high correlations among its dimensions, supported by existing studies (e.g., Straus et al., 2022; Parent-Rocheleau et al., 2023).

Social and economic exchange relationships. We used a combination of eight items from Shore et al. (2006) and Millward & Hopkins (1998) in the final questionnaire. The 5-point scale ranged from 1 (strongly disagree) to 5 (strongly agree). The coefficient α for the social exchange scale was .84, and the coefficient α for the economic exchange scale was .73.

Control variables. This study incorporated age and gender as control variables due to their recognized impact on employee engagement (Kim & Kang, 2017; Young et al., 2018). Age was treated as a continuous variable, while gender was categorized into binary forms (female and non-female). To ensure the reliability of our findings, we performed analyses using both the control variables and without them, following established best practices (Becker et al., 2016).

Study 1: Results

Given that Study 1 is cross-sectional and examines closely related constructs like exchanges and engagement, we took steps to mitigate the risk of common method variance (CMV). We used procedural remedies, such as ensuring respondent anonymity and using different response formats for predictor and criterion variables, to reduce potential bias. Additionally, we conducted statistical tests, including Harman's single-factor test (Podsakoff et al., 2003), which confirmed that CMV was not a significant concern, as no single factor accounted for the majority of variance.

Confirmatory Factor Analyses (CFAs).

Confirmatory factor analyses (CFAs) conducted in Stata confirmed the discriminant validity of the measurement items, showing that they loaded onto their respective constructs. A three-factor model comprising social exchange relationships, economic exchange relationships, and employee engagement was tested, with fit assessed using common indices and thresholds (Bentler, 1990): RMSEA (<.08); CFI (>.90); TLI (>.90); and SRMR (<.08). Results showed good fit for the three-factor model (RMSEA=.06; CFI=.94; TLI=.93; and SRMR=.05). The competing two-factor measurement models combining (1) social exchange and employee engagement (RMSEA=.11; CFI=.80; TLI=.77; and SRMR=.08), (2) employee engagement and economic exchange relationships (RMSEA=.09; CFI=.87; TLI=.85; and SRMR=.07), and (3) social and economic exchange relationships (RMSEA=.09; CFI=.85; TLI=.83; and SRMR=.08) did not fit the data well. The one-factor model, which assumed all items measured a single latent factor, exhibited the poorest fit to the data (RMSEA=.12; CFI=.74; TLI=.70; and SRMR=.09). These results supported the distinctiveness and reliability of the measurement items, indicating that they measure separate constructs as intended.

Descriptive Statistics and Correlations.

The means, standard deviations, and zero-order correlations among the variables are presented in Table 0-1 Means, standard deviations, correlations, and scale reliabilities (Study 1). Economic exchange was significantly positively associated with AM ($r=.11$, $p<.1$), whereas employee engagement was significantly negatively associated with economic exchange ($r=-.42$, $p<.01$) and significantly positively associated with social exchange ($r=.50$, $p<.01$).

Table 0-1 Means, standard deviations, correlations, and scale reliabilities (Study 1)

Variables	Mean	SD	AM intensity	Economic exchange relationship	Social exchange relationship	Employee engagement
AM intensity	3.73	3.90	NA			
Economic exchange relationship	2.75	.87	.11*	(.73)		
Social exchange relationship	3.47	.91	.02	-.36***	(.84)	
Employee engagement	3.47	.74	-.04	-.42***	.50***	(.88)

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

N=304. Scale reliabilities are on the diagonal in parentheses. Range for AM index is [0,12]; range for economic exchange, social exchange, and employee engagement is [1,5]

Hypothesis Testing

Hypotheses 1 to 7 were analyzed using structural equation modeling (SEM) in Stata. Given the theoretical relatedness between social and economic exchange, covariance between the two constructs was allowed. Bootstrapping was employed to estimate the confidence intervals for indirect effects, as it provides more accurate estimates for non-normally distributed data (Hayes, 2015). Following best practices, we executed the analyses both with and without control variables (Becker et al., 2016; Bernerth & Aguinis, 2016). Both models showed a good fit: for model without controls: RMSEA=.00; CFI=1.00; TLI=1.03; and SRMR=.01; for model with controls: RMSEA=.00; CFI=1.00; TLI=1.1; and SRMR=.00.

In the absence of control variables, the results (Figure 2) demonstrated no significant association between AM and social exchange ($\beta = .02$, $p > .10$), leading to the rejection of Hypothesis 1. Conversely, there was a significant positive correlation between AM and economic exchange ($\beta = .11$, $p < .05$), supporting Hypothesis 2. Furthermore, a significant positive relationship existed between social exchange and employee engagement ($\beta = .40$, $p < .001$), supporting Hypothesis 3, while a significant negative relationship was observed between economic exchange and employee engagement ($\beta = -.28$, $p < .001$), supporting Hypothesis 4. Upon including age and gender as controls (Table 2), we discovered that age is significantly associated with economic exchange ($\beta = -0.14$, $p < 0.05$), and the previously significant relationship between economic exchange and AM became marginally significant ($\beta = 0.09$, $p = 0.08$).

Hypothesis 6 and Hypothesis 7 predicted that social and economic exchange mediate the indirect relationship between the AM and employee engagement. To test these hypotheses, we calculated the indirect effect. The result was not significant ($\beta = -.01$, $p > .1$), hence Hypotheses 6 & 7 were rejected.

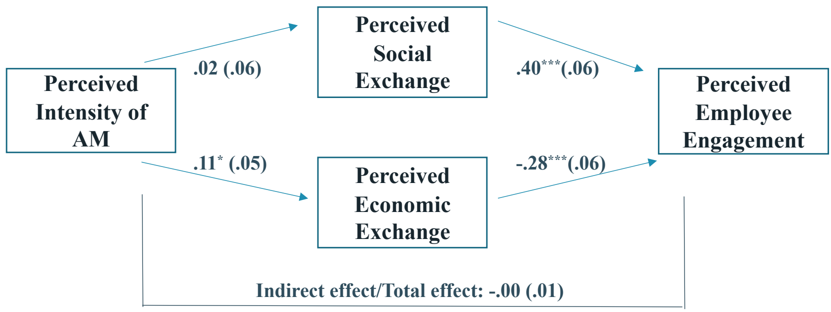

Figure 0-2 Results of parameter estimations of the structural model of Study 1 (without controls). Note: + p<.1, * p < .05, * * p < .01, * * * p < .001. Standard errors from 5,000 bootstrapped estimates in parentheses. N=304

Table 0-2 SEM Estimates of the mediation role of social economic exchange relationship between AM and employee engagement with age and gender (male =1) as controls (Study 1)

	Social exchange		Economic exchange		Job engagement	
	Model 1		Model 2		Model 3	
	β	SE	β	SE	β	SE
Age	0.03	(0.07)	-0.14*	(0.06)	0.19***	(0.04)
Male	0.07	(0.06)	0.05	(0.06)	0.02	(0.05)
Social exchange					0.40***	(0.06)
Economic exchange					-0.25***	(0.06)
AM intensity	0.03	(0.01)	0.09+	(0.01)		

*+ p<.1, * p < .05, * * p < .01, * * * p < .001 (two-tailed tests).*

N=304. Standard errors produced from 5,000 bootstrapped estimates.

	Social exchange		Economic exchange		Job engagement	
	Model 1		Model 2		Model 3	
	β	SE	β	SE	β	SE
Age	0.03	(0.07)	-0.14*	(0.06)	0.19***	(0.04)
Male	0.07	(0.06)	0.05	(0.06)	0.02	(0.05)
Social exchange					0.40***	(0.06)
Economic exchange					-0.25***	(0.06)
AM intensity	0.03	(0.01)	0.09+	(0.01)		

*+ p<.1, * p < .05, * * p < .01, * * * p < .001 (two-tailed tests).*

N=304. Standard errors produced from 5,000 bootstrapped estimates.

Study 2: Methods

Study 2 Experimental Vignette Study

Study 2 expanded upon Study 1 in four ways. First, it directly investigated causal relationships by manipulating AM conditions (zero, low, high), aiming to replicate and establish causal references to the cross-sectional correlational findings of Study 1. Second, an extended model incorporating the leader's social distance was employed to test Hypotheses 5a and 5b. Third, focusing on the US population, Study 2 leveraged its status as a prominent and diverse labor market where AM is widely adopted across industries (Radu, 2019). This familiarity with AM among participants increased the likelihood of empathizing with the research material. Fourth, the larger sample size in Study 2 (410 compared to 304) improves the statistical power of the study, enabling more robust analyses.

Participant Characteristics and Procedure

The vignette data consisted of 410 US-based employees recruited from Prolific, an online platform known for its data quality equivalent to various work settings (Miron-Spektor et al., 2018; Wu et al., 2018). The sample aimed to mirror the broader US population in terms of gender (50% female), age (mean=44.62, SD=14.82), and ethnicity (74.15% identified as White). Eligible participants were full-time employees in standard US organizations other than Prolific. Participants represented various sectors similar to Study 1 sample: 1% agriculture and reclamation, 10% industry and construction, 11% service to persons, 10% IT, 12% welfare care, 11.5% R&D and consulting, 7% retail, and 37.5% other service sector categories. Work experience varied, with 33% reporting 1-3 years and 56% reporting over 5 years. Additionally, 63% held a bachelor's degree or above. Most respondents were in executive or senior management roles, comprising 54% of the sample, with general management as the largest job function at 15%.

The experimental vignette design involved randomly presenting participants with a hypothetical scenario in which they were asked to imagine working under either zero, low, or high conditions of AM and a socially close or distant leader. The design of the vignettes went through several iterations based on feedback from management scholars, industry practitioners, and students during the pre-test phase. The pilot study involving 30 participants was conducted to verify the effectiveness of the manipulation (cf. infra).

Participants received £2 as compensation for completing the survey, with a median completion time of around 14 minutes. The survey instrument included an instructional manipulation check (Oppenheimer et al., 2009) to ensure data reliability. Multiple attention check questions were incorporated throughout the survey to identify and filter out inattentive participants (i.e., participants who failed more than one attention check question), thereby improving the overall quality of the data (Hauser & Schwarz, 2015).

Manipulation

We employed a two-by-three between-person experimental design that manipulated two levels of a leader's social distance (low vs. high) and three levels of AM (zero, low, high). Participants first read an introduction about working in the marketing department at TitanTech, an imaginary multinational consumer electronics company, before presented with one of three AM scenarios. In the high AM scenario, participants encountered high-intensity AM, where a computer program determined task assignment, performance evaluation, and pay. The low AM scenario involved low AM intensity, with tasks assigned by a computer program while a human manager managed performance evaluation and pay. In the zero AM scenario, the management process was entirely human driven, involving guidance and evaluation by a human manager, with pay determined based on this assessment.

We manipulate the distance between leaders and employees per Antonakis and Atwater's (2002) definition. In the distant leader scenario, participants encountered a manager who was absent physically, communicated less, and was not easily accessible for support or encouragement. Conversely, in the close leader scenario, the manager was physically present, engaged in conversations, and created a comfortable environment for employees to seek assistance and guidance.

Participants found the vignette realistic, giving it an average rating of 3.63 on a scale of 1 to 5 (standard deviation: 1.13). We conducted manipulation checks in a pilot sample (n = 33) from Prolific to ensure the manipulation check questions did not introduce unintended effects. Respondents rated the level of AM and a leader's social distance after reading the assigned scenario. Perceived algorithmic decision-making was significantly higher in the high AM condition compared to the low and zero conditions ($\chi 2 = 14.18$, df = 2, p=.00), and leader approachability was higher in the close condition compared to the distant condition (z= 4.07, p<.00, $\chi 2$ = 13.60, df = 1, p=.000), confirming the validity of the manipulations.

Measures

The multi-item scales used in this study can be found in the Appendix.

Employee engagement. Employee engagement was measured using UWES-3 (Schaufeli et al., 2019) in the vignette experiment to assess immediate reactions following vignette exposure. Considering the vignette's length, we chose this shorter engagement survey still akin to UWES-9 to alleviate participant fatigue, frustration, and potential non-participation due to perceived lengthiness, all while maintaining consistency and similarity with UWES-9 (Schaufeli et al., 2019). This approach aimed to ensure reliable data collection. The coefficient α was .90.

Exchange relationships. As in Study 1, we used a combination of items from Shore et al. (2006) and Millward and Hopkins (1998) to measure the type of exchange between workers and employers. The coefficient α for economic exchange was .82 and .90 for social exchange relationship.

Other measures and control variables. Two manipulation check questions were included in the pilot study. As a robustness check, we also estimated models with age and gender as additional control variables.

Study 2: Results

Confirmatory Factor Analyses (CFAs)

We performed a three-factor confirmatory factor analysis (social exchange, economic exchange, employee engagement) and assessed its fit using commonly used fit indices and thresholds (Bentler, 1990): RMSEA (<.08); CFI (>.90); TLI (>.90); and SRMR (<.08). The results indicated that the three-factor model fit the data well (RMSEA=.05; CFI=.98; TLI=.98; and SRMR=.03). On the other hand, the competing two-factor measurement models combining (1) social exchange and employee engagement (RMSEA=.14; CFI=.88; TLI=.85; and SRMR=.05);

(2) employee engagement and economic exchange (RMSEA=.15; CFI=.87; TLI=.83; and SRMR=.09); and (3) social and economic exchange (RMSEA=.14; CFI=.88; TLI=.84; and SRMR=.09) did not fit the data well. Finally, the one-factor model, which assumed all items measured a single latent factor, exhibited the poorest fit to the data (RMSEA=.19; CFI=.78; TLI=.73; and SRMR=.10). These results provided evidence for the distinctiveness and reliability of the measurement items.

Descriptive Statistics

Table 0-3 provides an overview of the descriptive statistics, including means, standard deviations, and zero-order correlations among the variables. There was a significant positive relationship between economic exchange and AM ($r = .11$, $p < .05$). In contrast, social exchange showed a significant negative association with AM ($r = -.11$, $p < .05$). Furthermore, employee engagement demonstrated a significant negative correlation with economic exchange ($r = -.52$, $p < .01$), a significant positive correlation with social exchange ($r = .70$, $p < .01$), and a significant negative correlation with AM ($r = -.14$, $p < .01$).

Table 0-3 Means, standard deviations, correlations, and scale reliabilities (Study 2)

Variables	Mean	Std. Dev.	AM	Leader social distance	Economic exchange	Social exchange	Employee engagement
AM	2.00	.82	NA				
Leader social distance	.50	.50	-.00	NA			
Economic exchange	3.40	.92	.11**	.23***	(.82)		
Social exchange	3.37	.97	-.11**	-.30***	-.52***	(.90)	
Employee engagement	3.58	1.02	-.14***	-.23***	-.52***	.70***	(.90)

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

N=410; Scale reliabilities are on the diagonal in parentheses. Range for AM is [1,3], leader social distance [0,1], economic exchange [1,5], social exchange [1,5], employee engagement [1,5]

Hypotheses Testing

As in Study 1, the analysis of Hypotheses 1 to 7 was conducted using structural equation modeling (SEM) in Stata. We conducted analyses with and without control variables, adhering to best practices (Becker et al., 2016; Bernerth & Aguinis, 2016). Both models showed consistent moderating and mediating results. For brevity, we present results without controls here, while regression results with age and gender as controls are available in the supplementary analysis. Our model exhibited good fit: RMSEA = .00; CFI = 1.00; TLI = 1.00; and SRMR = .02. The findings from Model 1 (Table 4) demonstrated a significant negative relationship between high AM and social exchange (β = -.54, $p < .01$) when compared to the zero scenario (zero AM). In Model 2 (Table 0-4), the results indicated a significant positive relationship between high AM and economic exchange (β = .34, $p < .05$) compared to the baseline scenario of zero AM. The low AM scenario did not significantly differ from the zero AM scenario for both social and economic exchange. These results partly supported Hypotheses 1 and 2.

For Model 3 (Table 0-4), we examined the relationship between AM, social exchange, economic exchange, and employee engagement. The results from Model 3 (Table 0-4) revealed a significant positive relationship between social exchange and employee engagement (β = .63, $p < .001$). Conversely, economic exchange was significantly negatively related to employee engagement (β = -.23, $p < .001$). These findings supported Hypotheses 3 and 4.

We conducted moderated regression analyses to examine Hypotheses 5a and 5b, as demonstrated in Model 1 (Table 0-4) and Model 2 (Table 0-4). We identified significant positive interaction effects between the leader's social distance and AM at the 5%-significance level in Model 1 and significant negative interaction at the 10%-significance level in Model 2. These findings are illustrated in Figure 0-3.

Table 0-4 SEM Estimates of the mediation role of social economic exchange relationship between AM and employee engagement of Study 2 (without controls)

	Social exchange		Economic exchange		Employee engagement	
	Model 1		Model 2		Model 3	
	β	SE	β	SE	β	SE
AM Intensity=low	-0.22+	(0.13)	0.20	(0.15)		
AM Intensity=high	-0.54**	(0.17)	0.34*	(0.16)		
Leader social distance=far	-0.89***	(0.15)	0.63***	(0.15)		
AM Intensity=low X Leader social distance=far	0.38+	(0.21)	-0.41+	(0.22)		
AM Intensity= high X Leader social distance=far	0.57*	(0.23)	-0.19	(0.21)		
Social exchange					0.63***	(0.04)
Economic exchange					-0.23***	(0.04)
N	410		410		410	

*+ p<.1, * p < .05, * * p < .01, * * * p < .001 (two-tailed tests).*

N=410; Standard errors from 5,000 bootstrapped estimates in parentheses. Leader social distance is coded 1=far, 0=close=reference category. AM Intensity is coded as 1=Zero=reference category, AM, 2=Low AM, 3=High AM. Reference category for the interaction effect is AM Intensity=zero and social distance=close.

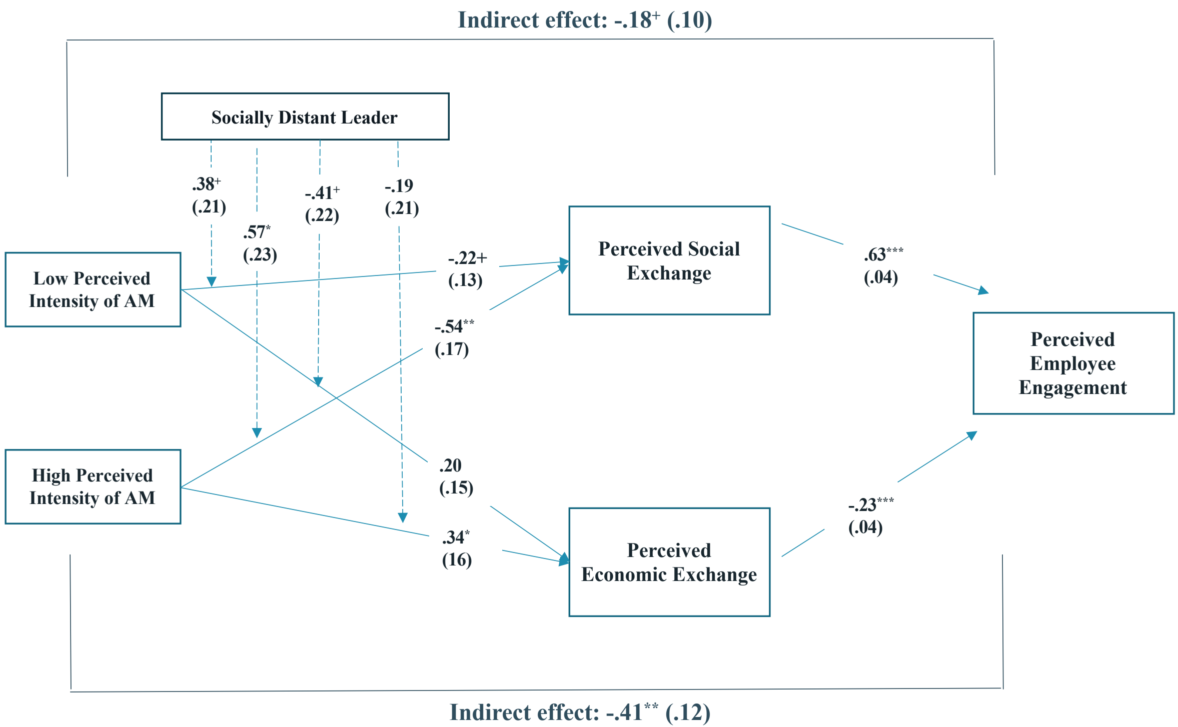

Figure 0-3 Results of parameter estimations of the structural model of Study 2 (without controls). Note: + p<.1, * p < .05, * * p < .01, * * * p < .001. Standard errors from 5,000 bootstrapped estimates in parentheses. N=410

To further explore the interaction effect, we followed Aiken and West's (1991) guidance and plotted the relationship between AM and the social and economic exchange relationships, considering two conditions: a socially (1) close and (2) distant leader.

The interaction plot depicted in Figure 0-4 demonstrates that in a zero or low AM work environment, a socially close leader contributed to significantly higher social exchange relationships in comparison to a socially distant leader ($p<.001$ for the zero AM scenario; $p<.01$ for the low AM scenario). In a high AM work environment, a socially close leader did not contribute to significantly higher levels of social exchange relationships than a socially distant leader ($p=.07$). Levels of social exchange in the high AM condition with a distant leader were as low as in the zero AM-distant leader and low AM-distant leader condition. These findings partly supported Hypothesis 5a, confirming the buffering effect of the leader's social distance in the low AM condition but not in the high AM condition. The results also showed that for social exchange, the control condition (i.e., no steering at all – nor by a leader nor by AM – or *laissez-faire, laissez passer*) can be as bad as a situation with high AM, which was not in line with the expectations.

The interaction plot depicted in Figure 0-5 demonstrated that when in a low AM work environment, a socially close leader did not contribute to significantly lower economic exchange relationships in comparison to a socially distant leader ($p=.17$). In a zero or high AM work environment, however, a socially close leader contributed to significantly lower levels of economic exchange relationship than a socially distant leader ($p<.001$ for the zero AM scenario; $p<.01$ for the high AM scenario). These results partly supported Hypothesis 5b, confirming the buffering effect of the leader's social distance in the high AM condition but not in the low AM condition. Here, as well, and contradictory to the expectations, the control condition with no AM and a distant leader showed the same high level of economic exchange as the AM conditions with a distant leader, which was not in line with our expectation.

Lastly, to examine the (conditional) indirect effect of AM intensity on employee engagement through social and economic exchange relationships, we followed the path analytic framework outlined by Edwards and Lambert (2007). We utilized bootstrap confidence intervals to test for the significance of the indirect effect, using 5,000 resamples (Hayes, 2009; Preacher & Hayes, 2008). The conditional indirect effect of low and high AM on employee engagement with a socially close leader showed significant negative effects (β = -.18, 95% CI [-.38, .01] for low AM, β = -.41, 95% CI [-.65, -.17] for high AM) (Table 0-5). These results supported Hypotheses 6 and 7.

Table 0-5 Path analytic results for employee engagement via social and economic exchange relationships of Study 2 (without controls)

		First stage				Second stage				Indirect effects	
Outcome at values of the moderator	**AM intensity**	**PMX1**	**(SE)**	**PMX2**	**(SE)**	**PYM1**	**(SE)**	**PYM2**	**(SE)**	**PYMPMX**	**[95% CI]**
Unconditional	low AM	-.03	(.11)	-.00	(.11)					-.02	[-.19, .15]
	high AM	-.26*	(.12)	.24*	(.11)	.62***	(.04)	-.22***	(.04)	-.21*	[-.40, -.03]
Close leader	low AM	-.22+	(.13)	.20	(.15)					-.18+	[-.38, .01]
	high AM	-.54**	(.17)	.34*	(.16)	.62***	(.04)	-.22***	(.04)	-.41**	[-.65, -.17]
Far leader	low AM	.16	(.16)	-.21	(.16)					.14	[-.10, .38]
	high AM	.03	(.16)	.15	(.14)	.62***	(.04)	-.22***	(.04)	-.01	[-.25, .22]

*+ p<.1, * p < .05, * * p < .01, * * * p < .001 (two-tailed tests).*

Note: n = 410 individuals. PMX1 = Path from X (AM intensity) to M1 (social exchange). PMX2 = Path from X (AM intensity) to M2 (economic exchange). PYM1 = Path from M1 (social exchange) to Y (employee engagement). PYM2 = Path from M2 (economic exchange) to Y (employee engagement). PYMPMX = Indirect effect of X (AM intensity) on Y (employee engagement) via M (social and economic exchange). Unstandardized regression coefficients (b) are reported with SEs in parentheses. 95% bootstrap confidence intervals in square brackets. Bootstrap sample size = 5,000.

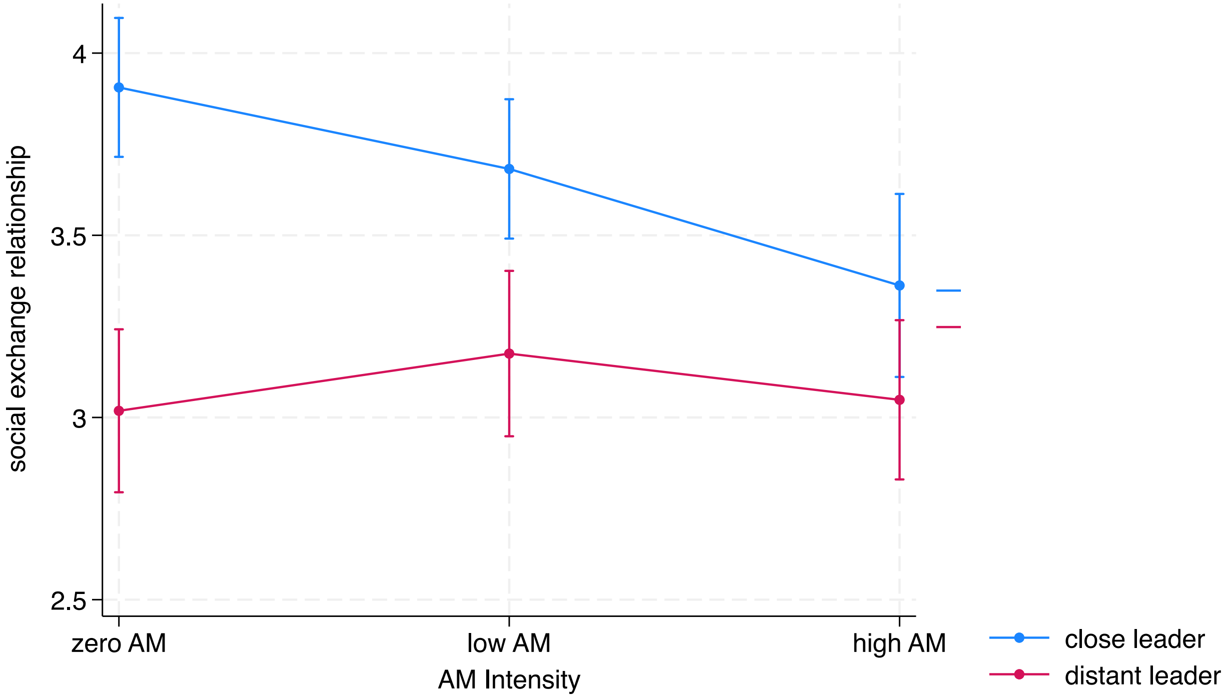

Figure 0-4 Moderating effect of the leader's social distance on the relationship between AM and social exchange relationship with 95% confidence intervals (without controls)

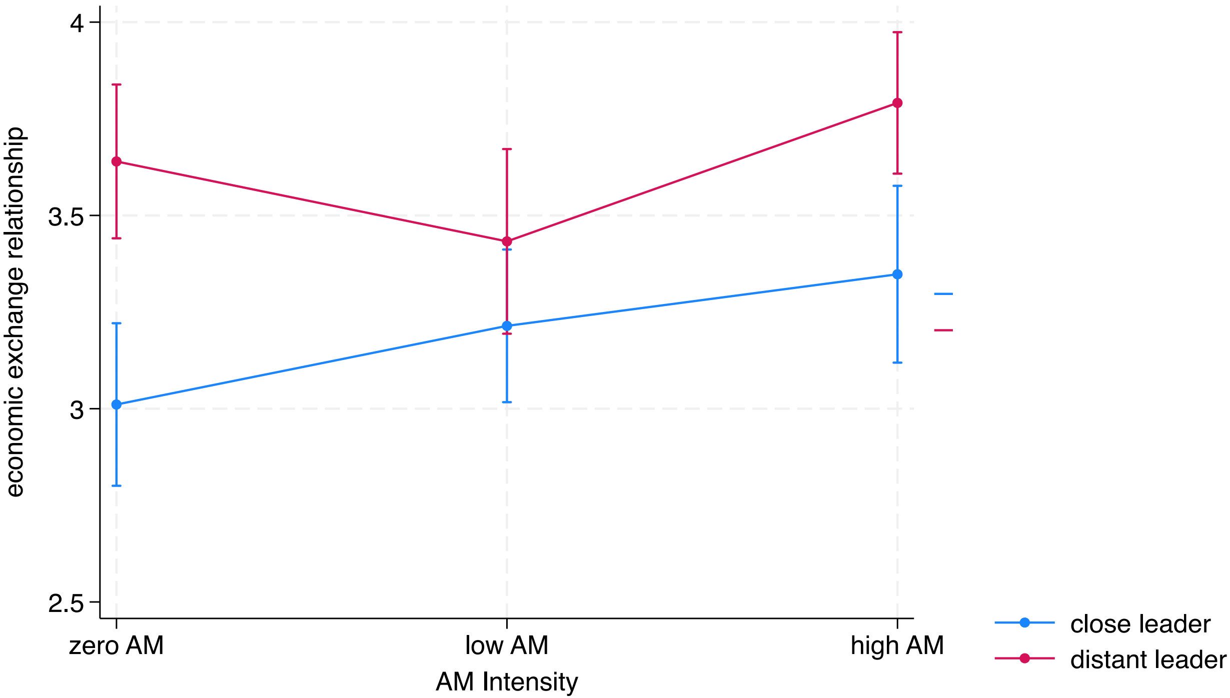

Figure 0-5 Moderating effect of the leader's social distance on the relationship between economic exchange and AM with 95% confidence intervals (without controls)

Supplementary Analyses for Robustness

We tested robustness and sensitivity of our results through additional analyses. Detailed analysis results are provided in the supplementary material. Firstly, in Study 1, we examined the relationships for the three AM subdimensions separately. Results for economic exchange are mainly driven by algorithmic direction, which seem to be most prevalent in the workplace. Secondly, regression results from Study 1 with the three engagement subdimensions (vigor, dedication and absorption) as dependent variables aligned with mediating results using the single construct approach. Thirdly, we treated the formative index of AM in Study 1 as a three-category categorical variable, akin to Study 2. This method yielded mediating results consistent with those from treating AM as a formative index.

General Discussion

Despite the extensive application of AM and concerns about its impact on worker well-being, empirical research in traditional work settings is scarce. In this paper, we synthesized literature on AM, social exchange theory (SET), and leader's social distance to investigate AM's well-being influence at work.

In Study 1, we surveyed a diverse sample to gauge employees' perceptions of AM intensity and its relationship with engagement. We found that AM promotes economic exchange, leading to decreased engagement. Social exchange did not mediate the relationship between AM and engagement. To validate and deepen our understanding, we conducted Study 2 with a US sample using experimental vignettes. Here, we confirmed the mediating role of social and economic exchange and provided evidence for the moderating effect of leader's social distance.

In Study 1, we did not find a significant AM-social exchange relationship. In Study 2, respondents in the high AM condition showed significantly lower social exchange, regardless of leader distance, compared to those with a close leader in the zero AM condition. Moreover, for the zero and low AM conditions in study 2, we saw that both lower and higher social exchange are possible and that the exact level of social exchange is dependent upon the presence of a distant or close leader. Although contradictory at first sight, we argue that these findings are reconcilable through the theoretical lens of SET. The discrepancy can be explained by the social distance between leaders and employees which influences the nature of the AM-exchange relationship link. The absence of social distance measurement in Study 1 may have contributed to the lack of relationship between AM and social exchange, as respondents in real-life zero and low AM conditions could have had either distant or close leaders. Additionally, Study 1 had fewer high AM respondents compared to Study 2 (mean of AM is 3.73 out of 12 in Study 1, while in Study 2, the scenarios were evenly and randomly distributed among respondents), potentially diluting the observed differences.

Our methodological approach, combining surveys and experiments, provided complementary insights. Despite seeming discrepancy, this triangulation enriches our understanding of AM's impact on engagement in traditional work settings.

Theoretical Contribution

Our studies contribute significantly to the theoretical understanding of how AM relates to employee engagement within standard organizational settings. Firstly, by demonstrating the mediating role of exchange relationships in the AM-employee engagement link, we elucidate the mechanism connecting AM and employee engagement, extending research on SET. Notably, the intensity of AM is negatively associated with social exchange and positively associated with economic exchange, which is linked to decreased employee engagement. The absence of a direct effect underscores the importance of considering the underlying mechanisms, such as exchange relationships, when examining the AM-employee engagement relationship.

Despite limited studies on AM and employee engagement, Parent-Rocheleau et al. (2023) offered insights into such intricate indirect relationships by revealing the mediating role of job autonomy and job complexity. Our study rather emphasizes the social dimension, by grounding our study in SET to elucidate workplace relationships. The strength of our study also lies in the innovative approach to quantifying the intensity of experienced AM through the development of a formative index, which allowed for a comprehensive representation of various aspects of AM perceived by participants, avoiding downward bias.

Tomprou and Lee's (2022) vignette study provided insights into how individuals form psychological contracts with algorithmic agents. Previous research linked engagement and psychological contracts to social and economic exchange but lacked explicit employee perception measurement in these exchanges (Aselage & Eisenberger, 2003; Coyle-Shapiro & Conway, 2004). Critics have also pointed out the overreliance on vignettes in current AM research (Langer & Landers, 2021). To address these gaps, our Study 1 explored real-world social and economic exchanges, utilizing a diverse field study approach to examine these dynamics in various organizational contexts.

Secondly, we addressed Tomprou and Lee's (2022) call for nuanced research on the employee-employer relationship in AM by investigating leaders' social distance as a moderator. This approach integrates insights from leader distance literature, which explores the dynamics and outcomes of leader-follower distance (Antonakis & Atwater, 2002), into the context of AM. Considering that AM technologies redefine traditional hierarchies and interpersonal dynamics (Wood, 2021), understanding leaders' social distance becomes crucial. Study 2 revealed that leaders continue to influence social and economic exchanges, even in AM systems. Specifically, the impact of a leader's social distance on social exchange is more pronounced in scenarios with no or low AM but becomes insignificant in high AM scenarios. Similarly, while distant leaders have a stronger influence in zero or high AM environments on economic exchange, their impact diminishes with limited AM use. This highlights a nuanced relationship between a leader's social distance, the extent of AM implementation, and their effects on social and economic exchanges within the workplace. All in all, we can conclude that human managers are needed in AM settings, be it to increase perceptions of social exchange or decrease economic exchange.

While much of the research on AM's impact on employee wellbeing has focused on the gig economy (e.g., Möhlmann & Zalmanson, 2017; Toyoda et al., 2020), its growing use in standard organizations demands closer scrutiny. Unlike the gig economy's transactional, short-term nature (Duggan et al., 2020), standard workplaces involve stable employment and complex social dynamics that (re)shape how AM is experienced (Jarrahi et al., 2021). Our study contributes to the HRM research by uncovering how the exchange relationships associated with AM play out in traditional work environments, where its impact on social and economic exchanges and ultimately, employee engagement, presents both expected and nuanced differences from gig work contexts. This nuanced understanding reveals that AM in standard settings can have context-specific (e.g., leaders' social distance and intensity of AM) consequences that either reinforce or challenge traditional managerial roles and relationships. By addressing this gap, we offer a 'cautionary tale' for HR managers and organizations alike: AM's influence on engagement and wellbeing is far from uniform, and its effects are deeply intertwined with the presence of human leadership and social economic exchanges. This also aligns with calls for a broader investigation into the varying impacts of AM in HRM across different work settings (von Krogh, 2018) and enriches management scholars' understanding of how algorithmic and human management can coexist and be optimized in standard work environments.

Practical Implications

The results regarding the leader's social distance highlight the need for a proactive human-centric approach and a strategic and nuanced fusion of human and AI elements in the changing workplace. A leader's social distance remains crucial when the company implements AM at work at a low-intensity level, underscoring the pivotal role of human line leaders in shaping social and economic interactions. However, with increasing AM intensity, immediate leadership's impact on social exchange weakens, likely due to the overarching influence of AM systems. Nevertheless, a socially close leadership remains effective in mitigating negative effects on economic exchange in a highly intense AM environment. Organizations should, therefore, prioritize cultivating socially close leadership qualities, recognizing these nuances when integrating AM systems (Vrontis et al., 2022; Xiao et al., 2023). Investment in leadership training programs enhancing interpersonal skills, empathy, and effective communication is essential (Hauff et al., 2022). Leaders who can bridge the gap between technology-driven management and human interactions are vital for fostering a positive workplace environment in the future of work (Wiblen & Marler, 2021). Acknowledging the impact of a leader's social distance, organizations can strategically select, train, and support leaders who are adept at navigating the complexities of AM, ensuring a harmonious balance between automation and human connection in the workplace.

Limitations and Future Research Directions

Despite the contributions of this study, we acknowledge its limitations and encourage future research to address these shortcomings and explore fruitful avenues linked to our current findings. Firstly, although the use of self-report measures can be theoretically accounted for (it is employees' perceptions that drive their attitudes), potential common source bias might arise due to relying on employee self-reported data alone (Podsakoff et al., 2003). Future studies collecting data from diverse sources (e.g., introducing a more objective measure of AM intensity by relying on data from the organization or supervisor or supervisor's ratings of employee outcomes) could enhance the robustness of the findings. Secondly, longitudinal studies are essential to capture the long-term effects of AM on employee engagement, considering that employee responses might change Figure 0-1 as they adapt or resist AM practices (Kellogg et al., 2020).

The discrepancies between Study 1 and Study 2 may arise from variations between the global sample and the US sample. Examining contextual nuances such as national culture, regulatory environments, societal norms, job market conditions, and technology adoption can offer insights into AM's operation within specific environments and its diverse impacts on employee engagement. In addition, the study's focus on specific variables like social exchange, economic exchange, and the leader's social distance limits a holistic exploration of factors influencing employee engagement and the well-being in an AM work environment. Important aspects like organizational culture, individual differences such as personality traits and attitudes toward AI, and features of algorithmic systems such as transparency and fairness remain unexplored in this study and warrant further investigation. Furthermore, future studies can employ the newly validated scale (Parent-Rocheleau et al. 2024) to explore AM as latent variables and conduct field studies to cross-validate our proposed model. In Study 1, the significant negative association between age and economic exchange, along with the loss of significance in AM-economic exchange relationship when controlling for age, suggests that age influences the relationship between economic exchange and AM. Older employees may perceive economic exchanges differently or may be less influenced by AM practices compared to younger employees. Further research should explore this in depth. Also, while algorithmic direction correlates positively with economic exchange, other domains like discipline and evaluation do not. Investigating these differences can optimize AM for better exchange relationships and employee engagement.

In addition, we are cognizant of the ongoing debate within AM research regarding the full spectrum between automation and augmentation. While we focused on the extreme scenario where automation predominates, we encourage future research to explore the diverse degrees of human-machine interaction and delve into the paradox of automation versus augmentation (Raisch & Krakowski, 2020). Finally, while we tested the relevance of SET in an AM environment, further exploration across diverse contexts is warranted, including human-cobot interaction and organizational changes in various cultural settings.

Declaration of Interest Statement

There is no conflict of interest.

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Appendices

Measurement scales:

Algorithmic management (adapted based on Parent-Rocheleau & Parker (2022) and Kellogg et al. (2020)):

Algorithmic Direction	Goal Setting	Algorithms are used to assign tasks to me.
		Algorithms are used to set my performance targets.

	Scheduling	Algorithms are used to schedule my tasks.
		Algorithms are used to send nudges for suggested working times for me.
Algorithmic Evaluation	Monitoring	Tools are used to collect data on me and/or on my performance.
		Tools are used to report data on me and/or my performance to my employer or myself.
	Performance Management	Algorithms are used to carry out my performance ratings.
		Algorithms are used to display my performance ratings.
		Algorithms are used to provide automated performance feedback for me.
Algorithmic Discipline	Compensation	Algorithms are used to calculate how much I am paid.
	Job Termination	Algorithms are used to notify me of unsatisfying results.
		Algorithms are used to decide on the end of the employment relationship or collaboration.

Social and economic exchange: Shore et al. (2006) & Millward & Hopkins (1998)

My relationship with my organization is strictly economic: I work and they pay me. (economic exchange)

I don't care what my organization does for me in the long run, I only care about what it does right now. (economic exchange)

I only want to do more for my organization when I see that they will do more for me. (economic exchange)

My loyalty to the organization is defined by the terms of my contract. (economic exchange)

I don't mind working hard today. I know that eventually I will be rewarded by my organization. (social exchange)

My relationship with my organization is based on mutual trust. (social exchange)

I try to pay attention to the interests of my organization, because I know that my organization will take care of me. (social exchange)

I feel this organization reciprocates the effort put in by its employees. (social exchange)

Employee engagement 9-item (Schaufeli et al., 2006)

At my work, I feel bursting with energy.

At my job, I feel strong and vigorous.

I am enthusiastic about my job.

My job inspires me.

When I get up in the morning, I feel like going to work.

I feel happy when I am working intensely.

I am proud of the work that I do.

I am immersed in my work.

I get carried away when I am working.

Employee engagement 3-item (Schaufeli et al., 2019)

Working at TitanTech, I would feel bursting with energy.

Working at TitanTech, I would feel enthusiastic about the job.

Working at TitanTech, I would feel immersed in my work.

Vignette scenarios

Scenario 1: no AM + distant leader:

Imagine you work as a **marketing assistant** at TitanTech, **a multinational company** that produces and sells consumer electronics such as smartphones, laptops, and tablets. You work for the **marketing department**, which plays a crucial role in driving sales and increasing brand awareness for TitanTech. Your work involves contributing to marketing campaigns and assisting project managers with tasks such as campaign planning, content creation, and social media management. You have been a part of the marketing team for three years and have been compensated well for your contributions.

At TitanTech, you receive guidance for your job from your **manager**. Furthermore, your job performance will be evaluated by your manager, and your pay will be determined based on this assessment. Your manager does not come to your desk to check in and chat with you, and you feel uncomfortable asking for help and advice. Your manager is **distant** and does not often give you words of encouragement.

You begin your workday by attending a meeting with your **manager** to get informed about ongoing marketing campaigns and upcoming projects.

During your workday, you work on tasks assigned to you by your **manager** and upload the work to the company's database. Your manager uses this information to monitor how well you are doing and to help set goals for you to achieve.

Your **manager** gives you specific tasks to do based on information in the company's computer system and provides feedback on how well you are doing based on your performance.

Your **manager** decides on how much you get paid, lets you know if your work is not good enough, and decides when to end your job at the company.

Overall, your day as a marketing assistant is busy, challenging, and rewarding. You work collaboratively with other team members and use your creativity and analytical skills to contribute to successful marketing campaigns that increase sales and brand awareness.

Scenario 2: no AM + close leader:

Imagine you work as a **marketing assistant** at TitanTech, **a multinational company** that produces and sells consumer electronics such as smartphones, laptops, and tablets. You work for the **marketing department**, which plays a crucial role in driving sales and increasing brand awareness for TitanTech. Your work involves contributing to marketing campaigns and assisting project managers with tasks such as campaign planning, content creation, and social media management. You have been a part of the marketing team for three years and have been compensated well for your contributions.
At TitanTech, you receive guidance for your job from your **manager**. Furthermore, your job performance will be evaluated by your manager, and your pay will be determined based on this assessment. Your manager regularly visits your desk to check in and chat with you, and you feel comfortable asking for help and advice. Your manager is **approachable** and often gives you words of encouragement.

You begin your workday by attending a meeting with your **manager** to get informed about ongoing marketing campaigns and upcoming projects.

During your workday, you work on tasks assigned to you by your **manager** and upload the work to the company's database. Your manager uses this information to monitor how well you are doing and to help set goals for you to achieve.

Your **manager** gives you specific tasks to do based on information in the company's computer system and provides feedback on how well you are doing based on your performance. Your **manager** decides on how much you get paid, lets you know if your work is not good enough, and decides when to end your job at the company.

Overall, your day as a marketing assistant is busy, challenging, and rewarding. You work collaboratively with other team members and use your creativity and analytical skills to contribute to successful marketing campaigns that increase sales and brand awareness.

Scenario 3: low AM + distant leader:

Imagine you work as a **marketing assistant** at TitanTech, a **multinational company** that produces and sells consumer electronics such as smartphones, laptops, and tablets. You work for the **marketing department**, which plays a crucial role in driving sales and increasing brand awareness for TitanTech. Your work involves contributing to marketing campaigns and assisting project managers with tasks such as campaign planning, content creation, and social media management. You have been a part of the marketing team for three years and have been compensated well for your contributions.

At TitanTech, you receive guidance for your job from either your **manager** or a **computer program**. Furthermore, your job performance will be evaluated by either your manager or the computer program, and your pay will be determined based on this assessment. Your manager does not come to your desk to check in and chat with you, and you feel uncomfortable asking for help and advice. Your manager is **distant** and does not often give you words of encouragement.

You begin your workday by logging into a **computer program** to get informed about ongoing marketing campaigns and upcoming projects.

During your workday, you work on tasks assigned to you by a **computer program** and upload the work to the company's database. This system uses computer programs to monitor how well you are doing and to set goals for you to achieve.

Your **manager** gives you specific tasks to do based on information in the company's computer system and provides feedback on how well you are doing based on your performance.

Your **manager** decides on how much you get paid, lets you know if your work is not good enough, and decides when to end your job at the company.

Overall, your day as a marketing assistant is busy, challenging, and rewarding. You work collaboratively with other team members and use your creativity and analytical skills to contribute to successful marketing campaigns that increase sales and brand awareness.

Scenario 4: low AM + close leader:

Imagine you work as a **marketing assistant** at TitanTech, a **multinational company** that produces and sells consumer electronics such as smartphones, laptops, and tablets. You work for the **marketing department**, which plays a crucial role in driving sales and increasing brand awareness for TitanTech. Your work involves contributing to marketing campaigns and assisting project managers with tasks such as campaign planning, content creation, and social media management.

You have been a part of the marketing team for three years and have been compensated well for your contributions.

At TitanTech, you receive guidance for your job from either your **manager** or a **computer program**. Furthermore, your job performance will be evaluated by either your manager or the computer program, and your pay will be determined based on this assessment. Your manager regularly visits your desk to check in and chat with you, and you feel comfortable asking for help and advice. Your manager is **approachable** and often gives you words of encouragement.

You begin your workday by logging into a **computer program** to get informed about ongoing marketing campaigns and upcoming projects.

During your workday, you work on tasks assigned to you by a **computer program** and upload the work to the company's database. This system uses computer programs to monitor how well you are doing and to set goals for you to achieve.

Your **manager** gives you specific tasks to do based on information in the company's computer system and provides feedback on how well you are doing based on your performance. Your **manager** decides on how much you get paid, lets you know if your work is not good enough, and decides when to end your job at the company.

Overall, your day as a marketing assistant is busy, challenging, and rewarding. You work collaboratively with other team members and use your creativity and analytical skills to contribute to successful marketing campaigns that increase sales and brand awareness.

Scenario 5: high AM + distant leader:

Imagine you work as a **marketing assistant** at TitanTech, a **multinational company** that produces and sells consumer electronics such as smartphones, laptops, and tablets. You work for the **marketing department**, which plays a crucial role in driving sales and increasing brand awareness for TitanTech. Your work involves contributing to marketing campaigns and assisting project managers with tasks such as campaign planning, content creation, and social media management. You have been a part of the marketing team for three years and have been compensated well for your contributions.

At TitanTech, you receive guidance for your job from a **computer program**. Furthermore, your job performance will also be evaluated by the computer program, and your pay will be determined based on this assessment. Your manager does not come to your desk to check in and chat with you, and you feel uncomfortable asking for help and advice. Your manager is **distant** and does not often give you words of encouragement.

You begin your workday by logging into a **computer program** to get informed about ongoing marketing campaigns and upcoming projects.

During your workday, you work on tasks assigned to you by a **computer program** and upload the work to the company's database. This system uses computer programs to monitor how well you are doing and to set goals for you to achieve.

The **computer program** gives you specific tasks to do based on information in the computer's computer system and provides automatic feedback on how well you are doing based on your performance metrics.

The **computer program** decides on how much you get paid, lets you know if your work is not good enough, and decides when to end your job at the company.

Overall, your day as a marketing assistant is busy, challenging, and rewarding. You work collaboratively with other team members and use your creativity and analytical skills to contribute to successful marketing campaigns that increase sales and brand awareness.

Scenario 6: high AM + close leader:

Imagine you work as a **marketing assistant** at TitanTech, a **multinational company** that produces and sells consumer electronics such as smartphones, laptops, and tablets. You work for the **marketing department**, which plays a crucial role in driving sales and increasing brand awareness for TitanTech. Your work involves contributing to marketing campaigns and assisting project managers with tasks such as campaign planning, content creation, and social media management. You have been a part of the marketing team for three years and have been compensated well for your contributions.

At TitanTech, you receive guidance for your job from a **computer program**. Furthermore, your job performance will also be evaluated by the computer program, and your pay will be determined based on this assessment. Your manager regularly visits your desk to check in and chat with you, and you feel comfortable asking for help and advice. Your manager is **approachable** and often gives you words of encouragement.

You begin your workday by logging into a **computer program** to get informed about ongoing marketing campaigns and upcoming projects.

During your workday, you work on tasks assigned to you by a **computer program** and upload the work to the company's database. This system uses computer programs to monitor how well you are doing and to set goals for you to achieve.

The **computer program** gives you specific tasks to do based on information in the computer's computer system and provides automatic feedback on how well you are doing based on your performance metrics.

The **computer program** decides on how much you get paid, lets you know if your work is not good enough, and decides when to end your job at the company.

Overall, your day as a marketing assistant is busy, challenging, and rewarding. You work collaboratively with other team members and use your creativity and analytical skills to contribute to successful marketing campaigns that increase sales and brand awareness.

Definition of Algorithmic Management

Definition of algorithmic management provided to the participants:

Algorithmic management is a diverse set of technological tools and techniques to remotely manage workforces. It includes continuous tracking of workers, constant performance evaluation, and the automatic implementation of decisions, with no or little human intervention. These algorithms are designed to optimize the efficient allocation of resources in the production of goods and services, help organizations reduce costs, maximize profits, and ensure competitiveness in the market.

Paper 2: Exploring the Relationship between Algorithmic Management and Job Autonomy: Identifying Boundary Conditions[7]

Abstract

This study clarifies the inconsistent findings on the relationship between algorithmic management (AM) and job autonomy in standard work settings and proposes a theoretical framework underpinned by Sociotechnical Systems Theory (STST) to identify boundary conditions shaping the relationship between AM and job autonomy. By considering the role of systemic justice and individual proactivity as sociotechnical moderators, we offer a more nuanced understanding of and empirical support for the relationship between AM and job autonomy. We collected survey data from an online cross-sectional sample of 190 workers worldwide and a two-wave Prolific sample of 229 US employees. The quantitative analysis revealed a small but significant moderating role of systemic justice, indicating that when employees perceive justice within the AM system, the loss of job autonomy is mitigated. Individual proactivity was significantly related to job autonomy, but did not show a significant moderating effect on its own. Three-way interaction analysis further showed that highly proactive individuals suffer a more acute loss of autonomy in an unjust AM system compared to less proactive individuals. Qualitative insights from open-ended questions reveal that AM's rigidity, focus on automating routine tasks, and lack of feedback hinder proactive individuals' autonomy. This study underscores the importance of socio-technical moderators in AM systems and offers guidance for designing fairer, more human-centric AM systems.

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[7] This paper was presented at the 2nd EIASM workshop on people analytics and algorithmic management in Leeds, in 2023, and has been accepted for the Dutch HRM Network Conference in Rotterdam, in November 2024. This paper will be submitted soon to a journal (still to decide, but it could be sent to New Technology, Work and Employment, The International Journal of Human Resource Management or European Journal of Work and Organizational Psychology).

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Introduction

In recent years, algorithmic management (AM) has garnered widespread adoption in various business sectors due to its potential to enhance operational efficiency, overall organizational performance, and transform employee experience (Cheng & Foley, 2019; Duggan et al., 2020; Meijerink & Bondarouk, 2023; Parent-Rocheleau & Parker, 2022). Initially, AM emerged to describe how platforms like Uber utilize software algorithms to manage their drivers (Lee et al., 2015). Defined by Lee et al. (2015) as software algorithms that assume managerial functions and surrounding institutional devices (i.e., monitoring systems, data analytics tools, and performance tracking software) that support algorithms in practice, AM has transcended the gig economy. Fueled by digitalization and accelerated by the Coronavirus disease 2019 pandemic (Fraccaroli et al., 2024), its widespread use in standard settings has significant implications on how work is directed, evaluated, and disciplined (Kellogg et al., 2020), intensifying work control and significantly thwarting job autonomy (Parker & Grote, 2022; Parent-Rocheleau & Parker, 2022).

Job autonomy, the extent to which a job allows freedom, independence, and discretion to schedule work, make decisions, and choose the methods used to perform tasks (Morgeson et al., 2005; Wall et al., 1995), is a critical job characteristic with far-reaching positive effects. Employees increasingly value autonomy, making it a key driver of satisfaction and a competitive advantage for organizations that offer it (Deci et al., 2017). According to Deci and Ryan's Self-Determination Theory (2000), providing autonomy fulfills a fundamental psychological need, leading to greater intrinsic motivation, job satisfaction, and professional functioning. Employees provided with job autonomy are more likely to be innovative, take initiative, demonstrate higher performance, and have a higher level of well-being (Oldham et al., 1976). Conversely, a lack of job autonomy can contribute to stress and burnout (Parker & Grote, 2022).

The proliferation of AM represents a new form of management where organizations can oversee workers with minimal human intervention (e.g., Noponen et al., 2023). Existing studies predominantly suggest that AM poses a significant threat to employee autonomy in their job, through its risk of creating an environment of constant monitoring and restricted actions (Woodcock, 2022). Such conditions often limit workers' control and discretion (Parker & Grote, 2020; Sandoval-Reyes et al., 2019), resulting in diminished job autonomy through imposing rigid structures and restricting self-control over task execution (Unruh et al., 2022). Additionally, monitoring and quantification of worker behaviors (Newman et al., 2020), creation of information asymmetries (Rosenblat, 2018; Shapiro & Kirkman, 1999), reduction of human sensemaking (Leicht-Deobald et al., 2019), and automation of discipline (Kellogg et al., 2020) further undermine employee autonomy.

However, scholars increasingly challenge the prevailing negative view of AM on job autonomy, advocating for more nuanced perspectives. In their review paper, Noponen et al. (2023) argue that the impact of AM depends on whether it is used in a *controlling* or *enabling* manner. They observed that existing empirical studies are primarily based on single-company case studies, mostly platform companies that adopt a more *controlling* approach, which may explain the negative findings prevalent in the literature. This observation highlights that the perception of job autonomy varies not only among workers within the same company (i.e., individual level)—a topic well-discovered in existing research, but also between companies, which might deploy AM systems in controlling or non-controlling/enabling manners (i.e., system level), necessitating the identification of moderators at both the system and the individual level (Gagné et al., 2022; Malik et al., 2022; Noponen et al., 2023).

Empirical findings on standard work settings have been sparse and inconsistent in non-gig settings. Ruiner and Klumpp (2022) employed mixed methods (25 interviews and 127 surveys) to study urban food logistics truck drivers in Germany, revealing both increased job autonomy and heightened surveillance and control. Conversely, Perez et al. (2022) observed decreased job autonomy among 27 bank employees through interviews following the introduction of machine learning systems. While qualitative studies provide valuable insights, their limited scope restricts the generalizability of results. Incorporating quantitative research is crucial to overcome this limitation (Creswell & Creswell, 2018), as it allows for precise quantification of variables and facilitates informed predictions and policy decisions (Bryman, 2012; Creswell & Creswell, 2018).

To clarify the inconsistent findings on the relationship between AM and job autonomy in standard work settings, we apply Sociotechnical Systems Theory (STST) to identify boundary conditions. Building on the insights of de Sitter et al. (1997) and Benders & van Bijsterveld (2000), we position job autonomy as a core component of the "quality of working life" emphasized by STST. This focus is particularly relevant in the context of AM, as these systems often reshape traditional task control dynamics (Parent-Rocheleau & Parker, 2021). According to STST, optimal organizational performance is achieved when the social (employees) and technical (technologies) subsystems are jointly considered and effectively integrated (Cherns, 1976; Emery & Trist, 1978). Within this framework, we conceptualize AM systems as part of the technical subsystem that directly influences the actors in the social subsystem, with job autonomy emerging as a key outcome of the interaction between these two interdependent components.

In line with STST's emphasis on the interplay of social and technical elements, we argue that perceived job autonomy in AM systems is shaped by both system-level factors and individual behaviors, as well as their interaction. Core to STST is the inseparability of technical and social elements, where their effects and meanings are often interwoven. At the technical level, we examine the intensity of AM practices, representing the cumulative implementation of algorithmic direction, evaluation, and discipline. However, algorithm design can moderate this effect, with perceived justice acting as a critical factor that blends technical and social dimensions. Justice perceptions, influenced by the opacity and impersonality of AM processes such as task allocation and performance reviews, significantly shape employee trust and autonomy (Lee, 2018; Parent-Rocheleau & Parker, 2021). Specifically, high perceived justice is expected to buffer the negative correlation between AM intensity and job autonomy. At the individual level, we focus on employee proactivity, recognizing workers’ potential active effort to shape and adapt technology to meet their needs, thereby regaining autonomy. Specifically, we expect that the loss of job autonomy is buffered in the case of high employee proactivity. We also examine the interactions between these two moderators, recognizing that AM is not just a technological tool but is co-shaped through continuous interactions between human agents and algorithms (Jarrahi et al., 2021; Parent-Rocheleau and Parker, 2021). Furthermore, given that the perception of these moderators varies among employees and are inherently subjective, we rely on self-reported data. This approach is consistent with practices used in similar studies in AM and human resource management (Parent-Rocheleau et al., 2023; Gilbert et al., 2011). We conducted a survey study using two samples, which were combined in our analysis to strengthen the robustness of our findings.

Our study contributes to the literature on AM and job autonomy by addressing the inconsistent findings on the relationship between AM and job autonomy in standard work settings. By examining both systemic and individual-level boundary conditions, we not only highlight the importance of fair designs in AM systems to mitigate the loss of job autonomy but also demonstrate the complex interaction between perceived system justice, individual proactivity, and AM. Our study also stands out as one of the first quantitative field investigations of AM and job autonomy in standard work environments, featuring a diverse sample and providing valuable empirical evidence on AM above and beyond the gig economy, thereby providing generalizable evidence, which is particularly appreciated in a literature that is dominated by qualitative and single-case findings. Practically, we guide organizations and policymakers in designing and implementing algorithmic systems that prioritize employee well-being via preserving job autonomy. Ultimately, this research supports the development of more effective and human-centric AM practices.

Hypotheses Development

Algorithmic Management and Job Autonomy

We adopt sociotechnical systems theory (STST) (Cherns, 1976; de Sitter et al., 1997; Emery & Trist, 1978; Trist & Bamforth, 1951) as the foundation of our approach. STST posits that optimal organizational performance comes from jointly optimizing the social aspect (people) and technical aspect (technologies) systems. However, rapid technological advancements have disrupted this balance (Makarius et al., 2020; Parker & Grote, 2020) and true sociotechnical capital—the advantage of AI-human collaboration—can only be realized when these systems work together seamlessly (Makarius et al., 2020). By focusing on the inseparability of technical and social components, which include the intensity of AM, perceived system justice, and individual proactivity, we explore how AM often diminishes autonomy while holding the potential to empower workers and enhance job autonomy under certain conditions.

AM systems, characterized by their reliance on data-driven decision-making, have significantly reshaped modern workplaces. These systems automate decisions, standardize routine workplace activities, and exert remote control over workers (Möhlmann & Zalmanson, 2017). AM systems, seen as an innovative tool for exerting control over workers (Gandini, 2019; Kellogg et al., 2020; Veen et al., 2019), are used to direct, evaluate, and discipline employees (Edwards, 1979; Kellogg et al., 2020). This aligns with labor process theory, which argues that managers adopt new methods to control labor and maximize its monetary value (Gandini, 2019). Therefore, this management approach has been increasingly adopted in various industries to enhance efficiency and productivity. However, the *controlling* nature of AM significantly correlates to job autonomy, which is a crucial work characteristic that encompasses the freedom, independence, and discretion workers have over their work scheduling, decision-making, and work methods (Hackman & Oldham, 1976; Breaugh, 1985; Wall et al., 1995).

AM systems often dictate how, when, and where tasks should be performed, which involves six managerial functions (goal-setting, scheduling, monitoring, performance management, compensation, and job termination.), leaving little room for individual discretion and creativity (Gagné and Parent-Rocheleau, 2022; Gagné et al., 2022). This level of control can lead workers to feel as though they are merely "working for data" rather than being driven by intrinsic motivations or personal goals, thereby diminishing their perceived autonomy (Lamers et al., 2022; Möhlmann et al., 2021).

Extant literature (e.g., Sandoval-Reyes et al., 2019; Parker & Grote, 2022) generally highlights the negative influence of AM on job autonomy which encompasses work scheduling, decision-making, and work methods (Hackman & Oldham, 1976). At an overall level of job autonomy, the literature suggests that AM creates information asymmetries where algorithms possess more knowledge about worker performance than the workers themselves, reducing human sensemaking and resulting in reduced job autonomy (Möhlmann & Zalmanson, 2017). For example, studies have shown that AM can lead to increased surveillance and control, standardization of work processes, and a focus on quantitative performance metrics (Leicht-Deobald et al., 2019; Möhlmann & Zalmanson, 2017; Rosenblat & Stark, 2016). In terms of work scheduling autonomy, AM systems often employ predictive scheduling, which determines when tasks should be performed based on algorithmic assessments (Kinowska & Sienkiewicz, 2022). This removes workers' discretion over their work schedules, leading to a lack of flexibility and increased stress levels due to constant monitoring and real-time adjustments (Wood et al., 2019). Regarding decision-making autonomy, AM typically centralizes decision-making power within the algorithm, leaving workers with minimal input. For instance, task assignments and performance evaluations are often dictated by pre-programmed rules and criteria, which can strip workers of their ability to influence these decisions (Kellogg et al., 2020). This reduction in decision-making power can lead to feelings of disenfranchisement, as workers are distanced from the decision-making processes that directly impact their work. Work methods autonomy is similarly affected, as AM systems standardize work methods through pre-programmed rules that dictate how tasks should be carried out (Gagné et al., 2022). This rigid standardization hampers workers' ability to choose their methods, reducing creativity and independence. As a result, employees may feel their skills and knowledge are underutilized, further diminishing their job satisfaction and motivation.

The emphasis on quantitative metrics can also pressure workers to prioritize speed and efficiency over quality and innovation, further diminishing their sense of control and autonomy (Rosenblat & Stark, 2016). In addition, the opacity of AM further exacerbates this issue. Workers often find it difficult or impossible to question the system and its decisions, reinforcing their loss of control as they are unable to challenge or alter the algorithms that govern their work (Rani & Furrer, 2020; Rosenblat, 2018; Rosenblat & Stark, 2016; Stark & Pais, 2020). Therefore, we propose the following:

Hypothesis 1: There is a negative relationship between AM intensity and job autonomy.

The above observations tend to focus on a work environment that is more *controlling* than *enabling* (Lehdonvirta, 2018), typically the gig economy platforms. However, we argue that AM also has the potential to be *enabling*, particularly in standard work settings. For instance, monitoring, one of AM's most common functions, can promote autonomy when designed to provide constructive feedback and support employee development, leading to positive outcomes (Aiello & Shao, 1993). In addition, Wood et al. (2019) argue that algorithmic control in standard work settings diverges significantly from Taylorism by operating primarily at the end of the labor process, i.e., focusing on results rather than dictating processes, thus potentially reconciling managerial control with worker autonomy in contemporary labor dynamics.

It is, therefore, crucial to identify key moderating mechanisms that influence job autonomy, especially in standard work settings where the interaction between algorithms and traditional management structures is more complex and nuanced. In these environments, algorithms are often integrated to complement, rather than replace, existing management practices, with a focus on enhancing productivity and decision-making instead of controlling every aspect of work (Hauff et al., 2014; Lepak & Snell, 2002).

Justice

Building on STS, we argue that the potential benefits of AM in standard systems are largely contingent upon the perceived fairness—or justice—of the system (Cropanzano & Ambrose, 2015). We argue that the perceived justice of the algorithmic system is crucial because it influences how employees interact with informational management tools. When employees view these tools as fair, they are more likely to accept the algorithm's decisions which can reduce resistance to algorithmic control and allow employees to engage more constructively with AM systems, which helps preserve their perceived job autonomy (Kellogg et al., 2020). On the other hand, if employees perceive the system as unjust, they may feel that the algorithm's decisions are arbitrary or biased, which undermines their trust in the system. This lack of trust can lead to resistance, increased stress, and reduced willingness to engage with AM systems, further eroding their sense of autonomy (Beunza, 2019).

The most cited components of algorithmic fairness are defined by the absence (or minimization) of bias and discrimination, confidentiality of data and decisions, and relevance as well as legitimacy and accuracy of the information used and of the decisions made by the algorithms (Parent-Rocheleau & Parker, 2021). These are all aspects of *procedural justice*, which has been shown to significantly influence need satisfaction (Olafsen et al., 2015). Traditional organizational justice frameworks extensively validate and emphasize three sub-dimensions of justice: *distributive justice*, *procedural justice*, and *informational justice* (Colquitt, 2001). Initially, researchers focused on the justice of decision outcomes, termed *distributive justice* (e.g., Leventhal, 1976). Distributive justice is fostered when outcomes are consistent with implicit norms for allocation, such as equity or equality. More recent work has focused on the justice of the processes that lead to decision outcomes, termed *procedural justice* (e.g., Leventhal, 1980). Procedural justice is fostered through voice during a decision-making process or influence over the outcome (Thibaut & Walker, 1975) or by adherence to fair process criteria, such as consistency, lack of bias, correctability, representation, accuracy, and ethicality (Leventhal, 1980). *Informational justice* pertains to the transparency and adequacy of the information provided during decision-making processes, allowing employees to understand and evaluate the fairness of decisions (Colquitt, 2001). These aspects of justice are distinct but correlated. Requiring decision-makers to explain their decisions promotes informational justice, aiding assessments of procedural and distributive justice. Thorough explanations (i.e., informational justice) help people assess decision-making procedures (i.e., procedural justice), and decisions perceived as procedurally just are more likely to be seen as distributively just, which supports giving individuals the right to access information about significant decisions. In addition, transparency is a critical component that blends with the notion of fairness and justice in AM systems, ensuring that AM systems are perceived as fair and enhancing employees' trust and cooperation (Zhdanov et al., 2022). Transparent algorithms, which provide clear explanations for the decisions, help employees understand the logic behind decisions, enhance perceptions of informational justice, and enable employees to assess procedural fairness (Shin et al., 2022).

Due to the interrelatedness of these three dimensions, it is challenging to isolate their unique effects without encountering multicollinearity issues. Research shows high correlations among these justice dimensions, suggesting that they often function together to shape overall perceptions of fairness (Colquitt et al., 2013). Given this interrelation, it is justifiable to conceptualize justice as an overarching construct rather than separate sub-dimensions. This approach aligns with cognitive models of justice perception, which view these dimensions as substitutable and functionally similar (Colquitt & Shaw, 2005).

In AM, both just and unjust systems are present. Efforts are increasing to make AM systems more equitable. Regulatory measures like the EU's GDPR and the US's ECOA aim to enhance fairness and transparency in AM systems (Diakopoulos & Koliska, 2016; Shin et al., 2020). AM systems have the potential to provide fairer and more objective decisions compared to human judgment (Ananny & Crawford, 2018). Research shows that small adjustments to algorithms can improve equity, such as in income distribution (Bokányi & Hannák, 2020). Furthermore, algorithmic scheduling is fairer when it respects equality, such as handling vacation requests equitably, though human decision support is preferred for resolving conflicts (Uhde et al., 2020). Despite these efforts, challenges remain. Injustices are more likely perceived when AM systems are developed by subcontractors rather than internal teams

(Wang et al., 2020). Perceptions of unfairness can also arise from issues such as data privacy, which impacts trust and fairness perceptions (Chory et al., 2017). Additionally, performance evaluations based on uncontrollable criteria are often seen as unfair, and AM systems solely responsible for task outcomes are frequently viewed as unjust and inefficient (Curchod et al., 2019; Lee et al., 2015).

In high-justice systems, where transparency and fairness are prioritized, employees are more likely to feel that their autonomy is respected and preserved, as decisions are perceived as impartial and aligned with clear rules. Conversely, in low-justice systems, opaque decision-making erodes trust, making employees feel over-monitored and powerless, thereby undermining their sense of autonomy.

Bring it all together, we suggest that in high-justice systems, where transparency and fairness are prioritized, the negative correlation between AM and job autonomy is mitigated. Conversely, low-justice systems with opaque decision-making processes undermine job autonomy. Thus, we hypothesize the following:

Hypothesis 2: Perceived justice moderates the relationship between AM intensity and job autonomy. Specifically, the negative relationship between AM and job autonomy is weaker in a just AM system compared to in an unjust AM system.

Proactivity

Proactivity is an important feature of individuals of the social systems (i.e., the humans within and around the organization), based on the STS theory. It refers to a personality trait of individuals who are not significantly constrained by situational forces and who actively effect environmental change (Seibert et al., 1999). Proactive individuals strive to create favorable conditions for themselves and their organizations (Bateman & Crant, 1993). In workplaces dominated by AM, proactivity seems particularly important as it can help employees navigate and mitigate the constraints imposed by algorithmic systems. This is achieved through various means: 1) developing algorithmic literacy and engagement (Reisdorf & Blank, 2021), 2) proactively navigating HRM algorithms (Möhlmann & Zalmanson, 2017), and 3) exploiting algorithmic opacity (Shin, 2020) and engaging in sensemaking (Leicht-Deobald et al., 2019).

First, proactive individuals are particularly adept at developing algorithmic literacy (Burrell, 2016; Reisdorf & Blank, 2021). Workers who actively engage with and understand algorithmic systems can retain a higher degree of autonomy (Jarrahi & Sutherland, 2019). Algorithmic literacy enables employees to comprehend the logic and functioning of algorithms, allowing them to work more effectively within these systems and identify opportunities to assert their autonomy (Oeldorf-Hirsch & Neubaum, 2023). Employees are not passive recipients of AI outputs; they actively interpret and engage with these outputs (Lamers et al., 2024). While algorithmic decision-making automates and standardizes workplace decisions, humans play a crucial role in interpreting the complex analyses provided by these algorithms (Bader & Kaiser, 2019). We assume that proactive employees can maintain a sense of autonomy in environments where AM systems provide outputs that are accessible and interpretable.

Second, AM often relies on proxy data, which may not fully capture the complexities of human behavior and performance (Newlands, 2021). This limitation presents an opportunity for proactive individuals to provide additional context or feedback, enhancing the accuracy and relevance of the data inputs to better align with their own specific needs and situations (McClelland, 2012; Newlands, 2021). By actively engaging with the algorithmic system, proactive workers can ensure their autonomy is not overly constrained by incomplete or biased data inputs. This proactive engagement helps to bridge the gap between the data captured by the algorithm and the actual work experience of employees (Wood et al., 2019; Coun et al., 2021).

Furthermore, AM incorporate automated processes to streamline workflows and increase efficiency, which limits employees' autonomy by standardizing tasks and decision-making (Cameron, 2020). Proactive individuals can, however, leverage these automated processes to their advantage by identifying opportunities for customization or optimization within the algorithmic framework (Faraj et al., 2018). By actively seeking ways to adapt and innovate within automated workflows, proactive workers can maintain a degree of autonomy and control over their tasks (Pasquale, 2015).

Lastly, algorithms often embed biases and worldviews (Leicht-Deobald et al., 2019), which proactive workers can identify with and adapt to while pursuing their personal goals and autonomy. The "black-box" nature of many algorithms creates uncertainty about decision-making processes (Pasquale, 2015; Gal et al., 2020). Proactive employees can use this uncertainty to interpret algorithmic outputs in ways that align with their personal motivations and work strategies (Sonenshein, 2007; Weick, 1995). Through sensemaking—the process of constructing meaning based on personal experiences and expectations—they actively seek to understand and influence their work environment (Orlikowski, 1992). This approach enables them to navigate algorithmic systems more effectively and maintain their sense of autonomy.

Synthesizing these points, we propose the following hypothesis:

Hypothesis 3: Proactivity moderates the relationship between AM intensity and job autonomy. Specifically, the negative relationship between AM and job autonomy is weaker for proactive employees compared to less proactive employees.

Together, perceived justice and proactivity operate synergistically. The work of Jarrahi et al. (2021) and Parent-Rocheleau and Parker (2021) reinforces this perspective by illustrating that the success of AM systems depends on how well they balance and integrate social and technical elements. Building on this, Jarrahi et al. (2021) stress that AM is not merely a technological tool but is co-constructed through ongoing interactions between human agents and algorithms, highlighting the necessity of aligning system design with individual behaviors to optimize job autonomy. Specifically, high perceived justice amplifies the benefits of proactivity, creating a reinforcing cycle that allows employees to engage with AM systems constructively. Conversely, low justice limits the potential of proactivity, reinforcing the need for systems that prioritize fairness and transparency. This integrated perspective justifies our focus on the interaction between these two moderators in moderating the effects of AM on job autonomy.

High perceived justice provides the trust and transparency necessary for employees to effectively engage with AM systems (Lee, 2018; Parent-Rocheleau & Parker, 2021), while proactivity empowers employees to navigate and influence their work environment (e.g., Sonenshein, 2007). When both factors are high, employees experience the greatest mitigation of AM's negative effects on autonomy. On the other hand, when both factors are low, employees face compounded challenges: distrust in the system limits their acceptance (Curchod et al., 2019; Lee et al., 2015)., and a lack of initiative prevents them from adapting effectively (Wood et al., 2019; Coun et al., 2021). In cases where one factor is high and the other is low, the effects are intermediate, as either trust or proactive engagement partially offsets the negative relationship between AM intensity and autonomy.

We therefore also propose a fourth hypothesis emphasizing the interaction between social and technical elements:

Hypothesis 4: Perceived justice and proactivity jointly moderate the relationship between AM intensity and job autonomy. Specifically, when both perceived justice and proactivity are high, the negative relationship between AM and job autonomy is the weakest. Conversely, when both perceived justice and proactivity are low, the negative relationship between AM and job autonomy is the strongest. In cases where one is high and the other is low, the moderation role is intermediate.

Figure 0-1provides a summary of our theoretical model and hypotheses.

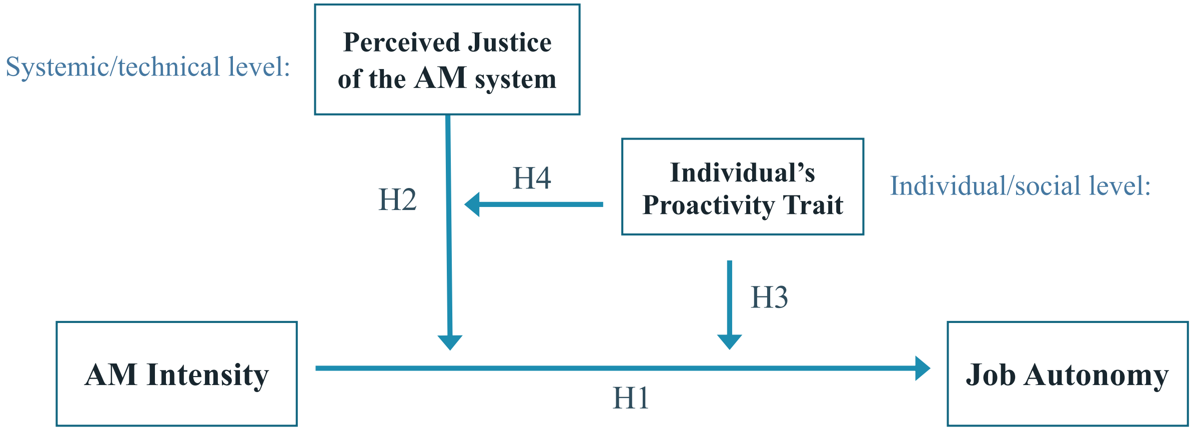

Figure 0-1 Conceptual model

Methods

Procedures

To test the proposed conceptual model, we collected data from two sources. From August 2022 to April 2023, we used convenience sampling to recruit a globally diverse sample of 190 participants for cross-sectional data (sample 1). Then, from April 2023 to May 2023, we recruited a diverse sample of 229 US employees through Prolific, collecting data in two waves with an 8-day time lag (sample 2).

The first sample consisted of 190 workers recruited from online social platforms. Inclusion criteria required participants to possess professional proficiency in English and be employed full-time in a standard, non-gig organization at the time of questionnaire completion. We disseminated the survey via LinkedIn and Facebook to reach a diverse group of participants. The researchers, along with two master's students, distributed the link across various Facebook and LinkedIn groups to ensure a diverse representation of professions and geographical locations.

The second sample was recruited using the online panel provider Prolific, an online platform designed to recruit participants specifically for academic research that has been shown to provide data of an equivalent quality to many work settings (Miron-Spektor et al., 2018; Wu et al., 2018). To reduce the potential influence of common method bias, we followed the recommendation of Podsakoff et al. (2003) and utilized a two-wave design with an eight-day interval (Tehseen et al., 2017). The temporal lag separated the measurements of the predictor and the rest of the variables to reduce biases (e.g., consistency motifs and illusionary correlations) that might occur in a cross-sectional study. The inclusion of the US sample aimed to leverage its status as a prominent and diverse labor market where AM is widely adopted across industries (Radu, 2019). Eligible participants were full-time employees of standard organizations in the US other than Prolific at the time of survey completion. The response rate for the second wave is 87%. This high response rate can be attributed to our initial clarification during the first wave survey, where we informed participants that full payment would be provided upon completion of both waves.

Across both samples, before participating in the survey, participants were provided with an information letter and a consent form outlining the purpose and structure of the study, as well as information on handling their personal data. Only those who provided their consent were allowed to proceed with the survey. This study has received approval from the Social and Societal Ethics Committee of the university involved.

To assess the differences between the two samples, we conducted rank-sum tests, a non-parametric method suitable for comparing independent groups when normality assumptions are not met (McKnight & Najab, 2010). The results indicated no significant difference in AM index between the convenience and Prolific samples ($p = 0.59$). To enhance statistical power and improve the robustness of our analyses, we combined the two datasets (Cohen, 1988).

The AM index, which we will explain in detail in the next section, serves as a key measure of the intensity of algorithmic management practices experienced by the participants. Similarly, job autonomy showed no significant difference between the two groups ($p = 0.27$). However, perceptions of justice were significantly higher in the Prolific sample compared to the convenience sample ($p = 0.00$; mean for sample 1 is 2.52, sd=0.92; mean for sample 2 is 2.81, sd=0.88). Finally, proactivity did not differ significantly between the two samples ($p = 0.78$). These findings suggest that while perceptions of justice vary between the samples, other factors such as algorithmic management, job autonomy, and proactivity remain consistent. Therefore, we analyze the combined results from both samples, while also providing separate analyses for each individual sample as a robustness check. Furthermore, the larger sample size in the combined sample (in total 419 participants) improves the statistical power of the study, enabling more precise and robust analyses.

Participant Characteristics

The first sample exhibited geographical diversity, with participants from different regions of the world. This distribution highlights a broad geographic representation (Table 0-1). The second sample features workers who are currently working in the US exclusively.

Table 0-1 Geographical distribution of Sample 1 participants

Region	Percentage (%)
Africa	4.74
Anglo-America, Australia, New Zealand	12.63
East Asia	12.11
East Europe	15.79
Latin America	1.05
Middle East	4.21
South Asia	6.32
South-East Asia	5.79
West Europe	37.37

The combined sample of 419 participants represented various sectors (Table 0-2)

Table 0-2 Industry distribution across the samples

	sample 1	sample 2	sample 1+2
Agriculture and Natural Resources & Manufacturing and Industrial Production	26 (13.7%)	31 (13.5%)	57 (13.6%)
Construction and Technology	25 (13.2%)	29 (12.7%)	54 (52.9%)
Trade and Logistics	32 (16.8%)	25 (10.9%)	57 (13.6%)

Business and Financial Services	30 (15.8%)	36 (15.7%)	66 (15.8%)
Healthcare, Education, and Social Services	27 (14.2%)	56 (24.4%)	83 (19.8%)
Government and Personal Services	50 (26.3%)	52 (22.7%)	102 (24.3%)
Total	190	229	419

The combined sample's age, gender, job level distribution are illustrated in Table 0-3.

Table 0-3 Age, gender, job level distribution across samples

Category	Combined Sample	Sample 1	Sample 2
Age Distribution			
Mean Age	38.932	32.479	44.287
Standard Deviation	14.059	9.887	14.759
Minimum Age	19	20	19
Maximum Age	80	70	80
Gender Distribution			
Non-female	198	82	116
Female	221	108	113
Job Level Distribution			
Non-Managerial Position	229	116	113
Managerial Position	190	74	116
Total Respondents	419	190	229

Measures

We used the same measures across the two samples. The multi-item scales as well as definition of AM used in this study can be found in the Appendix.

Algorithmic Management:

Due to the absence of a validated scale for measuring AM during the data collection period, a 12-item scale was developed based on the conceptual work of Parent-Rocheleau & Parker (2022) and Kellogg et al. (2020). The scale aims to assess the intensity of AM in the workplace, encompassing six key functions that reflect the three control mechanisms (direction, evaluation, and discipline): monitoring, goal setting, performance management, scheduling, compensation, and job termination. The responses were on a six-point scale (1 = No, 2 = I don't know or I'm not sure, 3 = Yes, rarely, 4 = Yes, sometimes, 5 = Yes, often, 6 = Yes, always.).

We created a formative index to quantify the intensity of experienced AM practices, by summing participants' responses to each item related to the intensity of AM (0 for "no" and "I don't know"; 1 for "yes"). The resulting index ranged from 0 to 12, with 0 indicating the perceived absence of AM practices at work and 12 representing the presence of all 12 AM practices. To make it possible to assess employees' perception of the justice of the system, we only retained those who reported having experienced at least one AM practice (i.e., index is larger than 0).

The formative index was developed due to its recognition that each item pertaining to AM signifies an alternate method of accomplishing the same objective and serves as a "cause" of the construct (Jiang et al., 2012). This perspective is supported by established literature, which suggests that AM practices can vary widely and may not necessarily reflect a single underlying latent variable (Kellogg et al., 2020; Parent-Rocheleau & Parker, 2021; Wood, 2021). By treating each item as a separate causal indicator, the formative index captures the diverse dimensions and nuances of AM experiences and is less likely to introduce downward bias (resulting in underestimating the construct's intensity) than Cronbach's α (McNeish, 2018). We present detailed descriptive statistics on this measure in the result section.

Justice:

For the system moderator (i.e., perception of algorithmic management systems' justice), we used items from Colquitt (2001) and adapted them to the specific context of algorithmic management. We included in total 13 items on justice, reflecting the informational, procedural, and distributive dimensions of justice. Because of conceptual overlap between interactional and procedural, as well as interactional and overall justice, we did not include interactional justice. Example items of justice are "To what extent has the algorithmic management system been candid in the communications with you"? In line with the original scale, answers were rated on a five-point Likert scale (1: strongly disagree, 5: strongly agree).

Factor analysis results suggest a single-factor solution for the 13 justice items, validating that these items form a coherent single factor encompassing informational, procedural, and distributive justice dimensions and justifying using the overall construct of perceived justice in formulating our hypothesis and further analyses, rather than individual subdimensions. Coefficient alpha is 0.95. However, since latest studies argue that alpha underestimates true reliability unless items are tau-equivalent, we also report coefficient omega, considered a practical alternative for estimating measurement reliability (Hayes & Coutts, 2020). The omega value is also 0.95.

Proactivity:

Furthermore, to evaluate participants' proactivity trait, we adopted Bateman and Grant's (1993) unidimensional Proactive Personality Scale. An example item is "I am constantly on the lookout for new ways to improve my life." All items were measured on a seven-point scale. Likewise, factor analysis results suggest a single-factor solution for the 10-item proactivity scale, providing further evidence to use the overall construct of proactivity in formulating our hypothesis and further analyses. Coefficient alpha and omega values are both 0.91.

Job Autonomy:

We adopted Morgeson & Humphrey's (2006) scale on job autonomy in our study. This scale encompasses work scheduling autonomy, decision-making autonomy, and work methods autonomy. Factor analysis shows that autonomy items form a coherent single factor, which can be used as an overall construct in further analyses. An example item is "My job allows me to make my own decisions about how to schedule my work." All items were measured on a seven-point scale, in line with the original scale. Coefficient alpha and omega values are both 0.94.

To further explore participants' perspectives on AM and its impact on job autonomy, we also included an open-ended question. The question asked participants to reflect on and propose features for an ideal algorithmic system that could support and enhance their job autonomy. Specifically, participants were prompted with the following:

"If you were to design an algorithmic system for your work, what features or functions would you want it to include to support and enhance your job autonomy? Please share your thoughts and ideas."

Controls:

We included individuals' job level, education level, and their working country's indulgence cultural dimension as controls for the following reasons. First, more educated employees are more likely to have greater job resources, such as job autonomy (Solomon et al., 2022). Second, the distinction between different job levels (i.e., manager vs. employee) is important in studying self-determination because managerial positions typically come with greater autonomy (Graves & Luciano, 2013). Third, given the heterogeneous nature of the survey sample, we also consider national culture as a control variable. Specifically, we used Hofstede's indulgence vs. restraint cultural dimension, measured on a scale of 0 to 100. Indulgent cultures prioritize pleasure, fun, and freedom, reflecting the extent to which natural desires and enjoyment in life are regulated by social norms (Minkov & Hofstede, 2011). The indulgence vs. restraint cultural dimension has been demonstrated to have important influences on workplace outcomes (Gu et al., 2022)

Results

Confirmatory Factor Analysis

To assess the potential influence of common method variance on our results, we conducted Harman's one-factor test following Podsakoff et al. (2003). We examined the unrotated factors for all variables, including AM intensity, proactivity, justice, and job autonomy. The analysis revealed that the first principal component accounted for 8.18% of the variance, which was lower than the threshold of 50%.

We conducted confirmatory factor analysis (CFA) to assess the discriminant validity of job autonomy, proactivity, and justice (Table 0-4). Since AM was not measured on a standard scale, it was excluded from the CFA. The hypothesized three-factor model showed significantly better fit compared to other models ($\chi 2 = 1715.38$, $df = 461$, $p < 0.001$, $CFI = 0.87$, $TLI = 0.86$, $SRMR = 0.05$, $RMSEA = 0.08$), confirming distinctiveness among proactivity, justice, and job autonomy.

The Average Variance Extracted (AVE) and Composite Reliability (CR) were computed to assess convergent validity and reliability, further reinforcing these findings. For the hypothesized three-factor model, AVE values for job autonomy (0.6511), proactivity (0.5141), and justice (0.5974) exceeded 0.50, indicating adequate convergent validity. CR values for job autonomy (0.9436), proactivity (0.9129), and justice (0.9505) were above 0.70, demonstrating strong reliability.8

[8]For the two-factor model combining proactivity and justice (PJ), the AVE for job autonomy was 0.6511, while the AVE for PJ was 0.3485, below 0.50, suggesting issues with convergent validity despite a high CR (0.8997), indicating a need for refinement.

For the two-factor model combining autonomy and proactivity (AP), the AVE for perceived justice (0.5975) and CR (0.9505) showed strong reliability and validity. However, JP had a lower AVE (0.3619), indicating convergent validity issues despite a high CR (0.9008), suggesting JP needs refinement.

For the two-factor model combining proactivity and justice (PJ), the AVE for job autonomy was 0.5142, while the AVE for PJ was 0.2703, indicating significant validity issues. The CR for autonomy was 0.9129, demonstrating strong reliability, while the CR for PJ was 0.8110, indicating acceptable internal consistency despite validity concerns.

The combined one-factor construct showed a CR of 0.8518, indicating acceptable internal consistency, but an AVE of 0.2206, suggesting poor convergent validity and the need for refinement.

Table 0-4 Model Fit Indices for Alternative Factor Models

Models	χ^2	*df_ms*	$\Delta\chi^2(\Delta df)$	CFI	TLI	SRMR	RMSEA
1. Hypothesized three-factor model	1715.38	461	-	0.87	0.86	0.05	0.08
2. Two-factor model (combining proactivity and justice)	3731.76	463	2016.38(2)	0.67	0.65	0.17	0.13
3. Two-factor model (combining proactivity and autonomy)	3465.65	463	1750.27(2)	0.70	0.68	0.14	0.13
4. Two-factor model (combining autonomy and justice)	3465.65	463	1750.27(2)	0.70	0.68	0.14	0.13
5. Single-factor model	7192.50	464	5477.12(3)	0.32	0.28	0.26	0.19

n = 419. All alternative models were compared with the hypothesized five-factor model. All $\Delta\chi^2$'s are significant at $p < .001$. Abbreviations: CFI is the comparative fit index. RMSEA is the root-mean-square error of approximation. SRMR is the standardized root-mean-square residual. TLI is the Tucker-Lewis index. df_ms is degrees of freedom for test of target model against saturated model.

Descriptive statistics and correlations

Figure 0-2 illustrates the distribution of AM practices across various functions. Most respondents indicated that tools are used to collect and report performance data (items 1 and 2, 348 and 346 "yes" responses respectively). A significant number also reported that algorithms are used to assign tasks (item 3, 168 "yes"), set performance targets (item 4, 180 "yes"), and carry out performance ratings (item 5, 178 "yes"). The least affirmed practice is the use of algorithms to decide on the end of employment relationships (item 12, 95 "yes").

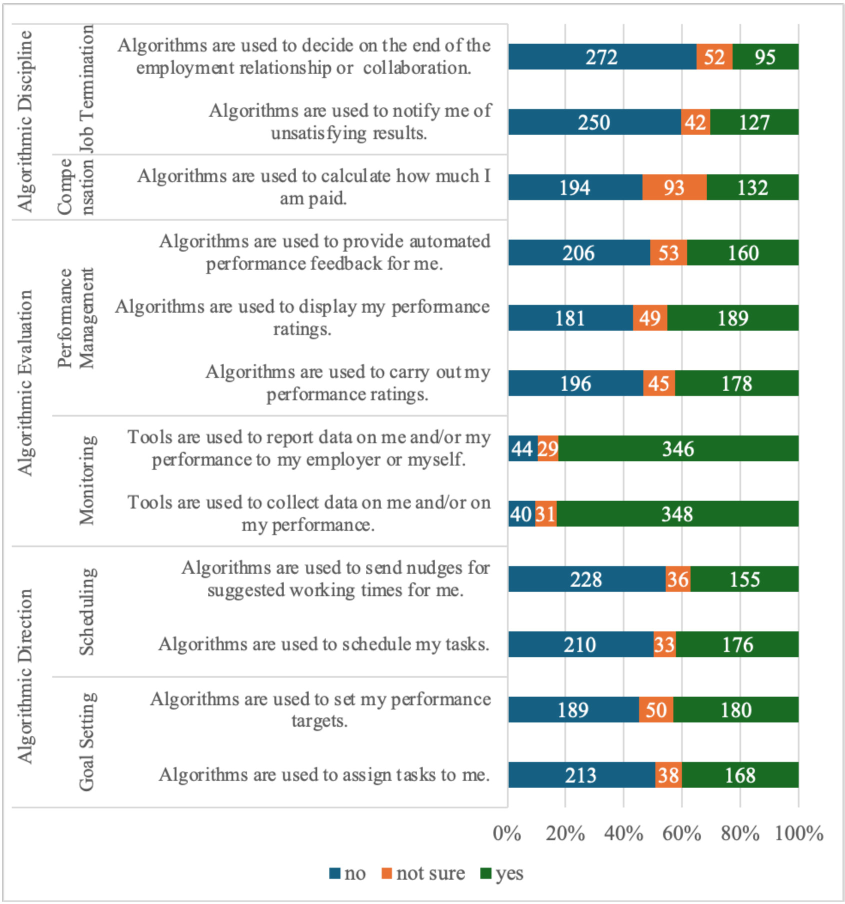

Figure 0-2 Distribution of AM practice

Table 0-5 presents the descriptive statistics, intercorrelations, and reliability coefficients of the variables, along with the number of observations, means, standard deviations, and range. Key variables include AM_index, job autonomy (at two time points), justice, proactivity (at two time points), university education, managerial position, and indulgence. Most measures showed adequate variability without floor or ceiling effects. Autonomy and proactivity, however, had high mean levels, suggesting possible ceiling effects. The results indicate a significant negative relationship between job autonomy and AM index ($r = -0.145$, $p < .001$ for job autonomy at T1; $r = -0.092$, $p < .01$ for job autonomy at T2), which offers preliminary support for H1.

Table 0-5 Descriptive Statistics (Sample 1+2)

Variables	N	M	Std. Dev.	Min	Max	AM	JA	JA_2	JUS	PRO	PRO_2	EUD_uni	MAN	INDUL
AM_index (AM)	419	5.379	3.85	1	12	-								
job autonomy (sample 1+sample 2 T1) (JA)	419	5.413	1.219	1	7	-0.145***	(0.94)							
job autonomy _T2 (sample 1+sample 2 T2) (JA_2)	419	5.379	1.205	1	7	-0.092*	0.897***	(0.94)						
justice (JUS)	419	2.675	0.91	1	5	0.506***	0.041	0.061	(0.95)					
proactivity (sample 1+sample 2 T1) (PRO)	419	5.39	0.9	1.8	7	0.074	0.256***	0.261***	0.132***	(0.90)				

proactivity_T2 (sample 1+sample 2 T2) (PRO_2)	419	5.413	0.939	1	7	0.084*	0.281***	0.323***	0.164***	0.905***	(0.91)			
university education (EDU_uni)	419	0.847	0.36	0	1	-0.010	0.157***	0.151***	0.040	-0.077	-0.089*	-		
managerial position (MAN)	419	0.453	0.498	0	1	0.047	0.247***	0.273***	0.094*	0.144***	0.136***	0.107**	-	
indulgence (INDUL)	419	60.592	15.127	0	97	-0.104**	0.161***	0.149***	0.091*	-0.017	-0.004	0.054	0.112**	-

**** p<0.01, ** p<0.05, * p<0.1*

N=419. Scale reliabilities (alpha and omega) are on the diagonal in parentheses.

Hypothesis Testing

The analysis begins with a regression model using bootstrapping to estimate the effects of AM on job autonomy, including interaction effects with perceived justice and proactivity. The bootstrapping procedure, set with 1,000 replications and a seed for reproducibility, ensures robust standard errors. The regression model includes job level, education level, and work indulgence as control variables. To mitigate potential multicollinearity, we mean-centered the variables of AM index and the two moderators before computing the interaction terms, following the approach outlined by Aiken and West (1991). The Variance Inflation Factor (VIF) values for the predictors ranged between 1.02 and 1.51, indicating that multicollinearity was not a concern across the three models.

Table 0-6 summarizes the results of regression analyses assessing the correlation of various predictors on job autonomy (JA). Models 1-3 incrementally add interaction terms to the baseline predictors using the combined dataset. Models 4 and 5, however, present separate analyses for the convenience sample and the Prolific sample sub-groups, respectively, to explore any potential differences in effects between these two groups. Finally, Model 6 reverts to the combined dataset and includes the three-way interaction term among AM index, justice, and proactivity.

In Model 1, the coefficient for managerial position (MAN) is positive and significant ($\beta = 0.60$, $p < 0.001$), indicating that being in a managerial position is associated with higher job autonomy. Higher education (EDU_uni) and indulgence (INDUL) are also positively associated with job autonomy ($\beta = 0.40$, $p < 0.05$ and $\beta = 0.01$, $p < 0.05$, respectively). Model 2 adds the AM index, justice (JUS), and proactivity (PRO). The AM index shows a negative relationship with job autonomy ($\beta = -0.04$, $p < 0.01$), while proactivity has a strong positive effect ($\beta = 0.40$, $p < 0.001$), appearing to play a much more central role in influencing job autonomy and overshadow the effects of AM. Justice, on the other hand, has no significant direct effect.

Model 3 includes interaction terms between the AM index and justice, and the AM index and proactivity. The interaction term between the AM index and justice is significant ($\beta = 0.04$, $p < 0.05$), suggesting that the negative correlation between AM index and job autonomy is moderated by perceived justice. Model 4 analyzes the convenient sample, showing similar patterns to the aggregated models but with a slightly weaker negative effect of the AM index on job autonomy ($\beta = -0.04$, $p < 0.10$). Model 5, focusing on the prolific sample, indicates a stronger negative effect of the AM index ($\beta = -0.08$, $p < 0.01$) and a positive interaction between the AM index and justice ($\beta = 0.08$, $p < 0.05$). Model 6, incorporating the three-way interaction among the AM index, justice, and proactivity, shows that this interaction significantly influences job autonomy ($\beta = 0.03$, $p < 0.05$).

The adjusted R-squared values range from 0.10 to 0.25 across the models, indicating varying degrees of explained variance. The chi-squared values demonstrate the overall fit of the models, with Model 6 showing the highest chi-squared value (142.20).

These findings highlight the importance of managerial position, education, and proactivity in enhancing job autonomy while illustrating the complex interplay between AM index, justice, and proactivity, providing support for Hypothesis 1 and 2, and partial support for Hypothesis 3 and 4.

Table 0-6 Bootstrapped Unstandardized Coefficients of the Hypothesized Model

	(1)	(2)	(3)	(4)	(5)	(6)
	JA	JA	JA	JA	JA	JA
MAN=1	0.60***	0.50***	0.47***	0.33*	0.70***	0.46***
	(0.11)	(0.10)	(0.11)	(0.15)	(0.16)	(0.11)
EDU_uni=1	0.40*	0.50**	0.46**	0.40	0.56*	0.46**
	(0.19)	(0.17)	(0.18)	(0.29)	(0.23)	(0.17)
INDUL	0.01*	0.01*	0.01*	0.00	0.01+	0.01+
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
AM index		-0.04**	-0.05**	-0.04+	-0.08**	-0.06***
		(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
JUS		0.06	0.07	0.03	0.23+	0.08
		(0.07)	(0.07)	(0.09)	(0.13)	(0.07)
PRO		0.40***	0.38***	0.41***	0.35***	0.33***
		(0.06)	(0.06)	(0.08)	(0.08)	(0.07)

AM index X JUS			0.04*	0.02	0.08*	0.03*
			(0.02)	(0.02)	(0.04)	(0.02)
AM index X PRO			-0.01	-0.00	-0.03	-0.02
			(0.02)	(0.02)	(0.03)	(0.02)
AM index X JUS X PRO						0.03*
						(0.01)
r2_a	0.10	0.20	0.20	0.16	0.25	0.21
N	419	419	419	229	190	419
chi2	42.56	132.87	137.83	53.50	85.84	142.20
df_m	3	6	8	7	8	9
Standard errors in parentheses						
+ p<0.10 * p<0.05 ** p<0.01 *** p<0.001						

Based on the methodology described by Aiken and West (1991), we examined the significant interaction effect of justice and AM index by graphing the association between job autonomy and AM index at one standard deviation above (high justice) and below (low justice) the mean for justice.

Figure 0-3 illustrates the moderating role of justice on the relationship between AM and job autonomy. The predictive margins of job autonomy are plotted against the AM index, with separate lines representing high and low levels of perceived justice. The blue line, indicating low justice, demonstrates a decrease in job autonomy as the AM index rises. In contrast, the red line, representing high justice, shows that job autonomy remains relatively stable across varying levels of AM. To complement the graph and deepen our understanding, we used Stata’s margins command to calculate the marginal effects of the AM index on job autonomy at high and low justice levels. At high justice, the marginal effect of the AM index is -0.02 ($p = 0.27$), which is not statistically significant. At low justice, the marginal effect is -0.09 ($p = 0.00$), indicating a significant negative correlation. This analysis reveals that the AM index is significantly negatively related to job autonomy when justice is low, but not when justice is high. These findings highlight the conditional nature of the relationship between AM and job autonomy. Specifically, higher levels of perceived justice mitigate the potential negative effects of AM on job autonomy, underscoring the critical role of justice in organizational settings where algorithmic management is prevalent.

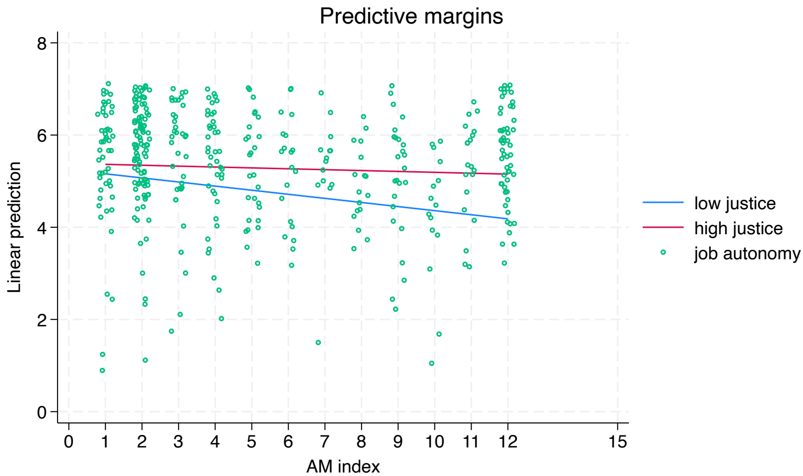

Figure 0-3 Interaction of Justice and AM Index on Job Autonomy

We also plotted the three-way to visualize the marginal effects to understand the interplay between AM index, justice, and proactivity on job autonomy, as show in figure 4.

Figure 0-4 illustrates the relationship between the AM index and job autonomy, moderated by levels of justice and proactivity. The lines represent different combinations of high and low justice and proactivity. For the group with low justice and low proactivity, represented by the blue line, job autonomy slightly decreases as the AM index increases. In contrast, the group with low justice and high proactivity, shown by the red line, experiences a more pronounced decrease in job autonomy with an increasing AM index compared to the low justice, low proactivity group. The group with high justice and low proactivity, depicted by the green line, shows a moderate decrease in job autonomy as the AM index increases. Finally, the group with high justice and high proactivity, represented by the yellow line, maintains relatively stable job autonomy levels regardless of the AM index.

The results illustrate the interaction effects of perceived justice and proactivity on the relationship between AM and job autonomy and shows that highly proactive individuals suffer the most in an unjust system. The predictive margins plot shows that job autonomy decreases as the AM index increases, but this decline varies depending on the levels of justice and proactivity. Specifically, the slope is steeper for individuals with low perceived justice and high proactivity, indicating a stronger negative relationship between AM and job autonomy for this group. Conversely, for individuals with high perceived justice and high proactivity, the decline in job autonomy is less pronounced, suggesting that higher levels of perceived justice mitigate the negative association between the AM index and job autonomy, and high proactivity further stabilizes job autonomy levels.

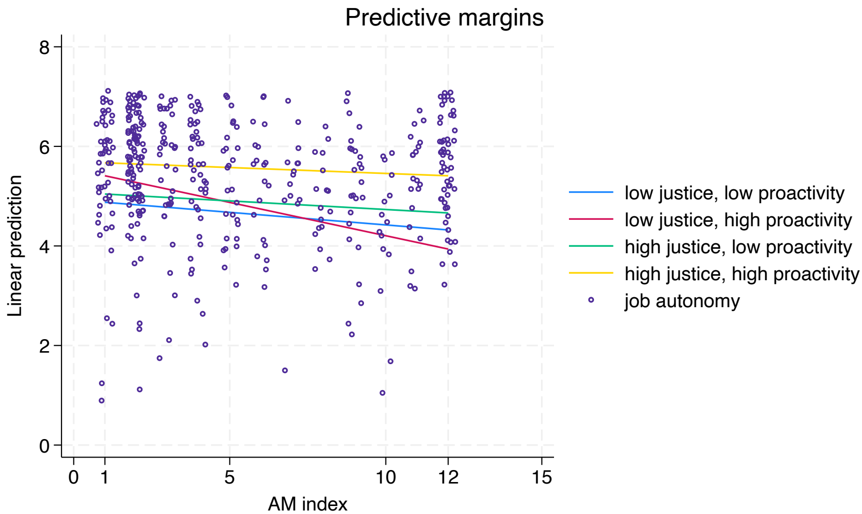

Figure 0-4 Correlation between AM Index and Job Autonomy Across Levels of Justice and Proactivity

We then compute tests of differences in simple slopes for margins. The analysis included pairwise comparisons to assess the differences in the marginal effects of the AM index on job autonomy across different levels of the interaction between justice and proactivity. To account for multiple comparisons, the Bonferroni correction was applied (Table 0-7). After this adjustment, the significant difference between the red line (low justice and high proactivity) and yellow line (high justice and high proactivity) persisted (adjusted p = 0.01), confirming the robustness of this finding. There is also a notable difference between low justice, high proactivity (red) and high justice, low proactivity (green), with a dy/dx of -0.09 (p = 0.29), although this is not statistically significant after Bonferroni correction. Additionally, difference is observed between low justice, low proactivity (blue) and low justice, high proactivity (red), with a dy/dx of 0.08 (p = 0.26), suggesting that higher proactivity increases job autonomy under low justice conditions, though this is not statistically significant. Overall, these findings indicate that levels of justice and proactivity interact with the AM index to influence job autonomy, with higher perceived justice and proactivity levels generally buffering the negative correlation between AM index and job autonomy. They also highlight that perceived justice plays a crucial role in moderating the relationship between AM and job autonomy, especially for individuals with high proactivity.

Table 0-7 Pairwise Comparisons of Average Marginal Effects with Bonferroni Correction

Contrast	dy/dx	Std. Err.	z	P>|z|	95% C.I. Lower	95% C.I. Upper
green vs yellow	-0.02	0.03	-0.33	1.00	-0.10	0.08
red vs yellow	-0.11	0.04	-3.05	0.01	-0.21	-0.01
blue vs yellow	-0.03	0.03	-0.81	1.00	-0.11	0.06
red vs green	-0.09	0.05	-1.98	0.29	-0.23	0.03
blue vs green	-0.02	0.04	-0.38	1.00	-0.13	0.10

blue vs red	0.08	0.04	2.0 1	0.26	-0.03	0.19

General Discussion

This study investigates the relationship between algorithmic management (AM) intensity, job autonomy, and the moderating roles of perceived justice and proactivity. The key findings provide modest support for the proposed hypotheses, offering critical insights into the relationship between AM and job autonomy.

The regression analyses show that while AM is negatively related to job autonomy (Hypothesis 1), the effect size is relatively small compared to the much stronger main effect of proactivity. In addition, the interaction term between AM and proactivity is not significant (Hypothesis 3). This suggests that, while both AM and proactivity independently predict job autonomy, their effects are additive rather than interactive. In other words, more proactive individuals generally maintain higher levels of autonomy regardless of AM intensity, and the degree of proactivity does not significantly alter the relationship between AM and autonomy.

The interaction between AM intensity and perceived justice supports Hypothesis 2, demonstrating that when employees perceive the AM system as more just, they tend to suffer less a sense of loss of autonomy at work. Furthermore, the three-way interaction among AM, justice, and proactivity reveals that those who are more proactive and view the AM system as fairer would experience the least decline in autonomy in a high AM system. In contrast, those who are not proactive and view the AM system as unfair would face a sharper decline in the sense of job autonomy. Notably, proactive individuals experience the greatest loss of autonomy in unjust systems, underscoring the paramount importance of justice in moderating these relationships (Hypothesis 4).

What is also worth noting is that in our sample, we observed high levels of reported job autonomy and proactivity[1], indicating that the sample comprises individuals who already possess a significant degree of control over their work and are inclined to take initiative. This calls for the need to consider baseline levels of autonomy and proactivity when evaluating the effects of AM on job outcomes. The high levels of these variables may reduce the observed negative relationship between AM

[1]Despite the high levels of job autonomy and proactivity, we still observed sufficient variance, with 1.2 for job autonomy and 0.9 for proactivity.

and autonomy, as these individuals might be better equipped to navigate and mitigate AM's constraints.

The lack of cross-validation on the moderating role of justice between the two samples, as well as the insignificant interaction term between proactivity and AM provoked us to probe deeper into the data. We therefore analyzed the qualitative input gathered from the open-ended question from the Prolific sample, using a thematic analysis approach. The qualitative insights suggest several additional reasons why proactivity might not significantly moderate the relationship between AM and job autonomy on its own, despite notable combined effects observed in the three-way interaction. Many respondents perceive the limitations and rigidity of AM systems, believing their proactive efforts have limited influence due to the system's inflexible nature, rendering such efforts futile. As one participant noted, "Job autonomy is antithetical to an algorithmic system. Humans aren't machines." Another echoed this sentiment, saying, "I feel like the algorithmic system would just interfere in my personal processes." Additionally, employees view AM as primarily beneficial for automating routine tasks rather than enhancing their ability to make autonomous decisions or engage in complex problem-solving. For instance, one respondent mentioned, "I would want it to handle all the inventory and ordering," while another stated, "Automate routine tasks to free up my time for more important tasks." Furthermore, (proactive) individuals seem to need feedback and opportunities to adapt their behavior to the AM system. The lack of these mechanisms diminishes the potential moderating effect of proactivity. As expressed by one participant, "I would want it to help me identify opportunities and queue up new work items," and another highlighted, "I would want it to help me detect errors in my work." The responses indicated that the rigidity of AM systems, their emphasis on automating routine tasks, and the lack of feedback mechanisms limit the ability of proactive individuals to maintain their autonomy. This helps to explain why proactivity has a limited moderating effect in the quantitative data and suggests that while proactivity generally enhances autonomy, its effectiveness is constrained in environments where perceived justice is low and the system is highly rigid.

Theoretical Implication

The findings of this study enrich the Sociotechnical Systems Theory by emphasizing the importance of balancing both social and technical dimensions in AI integration. As noted by Makarius et al. (2020), successful AI implementation, including AM systems, requires aligning technological capabilities with socialization processes. Our study provides empirical evidence in the AM context, showing that justice, a key system feature, and proactivity, a key human trait, individually and jointly shape the relationship between AM and job autonomy. This deepens the sociotechnical framework by highlighting the critical role of perceived justice and individual agency in effectively blending human and technological capabilities in the workplace. Organizations are appealed to support both the technical and social aspects of AM, enhancing sociotechnical capital (Makarius et al., 2020) by optimizing both human and technological elements. Adopting this perspective in future AM research can offer deeper insights into designing systems that better support employee autonomy.

Our study demonstrates that while AM is negatively related to job autonomy, organizational justice plays a key role in moderating this relationship. By revealing that perceived justice can alleviate the negative impact of AM on job autonomy, our research contributes to the intersection of sociotechnical systems theory and organizational justice theory, underscoring the critical role of fairness in shaping employee outcomes in an AM-driven environment. This aligns with findings from Bujold et al. (2022), who stress the importance of transparency in algorithmic systems. Our findings also contribute to the ethical AI discourse by emphasizing the need for just and transparent AM systems to foster positive employee outcomes (Shin & Park, 2019; Zhdanov et al., 2022).

The study also examines proactivity as a boundary condition. While proactivity did not directly moderate the relationship between AM and job autonomy, it became significant when combined with justice in the three-way interaction analysis. This results, together with insights gleaned from the qualitative input from the open-ended questions, can be interpreted through the lens of reactivity, where individuals change their behavior in response to being evaluated, observed, or measured (Espeland and Sauder, 2007). In highly controlled and opaque AM environments, the reactive behaviors triggered by constant evaluation might overpower proactive traits. Rahman (2021) describes this as an “invisible cage,” where workers feel controlled by opaque evaluation criteria, leading to divergent responses such as experimentation with tactics to improve scores or withdrawal from engagement. This suggests that reactivity might overshadow proactivity, especially in environments with high dependency on AM platforms.

This study also provides mixed empirical evidence on the duality of algorithmic management (Meijerink & Bondarouk, 2021) and algorithms as work designers model (Parent-Rocheleau & Parker, 2022). We found that AM is not inherently restrictive or controlling; instead, its effects are shaped by a blend of social and technical moderators. This challenges the traditional dichotomy of 'winners' and 'losers' often linked to AM and echoes the conceptual work from Meijerink & Bondarouk (2021) and Parent-Rocheleau & Parker (2022). However, the minimal moderating effect of perceived system justice and the insignificant interaction term between AM and proactivity, does not provide strong support for the dual nature of AM. This suggests that careful management is needed to balance control and autonomy, casts doubts on the dualistic perspective of AM, and raises questions about AM's value in enhancing autonomy for employees, thereby calling for more critical evaluation of AM in standard work settings.

Practical Implication

On a practical note, our study informs organizations of critically and carefully evaluating and designing AM systems that are perceived as just, which enable proactive employees to leverage their traits effectively, enhancing job autonomy instead of being overwhelmed by reactivity. This requires managers to strike a balance between control and autonomy within AM systems and develop strategies that encourage and support proactive behaviors.

Specifically, to ensure distributive justice, organizations should implement equitable task allocation and transparent reward systems (Grgić-Hlača et al., 2018). This involves establishing clear criteria for task distribution and openly communicating the mechanisms behind rewards. Such transparency helps employees understand the rationale behind task assignments and rewards, thereby enhancing their perception of fairness. Additionally, procedural justice can be achieved by transparently communicating decision-making processes, involving employee input, and establishing mechanisms for appeals. Allowing employees to participate in decision-making and providing avenues for contesting decisions can significantly enhance their sense of procedural fairness.

Maintaining informational justice is another critical aspect of designing fair AM systems (Shin & Park, 2019). Organizations should ensure open communication about AM systems and provide detailed explanations of how these systems operate. Employees need access to comprehensive information about the functioning and implications of AM systems to understand their role within these frameworks. Moreover, educating employees on the principles of fairness and the design of AM systems can improve their perceptions of justice. Training programs that explain the fairness protocols embedded within AM systems and how these protocols are intended to benefit employees can foster a deeper understanding and acceptance of these technologies.

Additionally, organizations should rethink employee training and development programs in the context of AM to cultivate proactivity. One approach is to focus on enhancing technological literacy and adaptability, ensuring that employees are well-prepared to engage with AM systems effectively (Jarrahi & Sutherland, 2018; Reisdorf & Blank, 2021). By focusing on AM-specific skills, organizations can prepare their workforce to navigate the technological landscape more efficiently. Furthermore, customized interventions tailored to meet specific needs and contexts are crucial. Tailoring training programs ensures that the content is relevant and directly applicable to employees' roles and the unique challenges they face within their work environment. This targeted approach to training can enhance the effectiveness of employee development initiatives and support the successful integration of AM systems into organizational processes.

By implementing these strategies, organizations can design fairer AM systems and develop effective employee training programs that foster proactivity. This approach enables optimal organizational performance by jointly optimizing both the AM system and the people within it, aligning with the principles of sociotechnical systems theory, which emphasizes the importance of balancing technology and human factors for successful outcomes.

Limitations and Future Study Directions

The study did not measure interpersonal justice due to its conceptual overlap with procedural justice and the challenges in distinguishing between different dimensions of fairness, particularly regarding the term "treat" (Greenberg & McCarty, 1990; Cropanzano et al., 2015). This decision might overlook important interactional aspects of employee perceptions of fairness, specifically the extent to which individuals are treated with dignity and respected by decision-makers (Blader & Tyler, 2003). Given that AM is becoming increasingly humanoid and interactive, future research should investigate interactional or interpersonal justice to capture these nuanced dimensions of fairness.

Although this study provided empirical evidence to the sociotechnical systems theory, we did not explicitly test (all) the socio-technical moderators as identified in "algorithms as work designers" framework (Parent-Rocheleau & Parker, 2021) (i.e., separately measure system transparency, fairness, and human influence). Additionally, other work design characteristics, such as feedback from the job, task significance, task variety, role variety, job complexity, emotional demands, and job insecurity, which are recognized as critical (Parent-Rocheleau & Parker, 2021), are not the primary focus of this study. This calls for future research to develop AM-specific measurements to test work design framework in AM system and investigate other work design characteristics as outcome variables.

It is also important to acknowledge the limitations of combining cross-sectional and time-lagged data, a sub-optimal decision we had to make because of challenges in data collection, including participants' unfamiliarity and unawareness of AM and limited budget and time in data collection. This approach may introduce biases or obscure temporal dynamics, potentially impacting the findings (Wang & Cheng, 2020). Future research should consider these methodological challenges, use more innovative research methods such as conducting behavioral or observational studies (Araujo et al., 2020; Huang, 2022), and aim to verify results through studies specifically designed to address these temporal and sampling differences.

The statistical analysis revealed high mean of job autonomy and proactivity, which may influence the generalizability of our findings, as it reflects a workforce that may be more resilient to the constraints of AM than a less autonomous and proactive group. It also indicates potential ceiling effects (Wang et al., 2008), where the high levels of job autonomy and proactivity in our sample limit the variability, may obscure the true relationships between AM, job autonomy, and proactivity. Consequently, the detected significant moderating role of systemic justice and the non-significant effect of proactivity must be interpreted with caution. Ceiling effects likely limit our ability to detect stronger associations or interactions, suggesting that our findings might underestimate the true relationship between these variables. Future research should consider addressing this limitation by incorporating a more diverse set of participants, preferably through increased offline recruitment, thereby minimizing ceiling effects and enable a more accurate assessment of these constructs across varied populations.

The study's reliance on self-reported data and the cross-sectional design, as well as the evolving nature of AM systems present certain limitations and further suggest several avenues for future research. One important direction is to investigate the role of user interface design in shaping proactive behaviors through experimental studies (Bader & Kaiser, 2019). The design of user interfaces in AM systems can evoke low involvement, affecting how employees interact with these systems. Exploring the underlying reasons for perceived futility and its implications on employee outcomes can provide deeper insights into the effective design of AM systems. Conducting longitudinal studies to examine the long-term effects of AM on job autonomy and how employees adapt their behaviors over time could provide valuable insights and contributions to the literature. Additionally, complementing quantitative methods with qualitative research, such as interviews or focus groups, will offer a deeper understanding of employees' experiences and perceptions of autonomy within AM systems (Creswell & Creswell, 2018).

The minimal moderating effect of justice suggests that even when employees perceive the system as fair, they experience only a marginal increase in job autonomy. More strikingly, when the system is viewed as unjust, highly proactive employees suffer an acute loss of autonomy. These findings challenge the dualistic perspective of AM proposed by Meijerink and Bondarouk (2021) and underscores the need for more critical and provocative voices in AM evaluation in standard work settings.

Addressing these future research directions can advance the understanding of the complex relationship between algorithmic management and job autonomy, which will ultimately contribute to the development of strategies that promote employee well-being in the digital workplace, ensuring that AM systems are designed and implemented in ways that respect and enhance employee autonomy.

Appendix

Measurement scales:

Algorithmic management (adapted based on Parent-Rocheleau & Parker (2022) and Kellogg et al. (2020)):

1. Tools are used to collect data on me and/or on my performance.
2. Tools are used to report data on me and/or my performance to my employer or myself.
3. Algorithms are used to assign tasks to me.
4. Algorithms are used to set my performance targets.
5. Algorithms are used to carry out my performance ratings.
6. Algorithms are used to display my performance ratings.
7. Algorithms are used to provide automated performance feedback for me.
8. Algorithms are used to schedule my tasks.
9. Algorithms are used to send nudges for suggested working times for me.
10. Algorithms are used to calculate how much I am paid.
11. Algorithms are used to notify me of unsatisfying results.
12. Algorithms are used to decide on the end of the employment relationship or collaboration.

Job autonomy (adapted from Morgeson & Humphrey (2006)):

1. My job allows me to make my own decisions about how to schedule my work.
2. My job allows me to decide on the order in which things are done on the job.
3. My job allows me to plan how I do my work.
4. My job gives me a chance to use my personal initiative or judgment in carrying out the work.
5. My job allows me to make a lot of decisions on my own.
6. My job provides me with significant autonomy in making decisions.
7. My job allows me to make decisions about what methods I use to complete my work.
8. My job gives me considerable opportunity for independence and freedom in how I do the work.
9. My job allows me to decide on my own how to go about doing my work.

Proactivity (adapted from Bateman and Grant (1993)):

1. I am constantly on the lookout for new ways to improve my life.
2. Wherever I have been, I have been a powerful force for constructive change.
3. Nothing is more exciting than seeing my ideas turn into reality.
4. If I see something I don't like, I fix it.
5. No matter what the odds are, if I believe in something, I will make it happen.
6. I love being a champion for my ideas, even against others' opposition.
7. I excel at identifying opportunities.
8. I am always looking for better ways to do things.
9. If I believe in an idea, no obstacle will prevent me from making it happen.
10. I can spot a good opportunity long before others can.

Justice (adapted from Colquitt (2001)):

1. To what extent has the algorithmic management system been candid in the communications with you?
2. To what extent has the algorithmic system explained the procedures thoroughly?
3. To what extent have the algorithmic system's explanations regarding the procedures been reasonable?
4. To what extent has the algorithmic system communicated details in a timely manner?
5. To what extent has the algorithmic system tailored the communications to individuals' specific needs?
6. To what extent have you had influence over the algorithmic decisions arrived at by those procedures?
7. To what extent have those procedures been applied consistently?
8. To what extent have those procedures been based on accurate information?
9. To what extent have you been able to appeal the algorithmic decision-making arrived at by those procedures?
10. To what extent does the algorithmic decision-making reflect the effort you have put into your work?
11. To what extent is the algorithmic decision-making appropriate for the work you have completed?

12. To what extent does the algorithmic decision-making reflect what you have contributed to the organization?
13. To what extent is the algorithmic decision-making justified, given your performance?

Definition of algorithmic management:

Algorithmic management is a diverse set of technological tools and techniques to remotely manage workforces. It includes continuous tracking of workers, constant performance evaluation, and the automatic implementation of decisions, with no or little human intervention. These algorithms are designed to optimize the efficient allocation of resources in the production of goods and services, help organizations reduce costs, maximize profits, and ensure competitiveness in the market.

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Paper 3: Rage Against the Machine: Sensemaking Amid Algorithmic Technologies[2]

Abstract

The pursuit of employee well-being and humanistic organizing has been increasingly complex with the rise of algorithmic technologies in modern organizations. These technologies introduce new tensions and challenges in defining and achieving an "ideal" notion of well-being and genuine humanistic organizing. Our qualitative study explores employees' sensemaking processes as they are confronted with the potential of algorithmic technologies to shape an "ideal" notion of well-being which promises humanistic organizing. Using a theatrical performance as a sense-giving device, we simulated and imposed a series future scenarios where intrusive corporate well-being technologies aim to create "perfect and happy" employees, compelling participants to negotiate the implications of such a plausible reality. Our results, based on 6 theatrical performances and 16 focus groups of a total of 131 participants, demonstrate that these performances act as sensemaking triggers, prompting employees to grapple the uncertain consequences of algorithmic management in promoting employee well-being. Our study demonstrated that employees are not passive recipients of these narratives but are active agents in the sense-receiving process, engaging in sense-scrutinizing and questioning imposed ideals. This study contributes to sensemaking theory and algorithmic management literature (of which corporate well-being technologies are a specific application) and provides practical implications for designing a genuine humanistic future of work.

Keywords: Employee Well-being, Algorithmic Technologies, Sensemaking, Theatrical Performance, Future of Work.

[2] This paper has been presented at the EGOS conference in Milan, 2024 and is still work in progress.

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Introduction

Today's workforce faces a widespread employee wellbeing crisis (e.g., Pirson, 2017). In response, scholars and leaders alike have called for leveraging advanced technologies such as artificial intelligence (AI) in business practices to promote collective flourishing (Angelucci et al., 2024; Berry et al., 2010). Central to this trend the stark divide in the existing academic debate on well-being. The dominant managerialist perspective frames well-being through a win-win lens, emphasizing happiness, physical health, and interpersonal relationships as mutually beneficial for both individuals and organizations (Grant et al., 2007; Warr, 2007). However, critical management scholars challenge this view, arguing that this narrative obscures and perpetuates unequal power structures while prioritizing organizational interests over genuine employee welfare (Heffernan and Dundon, 2016; Ramsay et al., 2000). These critics advocate for a more holistic conceptualization of well-being that acknowledges the influence of power dynamics and individual identity, extending beyond the positive-only focus in managerialist definitions of well-being. The critical management perspective has been effectively captured in the recent research by Town et al. (2024), who advocate for the concept of *genuine humanistic organizing*—prioritizes the dignity and intrinsic worth of individuals, as well as promotes organizational growth in service of collective well-being (Melé, 2003, 2016; Pirson & Lawrence, 2010).

As algorithmic technologies, or algorithmic management (AM) technologies rapidly advance and become increasingly pervasive, the tension between the managerialist perspective of workplace well-being and the critical management perspective, embodied in humanistic organizing, has intensified, further complicating efforts to achieve genuine workplace flourishing. Given this context, the research question becomes urgent:

How do employees, as individuals at the heart of workplace well-being, collectively deconstruct and reconstruct the notion of 'ideal' well-being empowered algorithmic technologies?

To address this research question, we employed a qualitative, performative research approach (Gergen & Gergen, 2012), utilizing theatrical performances to simulate future scenarios where algorithmic technologies significantly shape employee well-being. This method, grounded in work by Gümüsay & Reinecke (2022) and Savage et al., (2018), aligns with the call for proactive theorizing in the face of radical uncertainty, allows participants to engage with plausible futures in an immersive and reflective manner, and makes abstract concepts like algorithmic technologies more relatable. By triggering sensebreaking and sensegiving processes, the performances effectively prompt participants to deconstruct and reconstruct notions of well-being, well-suited to the research question.

Data were collected through 6 theatrical performances and 16 focus groups, involving a total of 131 participants from various industries. These sessions were recorded from multiple angles, providing us with 1,092 minutes of video footage and 1,452 minutes of audio recordings for analysis. The theatrical performances acted as sense-giving devices, encouraging participants to reflect on their experiences and make sense of the portrayal of algorithmic management and its implications for employee well-being. We conducted the data analysis using an abductive approach (Tavory & Timmermans, 2014), which involved iterating between the data and relevant theories, particularly sensemaking (Weick, 1995) and humanistic organizing (Melé, 2003, 2016; Pirson & Lawrence, 2010). This method allowed us to explore how employees engage in sensemaking around the narratives of algorithmic technologies and workplace well-being, revealing new insights into how they negotiate the managerialist framing of well-being (Grant et al., 2006) in contrast to the humanistic organizing perspective (Town et al., 2024).

Our study offers a deeper understanding of the ongoing tension between algorithmic technologies which promise improved managerialist well-being and the demand for genuine employee well-being, allowing us to contribute meaningfully to the discourse on the future of well-being in the age of algorithms. We offer several key contributions to the field, beginning with the expansion of sensemaking theory. Traditionally, sensemaking has emphasized sensegiving, focusing on how managers shape and influence organizational narratives (Bishop et al., 2020; Maitlis, 2005). This study, however, highlights the critical role of employees in interpreting and questioning the narratives imposed by algorithmic technologies and introduces the concepts of sense-receiving and sense-scrutinizing. Employees actively engage in sense-receiving by absorbing and interpreting the managerial well-being narratives surrounding AM, while participating in sense-scrutinizing by critically examining the ideals of well-being that algorithmic technologies claim to promote. Therefore, this study demonstrates that employees are not passive recipients of these narratives but actively resist and reinterpret them (Kellogg et al., 2020; Zuboff, 2023)—rather than accepting the managerialist view that algorithmic technologies automatically enhance well-being, employees critically evaluate these systems. This extension of sensemaking theory shifts the focus to employee agency and political potential in shaping organizational narratives.

The study also innovates methodologically by utilizing theatrical performances as a research method. Grounded in the work of Gergen & Gergen (2012) and supported by Savage et al. (2018), who argue that fiction plays a constitutive role in organizational understanding, the use of theater allows for an immersive and reflective examination of AM's impact. These performative methods enable participants to emotionally and critically engage with the complexities of algorithmic technologies, making abstract concepts like algorithmic technologies and well-being more accessible.

Furthermore, the study advances the concept of humanistic organizing in the age of algorithmic technologies. It advocates for a shift from a productivity-focused approach to well-being—prioritizes efficiency—to one that centers on dignity, autonomy, and the intrinsic worth of employees (Melé, 2003, 2016; Pirson & Lawrence, 2010). The findings emphasize that employees resist the dehumanizing aspects of algorithmic management, expressing a desire for genuine human interaction and well-being—elements that cannot be reduced to mere data points or productivity metrics.

Finally, the paper contributes to the ongoing discourse on the ethical implications of AM (Bélanger & Crossler, 2011; Rosenblat & Stark, 2016; Zuboff, 2023). It highlights employees' concerns regarding privacy, autonomy, and the blurring of boundaries between work and personal life as algorithmic technologies become more pervasive and intrusive. The findings urge organizations to implement AM systems with greater transparency and ethical safeguards, ensuring that these technologies support rather than undermine the exact genuine well-being that organizations strive to achieve.

Algorithmic Technologies

Defined as "computer-programmed procedures that transform input data into desired outputs in ways that are more *1) encompassing, 2) instantaneous, 3) interactive, and 4) opaque* than previous systems" (Kellogg et al., 2020), algorithmic technologies, or algorithmic management (AM) technologies, introduce new opportunities for well-being solutions, reshape organizational control, and fundamentally challenge our understanding and attainment of well-being in the workplace. First, algorithmic control is more *comprehensive* in directing, evaluating, and disciplining workers. These technologies facilitate comprehensive monitoring and evaluation, including biometric data collection for identity verification and real-time monitoring of emotional and physiological indicators (Ball & Margulis, 2011; Xu et al., 2014). Second, algorithmic control provides more *instantaneous* and individualized feedback and data transmission compared to previous control regimes (Sachon & Boquet, 2017). Third, algorithmic control enhances managerial power over workers by facilitating *interactive* and crowdsourced data and procedures and reducing the need for direct managerial oversight through the use of algorithm-powered chatbots (Cambo & Gergle, 2018). Fourth, algorithmic control is often *opaquer* in how it directs, evaluates, and disciplines workers. The opacity of these processes complicates workers' understanding and resistance, with machine learning algorithms posing comprehension challenges even for specialists (Burrell, 2016). These features profoundly reshape employer-employee dynamics and require a reevaluation of managing employee "well-being".

Managerialist Perspective of Well-being

From the *managerialist perspective*, algorithmic technologies offer new tools to enhance psychological, physical, and social aspect of well-being by providing scalable, efficient, and personalized well-being programs (Chui et al., 2022; World Health Organization, 2024). These technologies enable real-time monitoring and proactive health management, potentially increasing productivity and job satisfaction (Varley and Glaser, 2023), thereby benefiting both employers and employees, aligning with the managerialist goal of achieving mutual gains for both parties (Wright & MacMahan, 1992). In practice, accordingly, companies are increasingly leveraging these algorithmic technologies to improve employee well-being, with examples including VR relaxation (Meta for Work, 2023) and 24/7 mental health chatbots (Woebot Health, 2024). Beyond the technologies already pervasive in corporate environments, more advanced, invasive innovations are looming on the horizon: movements are being tracked (Lavrut, 2020), hormone levels can be monitored by chip implants in clinical settings (NHS, 2024), and thought-reading devices are being tested on humans (Neuralink, 2024). For the first time, these technologies enable individuals to achieve what we term "the ideal of well-being" from the managerialist perspective—optimal happiness, health, and social relationships (Grant et al., 2007), with unparalleled effectiveness and efficiency as a presumed consequence. However, this pursuit is marked by unprecedented intrusiveness, defined by technology presenteeism—constant reachability—and technology anonymity—the identifiability of users' activities (Ayyagari et al., 2011). This intrusion into their lives raises significant concerns about privacy, autonomy, and control, and brings with it unknown costs and ethical implications (Bhave et al., 2020). These issues prompt critical questions about the very nature of well-being for individuals and organizations, and whether such a pursuit, driven by algorithmic technologies, is prudent or sustainable in this manner.

Critiques of Algorithmic Technologies and Well-being

To understand these implications more deeply, it is crucial to consider the *critical perspectives* on algorithmic technologies and well-being. On one hand, critical studies on algorithmic technologies argue that these technologies often prioritize organizational interests over genuine employee well-being (Duggan, 2020; Parent-Rocheleau & Parker, 2021; Wood et al., 2019). Algorithmic technologies, with their encompassing, instantaneous, interactive, and opaque nature (Kellogg et al., 2020), could further intensify managerial control, surveillance, and exploitation, leading to increased work stress, reduced job autonomy, and compromised interpersonal relationships, thereby undermining managerialist well-being (Vrontis et al., 2022). On the other hand, critical management perspectives on well-being focus on power relations and the systematic exploitation of workers inherent in the economization of well-being (Ramsay et al, 2000). Critical management scholars challenge the perception that well-being is always positive or desirable (Wallace, 2019), arguing that this view oversimplifies and ignores the complex and varied nature of human experiences, and advocate for recognizing and appreciating neutral or negative states of employee well-being. Critics argue that workplace well-being programs often serve as mechanisms of control, prioritizing productivity over employee health. These initiatives shift health responsibility onto individuals, neglecting organizational factors in ill-health and reinforcing neoliberal ideals. Effective resistance involves holding employers accountable and addressing systemic work-related stressors (Cederström and Spicer 2015; Foucault 2001; Lupton 1995).

A Call for Proactive Exploration

Therefore, while algorithmic technologies have the potential to enhance well-being from a managerialist standpoint, they also demand a more humanistic understanding of well-being and present significant challenges that require scrutiny to prevent the exacerbation of existing power imbalances. The implementation of these technologies without adequate dialogue and informed consent from the workforce, who will be most affected, raises serious concerns. Given the historical precedent of technology adoption in workplaces, this scenario is not merely hypothetical but highly plausible (Cameron, 2024). This escalated tension and resulting uncertainty necessitate a proactive, future-oriented approach to investigating this impending future and initiate a public debate; failing to do so could result in a future where workplace flourishing, along with individual subjectivity and identity, core to humanistic organizing (Melé, 2016; Pirson & Lawrence, 2010), is redefined without the consent or understanding of those most affected, alienating us further away from the humanistic organizing that employers originally intend to strive for.

There is an understandable scarcity of critical empirical research on the implications of algorithmic technologies for well-being, despite their demonstrated potential, particularly due to their yet limited large-scale application. To proactively explore these technologies' potential impacts, we used an innovative performative approach, employing theatrical performances as a research method to leverage the immersive and emotive power of theater to simulate future scenarios (Gergen & Gergen, 2012). This method aligns with the notion that, in the face of radical uncertainty, fictional expectations and narratives are key to navigating unpredictable futures (Beckert & Bronk, 2018). The use of theater aligns with Beckert and Bronk's (2018) argument that fictional expectations help navigate uncertain futures by presenting narrative possibilities. Similarly, Gümüsay and Reinecke (2024) call for prospective theorizing, which moves beyond past data to imagine desirable futures. Through these performances, we simulate speculative futures and engage employees in a collective sensemaking process, allowing us to explore both the ethical and practical dimensions of algorithmic technologies in a way that traditional methods cannot.

We applied abductive analysis, which is a generative reasoning process beginning with the observation of anomalies and moving to generate and evaluate possible explanations for those anomalies (Sætre & Van De Ven, 2021). In our study, the anomalies emerged as the intensified tensions between the managerialist view of well-being and the critical humanistic perspective, induced by algorithmic technologies and illustrated through a theatrical talk performance. Through abduction, we sought to develop new theoretical insights into how employees negotiate the meaning of well-being within the context of algorithmic technologies.

Our abductive analysis reveals an ongoing debate over the meaning of employee well-being, where default managerialist frames are negotiated, contested, reconfigured, or replaced by alternative framings, particularly in this era of uncertain algorithmic advancements. Abduction, as defined in the literature (Sætre & Van De Ven, 2021; Tavory & Timmermans, 2014), involves generating new ideas and explanations. In our case, this process helped reveal how employees engage in sensemaking, deconstructing and reconstructing the concept of well-being in response to the growing influence of algorithmic technologies. It also uncovered a bottom-up demand for humanistic organizing (Town et al., 2024), which has the potential to create new field frames that could inspire innovative practices (Hirsch, 1986; Rao, 1998).

Method

The empirical context for this study is set within Belgium, a country that has recently adopted the National Convergence Plan for the Development of AI. This initiative, approved by the Council of Ministers in October 2022, outlines actionable steps to transform Belgium into a #SmartAINation (BOSA, 2022). The plan focuses on promoting trustworthy AI, ensuring cybersecurity, and boosting Belgium's competitiveness and attractiveness through AI over the coming years.

This study uses a performative approach inspired by performance social science (Gergen & Gergen, 2012), collaborating with an artist to bring fresh, unconventional insights. Performances make complex research concepts more tangible and accessible, aligning with Savage et al. (2018), who argue that fiction plays a constitutive role in how organizations are understood. The artist's 1.5 years of global research and interviews with stakeholders shape the performances' theme on the impact of technology on human happiness and productivity, reflecting concerns about burnout and success-driven societies. The performances, like organizational fictions (Savage et al., 2018), construct future scenarios that provoke critical thinking about technology's role in personal and professional life. This aligns with Ricoeur's narrative fiction (cited in

Savage et al., 2018), where the aim is to prompt reflection rather than provide clear-cut answers.

The performance deconstructs the notion of well-being and brings future scenarios of workplace well-being to life through a vivid theatrical experience. The performance features Robin Sharp, a People First Advisor who highlights the need for transforming workplace happiness and prioritizing employee well-being through innovative strategies and technologies. Robin introduces the People First Pilot Project, which uses algorithmic technologies to monitor and improve employee health and behavior. However, she emphasizes that genuine change requires deeper structural adjustments within organizations, not just superficial fixes. The script acknowledges the limitations of existing technologies, using the example of an employee named Pablo whose personal issues were missed by monitoring systems, calling for a holistic approach that integrates support for both work and personal life with more advanced, invasive technologies such as brain chip implants. Employee testimonials provide a balanced view of the pilot project, with some noting improvements and others expressing concerns about the technology's invasiveness. At the end of the performance, Robin calls on companies with a genuine social purpose to join the next phase of the project, advocating for a shift from profit-centric to people-centric priorities. The performance concludes with a statement from the artist, explaining that the character of Robin and her talk are based on extensive research and real technological advancements and that the goal of this performance is to spark a conversation about the future of work and shared values, promoting a more human-centric approach to employee well-being.

Based on the artist's observations from four years of performances, audience reactions vary, with some initially skeptical or hostile. However, noticeable shifts occur with the introduction of four technologies: multifunctional badge, well-being chip, thought-reading chip, and smart toilet (Table 0-1). From focus group analysis, we identified intrusion[3] as the key factor explaining these shifts. Moderate intrusion includes technologies like the Multifunctional Badge, which tracks movements without major privacy breaches. High intrusion involves technologies like the Well-being Chip and Thought-reading

[3] In the literature, technology intrusion is defined by technology presenteeism (constant reachability) and technology anonymity (identifiability of activities) (Ayyagari et al., 2011).

Chip, which deeply affect privacy by monitoring health and thoughts. Moderate to high intrusion is seen in Smart Toilets, which detect health indicators, blending personal health with workplace surveillance. The technologies and shifting points are detailed in the table below.

Table 0-1 Observed Shifts in Audience Perspective Based on Technological Implementation

Algorithmic Technology	**Function**	**Impact**	**Intrusion Level**
Multifunctional Badge	Replaces old employee cards, tracks movements, interactions, and dietary habits	Redefines identification and monitoring, disrupts privacy norms	Moderate
Well-being Chip	Monitors hormonal balances and brain activity	Influences emotional well-being and productivity, challenges traditional mental health management	High
Thought-reading Chip	Converts unspoken thoughts into scripts	Enhances brainstorming, disrupts communication boundaries and privacy	High
Smart Toilets	Detects health indicators	Enables early intervention, blurs lines between personal health information and workplace surveillance	Moderate to High

Data Collection

The data collection for this study was designed to deeply explore the sensemaking processes surrounding algorithmic technologies and employee well-being. In the first stage, we conducted interviews with the theatrical artist via video meetings and email exchanges, aiming to gain insights into the artist's perspective as both the primary presenter and a moderator in subsequent discussions. Additionally, we conducted a thorough analysis of the talk's script, which helped us understand the narratives being communicated.

In the second stage of our research, we observed and recorded six theatrical performances targeting at different organizations in Belgium. Participating organizations included a Belgian retail corporation, a pharmaceutical company (where two performances were conducted), a Flemish public employment service, a global professional services firm, and subscribers (mainly HR professionals) of a publication company in collaboration with a university student body specializing and/or interested in Human Resource Management. Each performance lasted approximately 50 minutes.

In the third stage of our research, we conducted focus groups. The focus group discussions began with the group discussion moderator, the artist herself and one of the trained researchers in the authorship, asking participants an initial yes-or-no question about whether they would like to use the technologies discussed in the talk. Subsequently, participants were encouraged to share their ideas, enthusiasm, and concerns about the introduced technologies. The moderator continued by challenging assumptions made by the audience (e.g., fear of technology, concerns about data safety, questioning being perfect all the time, etc.) to delve deeper into the underlying reasons for resistance. The moderator employed evidence-based discursive tactics, including playing the role of devil's advocate, a method shown to reduce groupthink and promote rigorous analysis by presenting opposing viewpoints (Nemeth et al., 2001). This approach is rooted in cognitive dissonance theory, which posits that exposing individuals to conflicting perspectives stimulates deeper reflection and a re-evaluation of their beliefs (Festinger, 1957). Additionally, the moderator intentionally fostered inclusive discussions, actively seeking the opinions of minorities and quieter participants. Research demonstrates that such inclusive practices enhance group cohesion and ensure diverse perspectives are heard, leading to more meaningful and equitable discussions (Cohen & Lotan, 1997). The focus groups concluded with a 20-minute plenary session, where participants from the two groups shared their discussion outcomes and continued to engage in a combined dialogue. Moderators applied these same evidence-based tactics to further deepen and enrich the conversation.

To further enrich our understanding, we also conducted quantitative pre- and post-performance surveys as part of the project (Creswell & Creswell, 2018), the results of which is not included in this paper. The pre-survey took place eight days before the performance. The temporal separation ensures minimal impact on participants' initial reactions. The post-survey, administered immediately after the performance, captured their first reactions. These surveys assessed tech readiness, emotional states, AI attitudes, issue engagement, and resistance tendencies. While providing valuable structured data, the administration of the survey played a limited role in the subsequent focus groups, thanks to the use of structured discussions with discursive tactics to deliberately explore a wide range of arguments to ensure a balanced examination of participants' perspectives (Nemeth et al., 2001).

Informed consent was obtained from all participants, ensuring they were aware of the study's purpose and their rights. Anonymity and confidentiality were rigorously maintained throughout the process (American Psychological Association, 2017). The schedule and details of the performances can be found in the appendix. The video and audio recordings from multiple angles of these sessions provided us with a total of 1,092 minutes of video footage and 1,452 minutes of audio recordings for analysis. This paper presents our initial findings based on this rich empirical material. The table (Table 0-2) below summarized the data collection stages.

Table 0-2 Data collection stages

Stage	Step	Description	Main Actors
Stage 1	Interviews and Script Analysis	Conducted interviews with the theatrical artist via video meetings and email exchanges to gain insights into the artist's perspective. Analyzed the talk's script to understand the narratives.	Theatrical artist, Researchers
Stage 2	Theatrical Performances	Observed and recorded six theatrical performances targeting different organizations in Belgium. Each performance lasted approximately 50 minutes.	Theatrical artist, Employees from five organizations (Belgian retail corporation, pharmaceutical company, Flemish public employment service, global professional services firm, HR professionals/subscribers of a publication company, and university student body)

Stage 3A	Focus Group Discussions with Managers	Conducted subgroup discussions with manager lasting around 25 minutes. Moderators asked initial questions and encouraged discussion on the technologies introduced in the talk, using discursive tactics to challenge assumptions and engage all participants.	Moderators (Theatrical artist and trained researcher), Participants (managers)

Stage 3B	Focus Group Discussions with Non-manager	Conducted subgroup discussions with non-manager lasting around 25 minutes. Moderators asked initial questions and encouraged discussion on the technologies introduced in the talk, using discursive tactics to challenge assumptions and engage all participants.	Moderators (Theatrical artist and trained researcher), Participants (non-managers)

Stage 4	Plenary Focus Group Discussions	Conducted a 20-minute plenary group discussion. Moderators asked initial questions and encouraged discussion on the technologies introduced in the talk, using discursive tactics to challenge assumptions and engage all participants.	Moderators (Theatrical artist and trained researcher), Participants (managers and non-managers)

Preliminary Analysis and Findings

Responding to the research question on how employees, who are central to humanistic organizing, make sense of the 'ideal' employee well-being promoted by AM technologies that claim to support humanistic organizing, as presented through theatrical performances, we draw on a discourse analysis using abductive approach to understand how meaning is co-constructed through an interactive and discursive process (Tavory & Timmermans, 2014). Discourse analysis is a method used to study how language and communication shape social practices and meaning (Atkinson et al., 2000). In this context, it allows us to examine the conversations, narratives, and interactions that arise during the performances to see how employees collectively construct and negotiate the concept of well-being. The abductive approach (Tavory & Timmermans, 2014) is a process of reasoning that involves moving back and forth between the data and theoretical frameworks to generate new insights. It differs from deduction, which tests theories, and induction, which builds theories purely from observation. Abduction combines both by starting with an observation (such as how employees respond to AM technologies) and iteratively developing explanations that best fit the data. This approach is ideal for exploring sensemaking because it helps reveal how employees interpret and reshape the narratives around well-being in an interactive and discursive process.

The coding process was conducted collaboratively to ensure robustness and reliability (Saldana, 2021). Initially, a primary coder conducted a preliminary analysis of the data. This was followed by consensus-building sessions, where the research team engaged in discussions to align their interpretations of the data. Consensus-building is a collaborative process aimed at reaching agreement on the codes and frames through dialogue and debate, ensuring that diverse perspectives are considered. This approach not only helped to cross-verify interpretations but also enhanced the reliability and validity of the findings by ensuring that the final coding scheme reflected a shared understanding of the data (Adu, 2019). After analyzing the data from interviews with the artists, performance scripts, and the first two sessions at a Belgian retail corporation and a pharmaceutical company at the initial stage, several frames related to sensemaking emerged. These include the shifting moments that the artist observed through her years of performance, the deconstruction and redefinition of the notion well-being at work, as well as employees' concerns and resistance to the notion of "ideal of well-being" in the focus group discussion. These initial insights led us to closely engage the literature on sensemaking until we completed the full data analysis including the six theatrical talk sessions. We alternated between data collection and analysis, and literature review on topics such as sensemaking theory, humanistic organizing, critical management studies on well-being, and algorithmic management. Throughout the analysis, our goal was to explore how existing research could refine the theoretical insights emerging from our data, while also identifying the potential contributions of our study to the broader field.

As the result of the abductive data analysis, three main frames emerged: "sense-breaking", "sense-giving", and "sense-receiving/sense-negotiating". After identifying the dominant frames, we revisited the data, re-coded it, and refined the categories within each theme (i.e., "structural issues and superficial solutions", "the interconnectedness of personal and professional life", "critical need for ongoing monitoring and adaptation" under "sense-breaking", "happiness", "health", and "social relationships" under "sense-giving", and "human-centric", "operation-centric" under "sense-receiving/sense-negotiating"), and started building the model.

The analysis of the theatrical script reveals key strategies employed by the protagonist, Robin, an authoritative HR consultant, to systematically deconstruct current workplace practices and redefine what future well-being should look like and discursively construct "ideal" future workplace well-being enabled by algorithmic technologies. We compare these findings with sensemaking literature and identified a combination of sense-breaking and sense-giving points.

Sensebreaking

In our study on employee well-being on algorithmic technologies, we expand the concept of sensebreaking—traditionally understood as deliberate actions by top managers to create meaning voids (Pratt, 2000)—to include the role of collective social arbiters (Bishop et al., 2020) in breaking down employees' existing understandings. In addition, research by Bishop et al. (2020) reveals that sensebreaking can be an intuitive and emotionally driven process, rather than solely a rational and deliberative one (e.g., Maitlis & Christianson, 2014). In our study, we deem theatrical performances as social arbiters, which employ immersive and emotive storytelling to effectively create and fill meaning voids. By challenging existing perceptions and connecting with the audience through relatable anecdotes and colloquial language, the theatrical performances prompt audiences to reflect on and re-evaluate their beliefs and assumptions, particularly concerning their understanding of workplace well-being.

Our preliminary analysis identified three categories of sensebreaking frames: structural issues and superficial solutions, interconnectedness of personal and professional life, and need for monitoring and adaptation.

Structural Issues and Superficial Solutions

Robin, the fictional character, highlights the necessity for structural changes in workplace practices, criticizing superficial interventions that fail to address the root causes of employee dissatisfaction and burnout. For instance, she underscores the inadequacy of cosmetic changes with the analogy by stating "Decorating a sick Christmas tree makes it look good from a distance, but it doesn't make the tree healthy". Robin also supports her argument with compelling statistics: "Despite significant investments and efforts, the persistent high costs of burnout, estimated at 87 billion euros annually, and the substantial financial burden on employers, approximately 80,000 euros per burnout, indicate that current efforts are ineffective". These points collectively emphasize the need for fundamental structural changes rather than mere superficial fixes.

Interconnectedness of Personal and Professional Life

The second frame explores the deep interconnection between employees' personal and professional lives, challenging the notion that these can be treated separately. Robin asserts, "People aren't robots. You can't separate the two (i.e., personal and professional lives) so easily", highlighting how personal issues inevitably impact professional performance. She introduces the concept of "Lifecycle Stress", explaining that stressors from various life stages continually affect employees, making it difficult to reduce burnout rates solely through workplace interventions. This interconnectedness necessitates a holistic approach to employee well-being, considering both personal and professional dimensions. Moreover, the cited inability of employees to communicate their personal struggles exacerbates the issue, leading to unaddressed problems that further diminish workplace productivity and morale, as is vividly shown by the following excerpt: "He asks me if he can use up all his leave days. 'I need some time for myself,' he says. 'Why didn't you go to your manager sooner? We could have helped you right away!' 'It's none of her business that's private.'" In response to this, Robin thinks to herself, "Your private matters are having a big impact on our company...These last weeks you're delivering bad work, your team members are getting annoyed because they can no longer rely on you...It costs us peace and trust in the organization and ultimately it costs us a lot of money." These excerpts illustrate how Pablo's unwillingness to share personal struggles with his manager led to unaddressed issues that affected his work and team.

Need for Monitoring and Adaptation

Lastly, Robin emphasizes the critical need for effective monitoring and adaptation in addressing employee well-being. She criticizes current technologies for their inability to fully understand and address the complexities of human emotions and behaviors. These limitations leave the root causes of employees' issues uncommunicated and unresolved, which in turn worsens the situation. As she states, "It [the monitoring system] cannot look inside. It only sees the symptoms but can't analyze them. Because of this, we miss too much; we see too little." This limitation underscores the gap between identifying superficial symptoms and understanding deeper, underlying issues. Additionally, Robin discusses the challenges of implementing change, noting that "Every change is resisted at first, right? And you often only see the results much later", attempting to justify the need for continuous monitoring and the flexibility to adapt interventions based on real-time data to achieve meaningful and sustained improvements in employee well-being.

Sensegiving

Sensegiving involves providing others with a revised frame for understanding events, especially in situations of meaning voids (Maitlis & Lawrence, 2007; Gioia & Chittipeddi, 1991). This process is where framing is the most prominent—use specific words, images, and presentation styles—to convey information (Gamson & Modigliani, 1989). Framing sets agendas and highlights certain aspects of events to promote a preferred definition, causal explanation, or moral judgement (Entman, 1993).

In our study, we identified these sensegiving moments as the actress attempted to construct a new "ideal" of employee well-being through algorithmic management, directly addressing the issues highlighted during sensebreaking. By emphasizing the positive aspects of these technologies, she framed the narrative around the three dimensions of managerialist well-being—optimizing happiness, health, and social relationships—through algorithmic interventions. This approach promoted a data-driven solution to the problems identified during the sensebreaking process, aiming to enhance employee well-being in the workplace.

Happiness Frame

The play script employs sensegiving frames that emphasize the role of personalized interventions in enhancing employee happiness. Robin explains how the integration of wearables and AI systems allows organizations to obtain a comprehensive and customized understanding of each employee's needs: "Thanks to the badge and certainly in combination with the wristband we can guide people better than ever before. Because we get a much more personal picture of someone, we can help in a much more targeted way. It's really customized to what the employee needs". This frame highlights the interconnectedness of professional and private life, responds to the need for continuous monitoring and adaptation, and is reinforced by the belief that employees who feel seen and heard are happier and more efficient: "We are making sure that everyone feels seen and heard... you are happier you work better and more efficiently". Additionally, the ability of the chip to monitor and influence hormonal balance to alleviate negative emotions further supports the narrative that technology can directly contribute to employee happiness, claiming to solve the root cause of employee dissatisfaction: "The (well-being) chip can also read and influence the hormonal balance and brain activity of a person. So we can see instantly when someone is happy, sad, stressed, tired, or enthusiastic and we can alleviate the negative emotions by adding the right hormones in very focused micro doses". The happiness frame aims to counter the concerns raised in the sensebreaking phase, presenting a compelling argument for the adoption of personalized, data-driven interventions to enhance workplace happiness.

Health Frame

We also identified a frame that highlights the continuous monitoring of health as a critical aspect of employee well-being. Robin describes the functionality of wearables that monitor various health metrics: "Pablo gets just like all the other employees 2 wearables: a light wristband -most of you know these of course it's very comfortable you can keep it on without any problem 24/7. It monitors the heartbeat and the condition and records all actions. a little like a Fitbit actually. The focus here is on the overall health". This continuous health monitoring, echoing the need for monitoring and adaption in the sensebreaking frame, is presented as an effective means to ensure that employees maintain good health and prevent potential issues and solve root issues. Furthermore, the script addresses mental health and addiction issues, emphasizing the role of psychological counseling combined with technological support: "Mental coaches use psychological counseling to address the underlying issues. The figures already show that 80% of those who have the chip and had an addiction were cured without relapse after treatment. Without the chip this is only 30%", referring back to the interconnection between professional and private lives. Additionally, smart toilets are introduced as tools that can monitor and detect a wide range of health indicators: "All the buildings have Smart Toilets. These can detect a wide range of health indicators. You see for example that someone is pregnant. That doesn't mean of course that we immediately have to do something, but it is more about knowing this at an early stage so that we can keep an eye on the situation and adjust our scheduling on time". The script also highlights the role of dietary monitoring, which uses the data from smart devices to ensure employees maintain optimal health: "Another special advantage of the chip is that it calculates your ideal dietary intake for each day. The chip gives this with your consent of course to the kitchen that is adapted for this". By framing technology as a tool that not only monitors but also actively improves health, the script attempts to address the concerns raised in the sensebreaking frames by advocating for a comprehensive approach to employee well-being that encompasses physical, mental health, and dietary components.

Social Relationships Frame

Finally, the play script frames the use of algorithmic technologies as beneficial to improving social relationships within the workplace, directly responding to the sensebreaking frames of "structural issues and superficial solutions" and "the critical need for ongoing monitoring and adaptation". Robin highlights how these technologies can identify and address hidden social issues such as bullying and discrimination: "The greatest advantage of the combination of all this technology is that we can also more quickly attack underlying often more hidden problems such as bullying and discrimination". The detailed behavior tracking enabled by the badge system helps in early identification and intervention: "The badge picks up certain words. The system records these and starts keeping track. If a pattern appears we get a notification. Because if you don't intervene in time other people will adopt the language and then it becomes a culture that often happens unconsciously but it's hard to get rid of again so it's really about intervening in time". Additionally, the script addresses the need for ongoing monitoring and adaptation by promoting enhanced workplace interactions through strategic positioning and interaction: "Every day he's actively choosing another workplace and, in this way, makes sure that he keeps meeting new people within the organization. These 'collisions' as we call them are very essential for someone's work happiness." By framing these technologies as tools that facilitate positive social interactions and address negative behaviors, the script advocates for their use to foster improved employee well-being.

Sense-receiving/Sense-negotiating

In the subsequent focus group discussions, our analysis of six sessions focused on how employees make sense of this managerialist norm of ideal employee well-being that is constructed and imposed through the theatrical talk revolved around these new algorithmic technologies. Analysis of focus group discussions from all the six sessions revealed how employees scrutinize, question, challenge, and contest the sense-breaking and sense-giving frames presented at the theatrical talk. Two critical frames emerged—namely, the Human-Centric Frame and Operation-Centric Frame—each reflecting different dimensions of the employees' concerns and negotiations regarding the meaning of well-being and the use of technology in the workplace. These frames demonstrate the employees' collective efforts to deconstruct, challenge, and resist the imposed managerialist norms.

Human-Centric Frame

The Human-Centric Frame emphasizes the importance of prioritizing genuine individual well-being, emotional experiences, and personal autonomy within the workplace. This frame reflects a deep concern for how organizational practices, especially those involving technology and monitoring, impact the human aspects of work.

Participants frequently voiced concerns about the potential negative effects of continuous monitoring on their mental and emotional health. One participant shared, “If now you’re also being monitored even more from dawn to dusk, maybe that can actually have a negative impact on your well-being.” This comment reveals a fear that the constant pressure of being observed could lead to heightened stress and anxiety. Another participant echoed this concern, giving an example highlighting the intrusive nature of such monitoring: “Some people are more sensitive to that, and they would constantly be thinking: ah, yes, now I have to drink water, or I have to live this way.” This suggests that monitoring might compel employees to focus excessively on their behavior, potentially leading to obsessive thoughts and behaviors that detract from their overall well-being.

The second recurring theme within this frame was the importance of nurturing authentic human connections and emotional well-being. Participants emphasized that experiencing and expressing a full range of emotions, including negative ones, is crucial for personal growth and resilience. One participant reflected, “Feeling bad is a natural part of life that contributes to resilience and emotional depth.” This statement underscores the belief that workplaces should allow for the expression of emotions, rather than suppressing them in favor of a relentless pursuit of productivity. Participants raised concerns about the impact of AI on genuine human relationships, asking, “If everything you say is monitored, I also wonder: how genuine are your interactions with your colleagues?” This question reflects a fear that AI-driven monitoring could erode the trust and authenticity that are essential for meaningful human connections in the workplace and illustrates the importance of implementing AI in ways that prioritize human well-being and preserve the authenticity of workplace interactions. Another participant stressed the role of organizational culture in fostering a supportive environment: “Ensuring a warm atmosphere, I think that’s important. That you can be human.” This sentiment suggests a strong demand from employees for work environments where employees feel valued as individuals, not just as cogs in a machine.

The human-centric frame also revealed deep concerns about the erosion of personal autonomy due to technological advancements in the workplace. Participants were particularly wary of the ways in which data collection and monitoring could infringe upon their freedom and self-determination. One participant passionately stated, “I’m my own person, I’m a human being, and I’m no one else’s property”, highlighting the intrinsic value placed on personal autonomy and the fear that technological control could undermine this fundamental human right. Another participant questioned the extent to which employees truly have control over their choices in a highly monitored environment, remarking, “You think you have your own choice, but the question is to what extent that’s true.” This points to a growing skepticism about the authenticity of choice in workplaces increasingly dominated by surveillance and data-driven decision-making. In addition, one participant stated, “What you’re really building here is a tool for a totalitarian fascist state”, illustrating the fear, anger, and anxiety that employees feel about the potential for AI to gradually lead to more invasive forms of monitoring, culminating in extreme scenarios that might once have seemed far-fetched but are now considered possible.

Operation-Centric Frame

The Operation-Centric Frame focuses on the pursuit of efficiency, productivity, and the role of technology in optimizing organizational performance. This frame often highlights the benefits of monitoring and data collection but also brings attention to the ethical and economic costs associated with these practices.

Participants recognized the potential benefits of monitoring for improving processes and enhancing job performance. One participant observed, “We’re using monitoring to improve processes, and to help people do their jobs better.” This perspective reflects a common belief that technological tools can be leveraged to streamline operations and boost productivity. However, there was also an underlying concern that such a relentless focus on efficiency might come at the expense of human-centric values. As one participant warned, “As long as we approach things from a perspective based on distrust, speed, efficiency, productivity, targets, KPIs, deadlines... we will increasingly turn to such tools.” This comment illustrates worry that the drive for efficiency leads to a work environment characterized by distrust and dehumanization.

Within the operation-centric frame, we also identified that participants expressed the need for ethical oversight in the implementation of monitoring technologies. There was a strong call for these tools to be scrutinized to ensure they do not violate employees’ rights or well-being. One participant emphasized, “That these things are always looked at with a critical eye,” highlighting the importance of maintaining a balance between operational goals and ethical and humanistic considerations.

This reflects a broader concern that without proper checks, the use of technology could easily cross ethical boundaries, leading to harmful consequences for employees. Data ownership and control were central concerns, as one participant noted, "As long as there is ownership over the data, I would be okay with doing it." This statement showed that participants were generally more comfortable with AI monitoring if they felt they had control over their data and understood how it would be used. These findings underscore the importance of transparency and clear agreements regarding data use in AI systems.

The inevitability of adopting new technologies in the workplace was another recurring theme. Participants acknowledged that the integration of advanced technologies, including AI, is progressing rapidly and often leaves little room for resistance or debate. "It's not a question of yes or no anymore; it's not a question of are we stopping this or are we allowing it to come in. It goes insanely fast." This quote from the moderator in the group discussion captures the overwhelming pace at which technological change is occurring, leaving employees feeling powerless to influence its direction. A participant voiced concerns about the long-term trajectory of this technological shift, commenting, "All of the steps in between are on the same slope towards that chip." This reflects a fear that the gradual increase in technological control could eventually lead to invasive and possibly irreversible forms of monitoring and surveillance.

Concerns about how technological monitoring, like "well-being chips," can stifle workplace innovation are prominent in this frame. One participant noted, "It will hamper innovation because you're forced into a restrictive 'new speak' mindset, similar to Orwell's 1984. The chip makes you game the system to appear as the best employee, but it's really about chasing short-term growth." This critique highlights how such technologies pressure employees to conform to short-term goals, hindering genuine creativity and long-term success, ultimately stifling true innovation.

Table 0-3 summarized the findings from above.

Table 0-3 Summary of the findings

Topic	Observational Results
Sense-breaking	
- Structural Issues and Superficial Solutions	Superficial workplace interventions (e.g., cosmetic fixes) fail to address root causes of burnout. Example: "Decorating a sick Christmas tree makes it look good from a distance but it doesn't make the tree healthy." Burnout costs remain high.
- Interconnectedness of Personal and Professional Life	Workplace well-being cannot be separated from personal life. Example: "People aren't robots. You can't separate the two." Personal struggles impact professional performance, leading to issues like burnout.
- Need for Monitoring and Adaptation	Current technologies fail to understand the complexity of human emotions. Continuous monitoring is necessary but flawed, as it only detects symptoms without addressing underlying causes. Example: "It cannot look inside. It only sees the symptoms."
Sense-giving	
- Happiness Frame	Algorithmic management through wearables customizes well-being, targeting happiness by reading and influencing hormones. Example: "We can see instantly when someone is happy, sad, stressed, tired, or enthusiastic."

- Health Frame	Continuous health monitoring (e.g., wearables, smart toilets) promotes workplace health. It addresses physical and mental health, using data for dietary and mental health guidance. Example: "All the buildings have Smart Toilets. These can detect a wide range of health indicators."
- Social Relationships Frame	Technologies identify and resolve hidden workplace issues (e.g., bullying, discrimination). Example: "The badge picks up certain words… if a pattern appears, we get a notification."
Sense-receiving/Sense-negotiating	
- Human-Centric Frame	Concerns about continuous monitoring affecting mental health, autonomy, and genuine social relationships. Emphasis on authentic human experiences and emotional well-being, opposing data-driven management. Example: "Feeling bad is a natural part of life that contributes to resilience and emotional depth."/ "I'm my own person, I'm a human being, and I'm no one else's property."
- Operation-Centric Frame	Focuses on productivity and efficiency, recognizing the benefits of monitoring but warning against ethical overreach. Participants express concern over data security, ethical management, and the pressure to conform to performance metrics. Example: "As long as we approach things from a perspective based on distrust, speed, efficiency, productivity, targets, KPIs, deadlines... we will increasingly turn to such tools."/ "The chip makes you game the system to appear as the best employee, but it's really about chasing short-term growth."

Uncovering Sense-Negotiation Mechanism: Employees Scrutinizing Sense-Breaking and Sense-Giving Frames

The Human-Centric and Operation-Centric Frames serve as lenses through which employees critically evaluate and resist the managerial narratives that attempt to redefine well-being through technological interventions. These frames not only address the sense-breaking frames—structural issues and superficial solutions, interconnectedness of personal and professional life, and the need for monitoring and adaptation—but also engage with the sense-giving frames of happiness, health, and social relationships, which are presented as the new ideals of employee well-being.

Scrutinizing Structural Issues and Superficial Solutions

The managerial narrative critiques existing workplace practices as superficial, advocating for technological interventions that promise deeper, structural improvements in employee well-being.

Employees challenge the assumption that technological solutions can address the root causes of workplace issues. In the discussion on workplace technologies, several employees expressed skepticism about the effectiveness of these interventions in addressing the root causes of workplace issues. For example, one participant critiqued the emphasis on a quick return to work for a grieving employee, arguing that such measures overlook deeper emotional needs: "For me that was like don't say put the employee first; that was just about how can we make sure that he returns to work as soon as possible. And the well-being of the employee is not prioritized because he's going home to a wife who's still grieving and it might endanger their relationship because they are not going through the process together anymore". This highlights concerns that technological solutions may inadequately address fundamental human aspects of workplace challenges.

Another participant emphasized the value of human support over technological fixes: "The fact that our boss took that position is more important to me… Not putting a chip into my head to make sure that my hormones are good enough to make me productive". This reflects broader skepticism about relying on technology to manage well-being, suggesting that authentic human interactions are more effective.

Finally, the need to deal with life's challenges meaningfully, rather than relying solely on technology, was emphasized: "We need to learn how to deal with illness and etc.", underscoring the belief that technology cannot replace the fundamental human need to process personal difficulties.

Scrutinizing Interconnectedness of Personal and Professional Life

The managerialist narrative, which emphasizes the interconnectedness of personal and professional life, suggests that traditional boundaries between these domains are outdated. It argues that advanced technologies, through continuous monitoring and algorithmic management, can effectively manage this complexity and, thereby, improve overall employee well-being. This perspective promotes the integration of personal and professional monitoring as a means to enhance work-life balance, productivity, and health. However, employees in the focus group discussions actively contested this narrative, advocating for a more nuanced understanding of well-being that respects personal autonomy and maintains clear boundaries between work and private life.

Employees consistently expressed significant discomfort with the blurring of the lines between personal and professional domains. This discomfort is rooted in concerns about privacy, autonomy, and the potential overreach of workplace technologies into personal lives. A participant articulated this concern succinctly: "The biggest issue is the fact that the distinction between personal life and work life is not there anymore and should be there", directly challenging the managerialist assumption that such boundaries are outdated, emphasizing the need to preserve a clear separation between work and personal life to protect individual autonomy.

One of the most potent expressions of resistance was directed against the idea that employers should have control over their employees' personal health and bodily autonomy. The integration of health monitoring into workplace management was seen as a particularly invasive form of overreach. "The trigger point was really had the company started to medicate you on your hormones that was for me wow! I really don't want my managers to give me drugs." Another participant noted the absurdity of employers dictating personal behaviors, stating, "I don't want my employer to tell me when I have to move and when I have to eat a banana, yeah." These reactions demonstrate the deep unease with and resistance to the idea that professional obligations could extend into personal, physical well-being, or personal routines—a clear rejection of the managerialist narrative that promotes such integration. This resistance was further articulated by another participant, who emphasized the importance of maintaining personal agency: “I’m my own person, I’m a human being, and I’m no one else’s property. So when looking at the workplace, I think: alright, I’m your employee, yes, but I’m more than an employee, and that part that’s more, that’s mine, and I want to be able to decide what to do with it.”

Moreover, participants underscored the importance of keeping personal health data private and distinct from professional responsibilities. One participant stated, “And also keeping track of your health data, they didn’t think was okay, how that is linked to work,” while another reinforced this sentiment with, “I just don’t think it’s the company’s business that level of information on my health and how I’m feeling.” These concerns highlight a broader resistance to the integration of health monitoring into workplace management, which employees perceive as an intrusion into their private lives. A participant captured this anxiety that such integration could lead to a loss of autonomy and individuality, stating, “When it comes to work I think it all goes a step too far. Because then I think who’s going to check this? What do you have access to?” This concern reflects a broader apprehension about the extent of control that employers might exert over personal lives if such technologies are allowed to blur the lines between work and home.

Employees also question the true intention behind workplace interventions beyond professional responsibilities and call for organizations to solve the “real issue”. This was captured by a participant who stated, “Because on the one hand it’s about having that sense of control and having the feeling that you’re in charge of your own decisions and long-term career path, but it’s also about what’s the purpose behind work intervening in certain parts of your life.” This statement questions the legitimacy of workplace interventions that extend beyond professional responsibilities into personal life, emphasizing the need for clear boundaries and ensuring that any integration of technology respects individual autonomy and informed consent. Additionally, as a participant stated, “It’s about having enough personal time and a good balance. If there’s an issue, solve it by giving extra time, not dopamine. We have the right to be unhappy and, as human beings, we are unhappy sometimes”, confronting the managerialist notion that well-being can be managed or optimized through technological interventions, advocating instead for solutions that respect personal time and emotional authenticity.

Through these collective expressions of resistance, employees effectively rebut the managerialist narrative that seeks to integrate personal and professional life through continuous monitoring and algorithmic management. They argue for the preservation of clear boundaries to protect personal autonomy and well-being, asserting that true well-being can only be achieved when employees maintain control over their personal lives, free from professional overreach. This pushback against the erosion of these boundaries highlights the employees' strong demand for respect for individual autonomy and the need to ensure that technological advancements do not compromise personal freedom, privacy, or the fundamental right to self-determination.

Scrutinizing Need for Monitoring and Adaptation

The managerial narrative posits that continuous monitoring and adaptation are essential for maintaining employee well-being and optimizing workplace performance. This perspective suggests that real-time data collection and surveillance enable organizations to proactively address issues, enhance productivity, and improve the overall work environment by facilitating swift responses to emerging concerns. However, employees expressed substantial reservations regarding the necessity and ethics of such monitoring, raising critical concerns about privacy, control, and the potential misuse of data.

Employees expressed significant concerns about continuous monitoring infringing on their personal autonomy and privacy. They viewed these practices as overreaching and ethically problematic, with fears that monitoring could lead to unwarranted intrusions into their private lives and reduce their control over personal decisions. For example, one participant remarked, "I would not want it to control my life to such an extent. I think that would go too far for me." Another participant echoed this sentiment, questioning, "When it comes to work I think it all goes a step too far. Because then I think who's going to check this? What do you have access to?" These statements reflect widespread anxiety that continuous monitoring could exceed its intended purpose, resulting in a significant loss of personal privacy and autonomy.

Employees were deeply skeptical about the ethical implications of continuous monitoring. They feared that such technologies could dehumanize them by reducing them to mere data points, stripping away their humanity and individuality. One participant articulated this concern by stating, "If you were to be controlled and steered to such an extent, that would be too much for me, I think. Especially that last example—I mean, I know it's fiction, but with the mourning, I really get the idea that you turn into a robot." This sentiment underscores a profound discomfort with the notion that continuous monitoring could erode personal agency, effectively dehumanizing employees.

Additionally, there was concern about the potential consequences of data-driven management, where personal choices could lead to adverse repercussions. As one participant noted, "But if you then look, like in the example that was given, if you click 'no' too often, there may be consequences." This observation highlights the fear that continuous monitoring could result in punitive actions based on personal data.

Moreover, employees raised broader ethical concerns about how data collected through continuous monitoring might be used or misused over time. One participant pointed out, "But I do find it interesting... If you interpret data today, it can be interpreted in a wholly different way in the future as well. And that can be the case in a particular company too. The company vision may change." This comment reflects skepticism about the long-term implications of data collection, particularly in how it could be reinterpreted or repurposed in ways that might negatively impact employees.

Concerns about data security were also prominent. As one participant highlighted, "There are a couple of red flags. They talked about giving micro-doses of dopamine, but the problem with a chip implant that is constantly connected is that it's hackable. What will we do with a major hack? All your data is on the internet." This underscores the vulnerability of personal data in the context of continuous monitoring, particularly the risk of exposure or exploitation through hacking.

In response to the managerial narrative advocating for continuous monitoring, employees consistently called for greater transparency and ethical oversight. They emphasized the importance of maintaining control over their personal data and ensuring clear, transparent practices regarding data usage to safeguard their privacy and autonomy. One participant expressed this need by stating, "And I want to be able to safeguard the boundary between private life and work myself because I think that's also something—." This statement reflects a strong desire among employees to maintain control over their personal lives and to ensure that any monitoring remains within clearly defined ethical boundaries.

The importance of transparency was further underscored in discussions about data usage. One participant insisted, "But I would like to have control over it myself and full transparency about what the employer ultimately wants to do with the data that is collected." This highlights the critical importance of trust and the need for employees to feel secure in how their data is being managed and utilized.

These frames collectively illustrate the employees' pushback against continuous monitoring and their demand for transparency and ethical practices to protect their autonomy, privacy, and overall well-being.

Employees in the focus group discussions actively rebutted the managerialist definitions of happiness, health, and social relationships as constructed by algorithmic technologies, and instead, they refined and asserted a more humanistic understanding of well-being. Their resistance was grounded in the belief that well-being cannot be reduced to data points or managed by algorithms alone, but rather must encompass a holistic, human-centered approach that respects personal autonomy, emotional depth, and genuine social connections.

Scrutinizing Algorithmic Happiness and Refinement of Humanistic Happiness

The managerialist narrative posits that employee happiness can be optimized through personalized interventions facilitated by wearable devices and AI, which are designed to create a tailored experience aimed at enhancing both efficiency and contentment. This perspective suggests that technology can monitor and influence hormonal balance to maintain employees in a positive emotional state, thereby boosting productivity and job satisfaction.

However, employees challenged the validity of this notion, expressing skepticism about the superficiality and authenticity of happiness derived from algorithmic interventions. For instance, one participant remarked, "It feels like they're selling us a solution to a problem we didn't even know we had." This statement reflects a broader concern that the happiness promoted by technology is perceived as artificial, externally imposed, and potentially manipulative, rather than stemming from genuine emotional fulfillment.

Rather than accepting a technologically mediated version of happiness, employees advocated for a more humanistic understanding of well-being that acknowledges the full spectrum of human emotions, including the negative ones. One participant emphasized, "Feeling bad is a natural part of life that contributes to resilience and emotional depth." This perspective highlights that true well-being involves the capacity to experience and process a range of emotions, not just those that can be optimized for productivity. Employees thus rejected the reduction of happiness to a state that can be engineered by technology, advocating instead for emotional authenticity and the recognition of the complexities of human experience.

Scrutinizing Algorithmic Health and Refinement of Humanistic Health

The managerial narrative advocates for continuous health monitoring as an essential element of employee well-being, proposing that wearables and AI can track and optimize both physical and mental health in real-time. This perspective suggests that by consistently monitoring health metrics, organizations can preemptively address potential issues, thereby maintaining a healthy and productive workforce.

However, employees expressed significant concerns regarding the invasion of privacy and autonomy inherent in such an approach. They resisted the idea that their health should be managed by their employers through continuous monitoring. As one participant noted, "I just don't think it's the company's business to have that level of information on my health and how I'm feeling." This statement reflects a broader apprehension about the erosion of personal privacy and autonomy, indicating that algorithmic health monitoring is perceived as intrusive rather than genuinely supportive.

In response, employees advocated for a more holistic approach to health that respects personal boundaries and considers overall well-being beyond mere physical metrics. As one participant remarked, "It's symptom control. A machine can't look within, looks at the surface layer at symptoms but not at the underlying cause of why someone is indeed unhappy." This comment refines the concept of health by emphasizing the importance of addressing underlying causes rather than merely managing symptoms, calling for a deeper, more nuanced approach to well-being that transcends the limitations of algorithmic interventions.

Scrutinizing Algorithmic Social Relationships and Refinement of Humanistic Social Connections

The managerial narrative posits that technology can enhance social relationships within the workplace by identifying and addressing issues such as bullying and discrimination early on. It suggests that by monitoring interactions and behaviors, technology can foster a healthier and more positive work environment.

However, employees expressed concerns about the erosion of genuine human interaction under such a system. They challenged the idea that technology can effectively manage or enhance social relationships. As noted before, one participant critically remarked, “If everything you say is monitored, I also wonder: how genuine are your interactions with your colleagues?” This comment reflects a fear that constant monitoring could undermine the authenticity of social interactions, transforming relationships into calculated, monitored exchanges rather than fostering genuine connections.

In response, employees emphasized the value of unmediated relationships and advocated for preserving the authenticity and spontaneity of social interactions, which they viewed as being threatened by algorithmic management. One participant strongly argued, “HR stands for the human being... It should stand for the human being.” This sentiment highlights the importance of nurturing social relationships through trust and genuine interaction, rather than relying on technological surveillance to manage them.

Refinement of Humanistic Well-Being

Across the domains of happiness, health, and social relationships, employees advocated for a holistic, human-centered approach to well-being, rejecting the idea that technology alone can optimize it. They emphasized the importance of emotional authenticity, personal autonomy, and genuine human connections.

Employees argued for a workplace culture that values the full range of emotions, challenging the reduction of happiness to a state that can be optimized through data. They also resisted continuous health monitoring, stressing that true well-being requires addressing underlying issues rather than relying on invasive technologies. In social relationships, employees preferred genuine, unmonitored interactions over technology-mediated ones, highlighting the need for trust and spontaneity.

In summary, employees rejected the reduction of well-being to data-driven metrics, advocating instead for a holistic and human-centered approach. This pushback emphasizes the importance of preserving autonomy, authenticity, and genuine connections, challenging managerial norms that seek to redefine well-being through technology.

Discussion

Bring It All Together

Figure 0-1 provides a conceptual framework for understanding the dynamic processes through which AM is linked to employee well-being, highlighting the roles of different types of enactors in the sensemaking process. The model illustrates how AM technologies, such as multifunctional badges, well-being chips, thought-reading chips, and smart toilets, are introduced within a broader organizational context to influence perceptions of well-being.

At the core of the model is "AM-empowered well-being," which represents the integration of these algorithmic technologies into the workplace. The process begins with sensebreaking, where theatrical talk serves as the sensebreaking and sensegiving enactor. Through dramatized scenarios, this theatrical element disrupts existing understandings of well-being, challenging employees' perceptions and creating a space for new interpretations. The theatrical talk not only breaks down established frames but also provides new ones, thereby guiding employees towards a managerialist view that emphasizes happiness, health, and relationships as key components of well-being.

Employees, positioned as sense-receiving and sense-negotiating enactors, engage with the new frames introduced by the theatrical talk. They actively interpret and negotiate these frames, integrating them into their personal understanding of well-being. This negotiation process involves critical reflection on the implications of AM technologies, particularly concerning structural issues, the interconnectedness of personal and professional life, and the need for continuous monitoring and adaptation. Employees do not passively accept the managerialist frames; instead, they assess how these frames align with or conflict with their values and experiences.

The graph further delineates two overarching organizing perspectives that influence this sensemaking process: human-centric and operation-centric. The human-centric perspective advocates for a holistic, ethically grounded approach to organizing that prioritizes employee autonomy, authenticity, and genuine social connections. In contrast, the operation-centric perspective aligns more closely with the managerialist approach, focusing on optimizing employee performance and productivity through technological interventions.

As employees engage in sense-receiving and sense-negotiating, they navigate between these competing perspectives. Their collective responses determine the extent to which the organization moves towards humanistic organizing, where well-being is prioritized and ethical considerations are integrated into the implementation of algorithmic technologies, or remains entrenched in an operation-centric model that emphasizes efficiency and control.

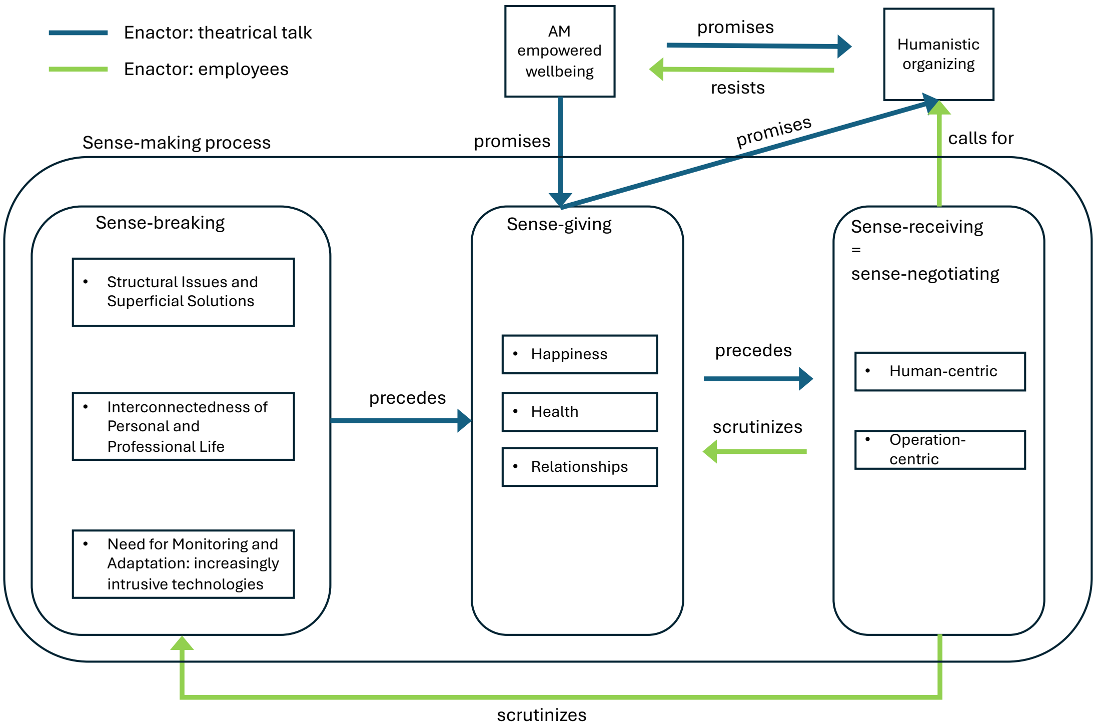

Figure 0-1 Theoretical model

Theoretical Contributions

Our research makes several key theoretical contributions to the literature on algorithmic management (AM) and employee well-being.

Firstly, it challenges the traditional managerialist perspective, which posits that algorithmic technologies can mutually benefit organizations and employees by enhancing well-being and providing empirical evidence. Our findings reveal that these technologies, although seemingly well-intentioned, can exacerbate power imbalances and control over employees, thereby undermining genuine well-being. Secondly, we contribute to the sensemaking literature by showing how theatrical performances can effectively function as sensegiving tools. These performances provide a space for critical reflection and discussion among employees and managers, helping them to develop a deeper understanding of the implications of algorithmic technologies on well-being. Additionally, by emphasizing a bottom-up approach, we demonstrate that employees are not passive recipients in this process; rather, they actively engage with and integrate these new frames into their understanding of well-being, playing a crucial role as agents in the sensemaking process. Lastly, our study underscores the importance of humanistic organizing within the context of algorithmic management. By focusing on employee well-being beyond productivity and efficiency, we advocate for organizational practices that prioritize ethical considerations and the holistic well-being of employees.

Critiquing the Managerialist Perspective: The Impact of Algorithmic Technologies on Power Dynamics and Employee Well-Being

The traditional managerialist perspective posits that algorithmic technologies can create mutually beneficial outcomes for both organizations and employees by enhancing well-being and providing empirical evidence to support managerial decisions (Peccei, 2004; Peccei & Van De Voorde, 2019). Proponents argue that these technologies improve efficiency, streamline processes, and offer precise metrics for evaluating and enhancing employee performance and well-being (Peccei & Van De Voorde, 2019; Van De Voorde et al., 2012). However, emerging research and critical management studies challenge this perspective, suggesting that the implementation of algorithmic management systems can exacerbate power imbalances and undermine genuine employee well-being (Foucault 2008; Townley 1994; Willmott 1993).

Firstly, algorithmic management systems often reinforce existing hierarchical power structures within organizations, intensifying managerial control over employees. As Kellogg et al. (2020) argue, these systems can make surveillance more pervasive, leading to an environment where employees are constantly monitored. The lack of transparency in how algorithms make decisions further limits employees' autonomy, as they often have little insight into how their data is being used to evaluate their performance (Pasquale, 2015). This opaque nature of algorithmic management not only diminishes employee autonomy but also increases stress and anxiety, as workers may feel they are being unjustly scrutinized without recourse (Shin et al., 2022).

Moreover, the rise of algorithmic technologies in workplaces has raised significant concerns regarding privacy and the potential for exploitative practices. Zuboff (2023), in her seminal work *The Age of Surveillance Capitalism*, argues that these technologies enable unprecedented levels of surveillance, fundamentally altering the power dynamics between employers and employees. Constant monitoring erodes the boundary between work and personal life, leading to an environment where employees feel their privacy is constantly infringed upon (Allen et al., 2007). This pervasive surveillance can create a climate of fear and stress, undermining the very well-being these technologies claim to enhance (Bélanger & Crossler, 2011).

Further compounding these issues is the potential for algorithmic management to obscure decision-making processes, making it difficult for employees to challenge or understand how their performance is being evaluated. Rosenblat et al. (2014) highlight how this opacity can lead to feelings of helplessness and stress among workers, particularly in gig economy platforms where algorithmic decisions directly impact earnings and job security (Goods et al., 2019; Lewchuk, 2017). The lack of clarity and the perceived arbitrariness of algorithmic decisions (Gomez et al., 2024) can result in a work environment that prioritizes efficiency and control over employee satisfaction and well-being.

Critical management scholars have long questioned the assumption that managerialist practices inherently benefit both organizations and employees. Fleming and Spicer (2003) argue that these practices often serve to mask deeper issues of control and exploitation, presenting a façade of mutual benefit while primarily advancing organizational interests (Mohamed et al., 2020; Birhane et al., 2022). This critique is particularly relevant to algorithmic management, where the emphasis on data-driven efficiency can overshadow the human aspects of work. As the findings suggest, while algorithmic technologies may offer some benefits, they also risk reducing employees to mere data points, stripping away their individuality and diminishing their well-being (Kinowska & Sienkiewicz, 2022).

Introduction of Sense-Receiving and Sense-Scrutinizing in Expanding Sensemaking Theory

Our study introduces the concept of sense-receiving as a crucial aspect of the sensemaking process, expanding beyond the traditional focus on sensegiving and sensemaking. We define sense-receiving as the process in which employees interpret, evaluate, and respond to the sensegiving narratives imposed on them. This concept shifts the emphasis from the active construction of meaning by managers or social arbiters (i.e., sensegiving) (Bishop et al., 2020) to the equally critical process of how these meanings are received and processed by employees.

Maitlis (2005) notes that sensemaking is triggered when organizational members encounter surprising or confusing events, prompting them to seek understanding. This highlights the importance of sense-receiving, where employees are not passive recipients but active agents who engage in sense-scrutinizing—critically evaluating and questioning the narratives presented to them. This aligns with the social and collective nature of sensemaking, where individuals collaboratively interpret cues and construct meaning (Weick, 1995). Our study emphasizes a bottom-up approach to understanding organizational change, in the context of technological interventions aimed at enhancing employee well-being. Our findings show that employees actively engage in sense-scrutinizing, questioning, and resisting imposed well-being ideals, thereby shaping the narratives that define their work environments (Maitlis, 2005).

By emphasizing sense-receiving and sense-scrutinizing, our study adds depth to the sensemaking literature. We suggest that the success of sensegiving efforts is contingent not just on the clarity and coherence of the narrative (Abolafia, 2010; Yaniv, 2011) but also on the extent to which it resonates with employees' own experiences and perspectives. As highlighted by Weick et al., (2005), *power dynamics* and *emotions* significantly influence how individuals interpret and respond to events, crucial in understanding employees' reactions to managerial narratives.

Power dynamics are central to the sensemaking process (Ibarra & Andrews, 1993), particularly when organizational changes are introduced from the top down. In our study, these dynamics manifest in how managerial narratives are constructed and imposed upon employees, often without their input or consent. The introduction of algorithmic management technologies, including multifunctional badges, well-being chips, and other surveillance tools, exemplifies a top-down approach where power is concentrated in the hands of management. These technologies are framed as tools for optimizing employee well-being, but they also function as instruments of control, reinforcing hierarchical structures within the organization (Gioia & Chittipeddi, 1991; Weick, 1995; Kellogg et al., 2020). Employees, in their role as sense-receivers, are acutely aware of these power dynamics. The sense-scrutinizing process reveals how employees recognize and resist the subtle ways in which these technologies reinforce managerial control. For instance, sensemaking is often triggered by cues that are surprising or violate expectations, prompting employees to question the true intent behind these interventions (Louis, 1980; Weick, 1995). They may perceive these technologies as mechanisms for increased surveillance rather than genuine efforts to enhance well-being (Zuboff, 2023). This resistance is a direct response to the perceived power imbalance, where employees feel that their autonomy and privacy are being encroached upon (Weick et al., 2005). Moreover, power dynamics influence the extent to which employees feel empowered to challenge or reshape these narratives (Townley, 1994). Those who perceive themselves as having less power within the organizational hierarchy may be more likely to internalize feelings of helplessness or resignation, while others may engage in active resistance, using sense-scrutinizing to push back against the imposed narratives (Bartunek et al., 2006; Maitlis & Lawrence, 2007).

Emotional responses are equally significant in shaping how employees interpret and react to organizational changes (Myers, 2007; Maitlis et al., 2013). The introduction of algorithmic management technologies often triggers a range of emotions, from anxiety and fear to frustration and anger (Bartunek et al., 2006). These emotions are not just individual reactions but are also socially constructed and shared within work units, leading to collective emotional climates that influence the overall sensemaking process (Weick, 1995; Rafaeli & Vilnai-Yavetz, 2004; Maitlis, 2005). For instance, when employees feel that these technological interventions infringe upon their privacy, they may experience a sense of violation, leading to negative emotional responses such as distrust or resentment towards management (Rosenblat et al., 2014; Barati & Ansari, 2022). These emotions play a crucial role in sense-receiving, as they color how employees interpret the intentions behind managerial narratives and the potential impact of these technologies on their well-being (Weick et el., 2005). The emotional reactions of individuals can spread within work units, amplifying the collective response to these interventions (Bartunek et al., 2006). If a significant portion of the workforce expresses anxiety or frustration, this can create a shared emotional climate that heightens resistance and skepticism towards the imposed changes (Maitlis, 2005). In contrast, if employees perceive some positive aspects of the interventions—such as potential improvements in work-life balance—positive emotions like hope or optimism might emerge. However, these positive emotions are often contingent upon the extent to which employees feel they have agency in the process and whether they perceive the changes as genuinely beneficial rather than merely serving managerial interests (Gioia & Chittipeddi, 1991).

The *interplay of power dynamics and emotional responses* is most evident in the sense-scrutinizing phase, where employees critically evaluate the narratives presented to them. This phase is also where the political potential of employees becomes most apparent. The resistance observed in this phase is not just a cognitive rejection of the managerial narratives but is also fueled by the underlying power struggles and emotional tensions within the organization.

Employees' capacity to resist and challenge these narratives reflects their political agency within the organization (Lapointe & Rivard, 2005). By engaging in sense-scrutinizing, employees do more than merely react to changes—they actively participate in the ongoing negotiation of organizational meaning and identity. This participation has significant political implications, as it demonstrates that employees are not passive recipients of managerial directives but are instead capable of influencing the trajectory of organizational change (Fleming & Spicer, 2007; Courpasson et al., 2012). For example, as we noticed from the focus group discussions, employees scrutinize the narrative that algorithmic technologies will enhance their well-being by asking critical questions such as, "Whose well-being is actually being prioritized?" or "Is this really about improving my work experience, or is it about increasing productivity and control?" These questions are often driven by a combination of distrust in managerial motives—a reflection of power dynamics—and negative emotional responses to the perceived loss of autonomy and privacy (Maitlis & Lawrence, 2007; Weick et al., 2005).

Furthermore, by collectively engaging in these critical evaluations, employees can foster a sense of solidarity and shared purpose, which enhances their political potential to challenge and potentially reshape organizational policies and practices. This collective action underscores the importance of recognizing employees as active political agents who can influence not only the discourse around technological interventions but also the broader organizational power structures that these interventions are intended to support (Mumby, 2005; Scott, 2008).

Distinguishing Between Exploitative Algorithmic Technologies and Genuine Humanistic Organizing

The sensemaking process reveals critical distinctions between AM well-being initiatives that exploit employee well-being and genuine humanistic organizing practices. These distinctions are crucial in understanding how different approaches to employee well-being can either undermine or enhance the holistic experience of work.

Exploitative AM well-being initiatives are characterized by a heavy reliance on monitoring and controlling employee behavior (Zuboff, 2023), often infringing on autonomy and privacy (Cameron, 2020). Rooted in an economistic approach, these initiatives view employees primarily as tools for maximizing organizational efficiency, focusing on performance metrics and productivity outputs rather than genuine well-being (Dierksmeier, 2016; Pirson, 2017). This approach, which prioritizes profit over people, tends to address the symptoms of well-being issues—such as stress or burnout—without tackling the underlying causes that lead to such conditions.

A key issue with exploitative AM initiatives is the lack of transparency regarding how employee data is collected, used, and shared (Barati & Ansari, 2022; Bujold et al., 2022; Chowdhury et al., 2022; Claure et al., 2022). This opacity generates mistrust among employees, who may feel that their personal information is being utilized in ways that serve organizational interests rather than their own well-being (Purser & Milillo, 2015).

Moreover, these initiatives are typically imposed on employees without their input or consent, leading to resistance, disengagement, and a sense of dehumanization within the workplace (Pirson & Lawrence, 2010; Shulzhenko & Holmgren, 2020). The superficial nature of these initiatives is further highlighted by their focus on short-term gains rather than sustainable well-being, deviating from the complexities of employees' work and personal lives (Cooren et al., 2011; Munro, 2012). Algorithmic tools may recommend quick fixes—such as microbreaks or wellness tips—that do not address the organizational structures contributing to employee dissatisfaction, thereby exacerbating the very issues they are meant to resolve (Town et al., 2024).

In contrast, genuine humanistic organizing practices prioritize the empowerment of employees by actively involving them in the design and implementation of well-being initiatives. These practices challenge the traditional economistic paradigm by emphasizing the intrinsic value of human beings and placing the well-being and dignity of all stakeholders, including employees, at the center of organizational practices (Hicks & Waddock, 2016; Melé, 2016). By addressing both personal and professional aspects of well-being, humanistic organizing creates a more holistic approach to fostering a supportive work environment.

A cornerstone of humanistic organizing is the emphasis on autonomy and control over personal data (Deci et al., 2017). Employees are given agency in deciding how their data is collected, used, and interpreted, fostering a sense of trust and security (Pirson & Livne-Tarandach, 2020). Transparent communication about data usage is crucial in building this trust (Treem, 2021), ensuring that employees are aware of how their information will be utilized to benefit their well-being rather than to monitor or control them. Moreover, well-being initiatives under humanistic organizing are co-created with employees, reflecting their needs, preferences, and lived experiences (Lee et al., 2021; Park et al., 2022; Zytko et al., 2022). This collaborative approach enhances the relevance and effectiveness of the initiatives, fostering a sense of ownership and commitment among employees.

Practical Implications

The findings of this study offer several practical implications for organizations implementing algorithmic technologies while prioritizing humanistic values. First, organizations must critically assess AM technologies to prevent exacerbating power imbalances or infringing on employee autonomy. As Zuboff (2023) notes, the pervasive surveillance enabled by AM can alter power dynamics, eroding trust and well-being. Moreover, concerns about data privacy and security, as highlighted by Rosenblat et al. (2014), necessitate robust guidelines for data governance. Transparent practices that prioritize employee privacy and control are essential for building trust and ethical use of AM technologies, aligning with the principles of humanistic organizing that emphasize autonomy and dignity (Town et al., 2024).

Second, involving employees in designing and implementing AM-driven well-being initiatives is crucial. Rather than imposing top-down solutions, organizations should adopt a participatory approach, allowing employees to co-create initiatives that reflect their genuine needs. This aligns with Bartunek et al. (2006), who emphasize the importance of employee engagement in the sense-receiving process. Such involvement enhances the effectiveness and integrity of well-being programs and reduces resistance.

Third, while AM technologies offer significant potential for optimizing efficiency and well-being, organizations must balance these innovations with a commitment to human-centric values. The study reveals concerns about the dehumanizing potential of AM, particularly when it reduces complex human experiences to data points. To address this, organizations should integrate ethical considerations into their technological strategies, ensuring that efficiency does not come at the expense of genuine human connections (Town et al., 2024; Weick et al., 2005).

Forth, in real organizations, the process of implementing AM-empowered well-being might not involve theatrical talks but would be achieved through workshops, leadership communication, employee training, or technological rollouts. Organizations should establish comprehensive communication strategies and employee training programs to effectively introduce AM technologies. These strategies must clarify how the technologies enhance well-being, addressing potential concerns such as surveillance and privacy. Structured communication, including workshops and informational sessions, is crucial for sensegiving and fostering employee acceptance of the new systems.

Finally, the study highlights the political potential of employees as active agents who can shape and influence organizational practices. Recognizing this, organizations should engage with employees' concerns and contributions, fostering an inclusive and equitable environment. This approach not only enhances well-being but also builds a culture of trust and mutual respect (Maitlis & Lawrence, 2007).

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Appendix:

Organization	Date	Participants
Belgian Retail Corporation	April 17, 2024	22 (8 managers

Organization	Date	Participants
		and 14 employees)
Pharmaceutical Company	May 21, 2024	26 (13 managers and 13 non-managers)
Publication Company and University	May 22, 2024	31 (15 from the publication company, 16 HR students)
Pharmaceutical Company (Second Performance)	June 6, 2024	Strategic HR meeting with global HR personnel, 9
Flemish Public Employment Service	June 25, 2024	22 (11 managers and 11 workers)
Global Professional Services Firm	July 4, 2024	30 (14 managers and 16 non-managers)

Figure 0-2 Company information

Epilogue

As I conclude this thesis, it is essential to step back and reflect on the collective insights garnered from the three studies that comprise this work. Each paper has explored different facets of algorithmic management (AM), a phenomenon that is rapidly transforming the landscape of modern workplaces. While the studies individually focused on specific aspects—ranging from the impact/association of AM on employee engagement and job autonomy to the nuanced ways employees make sense of and resist these technologies—their findings, when viewed together, offer a more holistic understanding of the complex dynamics at play.

The purpose of this epilogue is to synthesize the key findings from these studies, drawing connections between them and exploring their broader implications via six learning points. In doing so, we can clarify how these insights contribute to the growing body of knowledge on AM and its role in shaping organizational behavior. Additionally, this epilogue will reflect on the practical implications, acknowledge the limitations inherent in the research, and propose directions for future studies that can build on this work.

Six Learning Points

As I reflect on the journey of conducting these studies, several critical insights have emerged that extend beyond the specific findings of each individual paper. These learning points highlight not only the complexities and challenges encountered but also the valuable lessons that have shaped the overall understanding of AM and its implications for well-being at work.

Learning Point 1: A Unified Perspective on Algorithmic Management: The Dualistic Nature of AM and Interdisciplinary Integration

A key takeaway from this research is the necessity of adopting a comprehensive, interdisciplinary approach encompassing organizational behavior, HRM, and technology studies to understand the complex nature of AM. The three studies collectively reveal that AM is not a monolithic force; rather, its effects vary significantly based on socio-technical factors, such as leadership practices, perceptions of fairness, individual's proactivity trait, and the preservation of humanistic values within organizations. Across all studies, a recurring theme is the dualistic nature of AM.

Orlikowski's (1992) pioneering work on the duality of technology laid the foundation for understanding how technology is both shaped by and shapes human action. Building on this, Meijerink and Bondarouk (2021) propose that algorithmic management systems simultaneously restrain and enable autonomy and value for workers. They highlight that while algorithms can limit job autonomy (e.g., by automating decision-making and creating information asymmetries), they can also offer new forms of autonomy and value (e.g., by enabling workers to optimize their work through data-driven insights). This duality is recursive, meaning that the use of algorithms can lead to changes in the algorithms themselves, influenced by worker behavior and responses (Meijerink and Bondarouk, 2021). Similarly, in their strategic framework on AI-assisted HRM, Malik et al. (2022) discuss the dual role of AI in HRM, noting that AI can simultaneously produce positive outcomes like increased productivity and job satisfaction, while also leading to negative effects such as ethical issues, job insecurity, and high turnover, depending on how AI applications are implemented and managed.

Our research builds on this body of literature and provides a framework to illustrate how the mediating and moderating mechanisms, along with the sensemaking process, shape, or have the potential to shape the outcomes of AM. To elaborate, the first paper emphasizes the critical role of leadership in moderating the relationship between AM and employee engagement. By showing that while AM can diminish social exchanges, a socially close leader can buffer these negative effects, the first paper highlights the importance of leader distance in maintaining employee engagement in AM environments. The second paper demonstrates that perceived justice in AM processes can mitigate the negative impact of AM on job autonomy, emphasizing that fair and transparent systems are essential for preserving employees' sense of control in algorithmically managed environments. The third paper shifts focus to the broader implications of AM on human well-being, advocating for a more humanistic approach that respects emotional, social, and personal dimensions of work. This perspective challenges the notion that AM can solely optimize well-being, suggesting instead that such efforts might lead to superficial outcomes unless they genuinely address underlying human needs, emphasizing the integration of humanistic values in AM as essential to ensuring that technology serves to enhance, rather than diminish, the overall well-being of employees.

Learning Point 2: Integrating the Socio-Technical Perspective

Building on the first learning point, another critical insight is the importance of adopting a socio-technical perspective when analyzing the impact of AM on the workplace. Rooted in Sociotechnical Systems (STS) theory (Cherns, 1976; Emery & Trist, 1978), this approach emphasizes the need for organizations to jointly optimize both social (human) and technical (technological) systems to achieve balanced and effective outcomes. Recent applications of STS theory to AI and workplace digitalization (Makarius et al., 2020; Parker & Grote, 2020) highlight that rapid technological advancements often disrupt this balance, leading to a misalignment between technical systems and human needs. To counter this, we adopted the concept of "sociotechnical capital," (Makarius et al., 2020) which underscores the benefits gained when AI technologies and human workers are seamlessly integrated into a cohesive, responsive system.

The work of Jarrahi et al. (2021) and Parent-Rocheleau and Parker (2021) reinforces this perspective by illustrating that the success of AM systems depends on how well they balance and integrate social and technical elements. Jarrahi et al. (2021) stress that AM is not merely a technological tool but is co-constructed through ongoing interactions between human agents and algorithms, while Parent-Rocheleau and Parker (2021) highlight how AM affects key aspects of work design, such as autonomy and job demands.

This thesis extends STS theory by integrating the often-overlooked micro-level of well-being into the socio-technical perspective. While STS theory traditionally emphasizes organizational or macro-level optimization (de Sitter et al., 1997; Benders & van Bijsterveld, 2000), this research focuses on employees as unique individuals, shedding light on how AM impacts their personal and emotional experiences at work. The three studies collectively contribute to this perspective by emphasizing the alignment of technical systems, such as AM, with the social and emotional dimensions of work to optimize work design, employee well-being, and organizational outcomes.

The first paper implicitly reflects this perspective by exploring how AM influences employee engagement through Social Exchange Theory (SET). The findings suggest that while AM, as a technical system, can disrupt traditional social exchanges, these effects can be mitigated by human-centric factors, such as socially close leadership practices that maintain trust and reciprocity.

The second paper explicitly engages with the socio-technical perspective by examining how AM impacts job autonomy, a crucial element of work design. This paper underscores the role of systemic justice as a moderator that can either constrain or support job autonomy within AM systems. It emphasizes that achieving a balanced socio-technical system requires careful consideration of fairness and employee proactivity to avoid the detrimental effects of overly rigid AM systems.

The third paper brings the socio-technical perspective to the forefront by focusing on employees' sensemaking processes in response to AM's impact on their well-being. It introduces the micro-level lens by revealing that employees' well-being is significantly influenced by how well the technical aspects of AM are aligned with their unique social and emotional needs. This study highlights the importance of system transparency, fairness, and human influence—key socio-technical parameters—in shaping a positive employee experience. By addressing individual well-being within the socio-technical framework, this research adds a new dimension to STS theory, demonstrating its relevance for understanding and improving the interplay between AM systems and employee experiences at the micro level.

Learning Point 3: Bridging Quantitative and Qualitative Insights & Call for Methodological Innovation

A significant aspect of this research is the innovative integration of both quantitative and qualitative methods, which has enriched the exploration of AM and its role in workplace dynamics. Given that much of the existing literature on AM tends to be conceptual or focused on single-platform qualitative studies (e.g., Galière, 2020; Rosenblat & Stark, 2016; Terry et al., 2021), this research initially employed quantitative methods to establish a robust empirical foundation. By identifying key variables such as socio-economic exchanges, leadership involvement, systemic justice, and proactivity traits, these quantitative studies provided essential statistical evidence and illuminated broader patterns in the relationship between AM, employee engagement, and job autonomy.

However, as the research evolved, it became evident that quantitative methods alone could not fully capture the nuanced, emotional, and contextual experiences of employees, particularly in envisioning future scenarios involving AM. This realization prompted a methodological shift towards qualitative approaches, most notably through the use of theatrical performance to simulate future work scenarios. This innovative method allowed for a profound exploration of the ethical and emotional dimensions of AM, uncovering insights that traditional quantitative approaches might overlook.

The use of theatrical performance as a research tool was particularly groundbreaking, offering a vivid and immersive way to engage participants with the complex, often abstract issues surrounding AM and its potential future implications. Unlike fieldwork within organizations that already apply these technologies, theatrical performance creates a controlled yet imaginative environment where participants can explore potential scenarios without the constraints of real-world workplace dynamics, responding to the call for proactive theorizing in the face of radical uncertainty (Gümüsay & Reinecke, 2022; Savage et al., 2018). This approach fosters reflective and critical engagement by situating participants in a space where they can confront hypothetical but plausible futures, free from existing organizational pressures or norms. This approach effectively captured the lived experiences and emotional responses of participants, providing a richer, more nuanced understanding of how employees perceive and interact with AM.

By bridging quantitative and qualitative insights and experimenting with performance-based social science approaches (Gergen & Gergen, 2012), this research achieved a more comprehensive and layered understanding of AM. The methodological diversity not only enriched the findings but also underscored the value of creative and non-traditional approaches in academic research, setting a precedent for future studies to adopt similarly innovative methods.

Learning Point 4: Agency and Resistance

Another recurring theme throughout these studies is the concept of agency—manifested both at the level of leadership and among employees. These findings contribute significantly to the existing literature on algorithmic management and resistance. Scholars like Abílio (2020), Bonifacio (2021), and Vasudevan & Chan (2022) have focused extensively on the gig economy, where AM is prevalent, exploring how workers resist algorithmic control, often through subtle or covert strategies, such as manipulating algorithms by strategically accepting or rejecting tasks to optimize their earnings, or sharing tips on bypassing algorithmic surveillance in online forums. Other studies, such as those by Arubayi (2021) and Gent (2018), examine the diverse forms of resistance, ranging from algorithm manipulation to collective organizing. For instance, drivers on ride-hailing platforms have coordinated strikes in informal networks or unions to protest changes in algorithmic pay structures, effectively leveraging their collective power to negotiate with platform operators.. Furthermore, Moore & Joyce (2020) and Pignot (2021) expose and challenge the opacity of AM, emphasizing resistance as both an individual and collective phenomenon.

Research by Kellogg et al. (2020) and Pastuh & Geppert (2020) delves deeper into the broader implications of algorithmic control on work relations, exploring how resistance can reshape these dynamics. Our research builds on this discourse by highlighting the critical role of agency in how AM is perceived and implemented. Rather than being solely passive recipients of algorithmic directives, leaders and employees demonstrate various levels of agency in how they engage with, adapt to, and resist AM. This research highlights the dynamic interaction between AM and human actors within organizations, revealing the importance of both leadership and employee agency in shaping how AM is implemented and experienced.

In the first paper, the role of leadership emerges as pivotal in moderating the relationship between AM and employee engagement. Leaders who maintain close social relationships with their teams can buffer some of the negative impacts of AM by fostering trust and facilitating more positive exchange relationships. This demonstrates that leaders are not merely enablers of AM but are also critical mediators who influence how AM is integrated into organizational practices. On the other hand, the second paper reveals that proactive employees themselves possess significant agency in navigating AM, although their level of agency is significantly limited in a rigidly controlled AM system. The third paper further explores this theme by examining how employees might react in a future where AM manages their well-being. The strong resistance observed in this paper illustrates that employees are not willing to relinquish their humanity in the face of technological advancement. They challenge the notion that well-being can be algorithmically managed, emphasizing their desire for genuine human interaction, emotional depth, and personal autonomy. This resistance reflects employees' political potential to influence the discourse around AM and its implementation in the workplace, advocating for more human-centered approaches to management.

Learning Point 5: Ethical and Humanistic Concerns and Employee Well-Being

The fifth breakthrough in this research journey was the reframing of the narrative surrounding AM from being purely a tool for optimization and efficiency to the realization of its potential as a challenge to humanistic values in the workplace. This shift in perspective was crucial for developing a more critical understanding of AM, which not only evaluates its effectiveness but also critically examines its broader implications for employee well-being, autonomy, and organizational ethics.

The studies collectively highlight the ethical concerns related to AM, particularly regarding employee autonomy and well-being. These concerns were most prominently explored in the third paper, which critically examined the potential future of AM in managing employee well-being. The research uncovered deep skepticism among employees about the ethical implications of continuous monitoring and data collection, especially when these technologies are used to manage aspects of their health and personal lives. Participants expressed fears that such monitoring could lead to dehumanization, a loss of personal autonomy, and a blurring of boundaries between work and private life.

These findings resonate strongly with existing literature on worker autonomy and resistance. For instance, Gal et al. (2020) use a virtue ethics approach to critique the use of people analytics in organizations, highlighting how it can undermine worker autonomy and integrity. Similarly, Unruh et al. (2022) discuss the challenges to human autonomy posed by algorithmic management, particularly in contexts where workers are heavily monitored and managed by algorithms. Langer and König (2021) also emphasize the importance of transparency and propose strategies to reduce the opacity in algorithmic HRM systems, advocating for a multi-stakeholder perspective to address these issues.

Further contributing to the discourse on ethics and AI in work and society, Fosso Wamba et al. (2021) provide a bibliometric review and research agenda focused on preparing society to handle the ethical implications of AI, particularly in HRM. Schaupp (2021) offers a framework for analyzing the digital politics of production, with a particular focus on how workers resist and navigate the technopolitics of algorithmic management.

This body of literature collectively underscores the importance of a humanistic approach to AM—one that balances technological efficiency with the preservation of human dignity and autonomy. The insistence on ethical practices, as reflected in employee calls for clear boundaries between personal and professional life in paper 3, points to a broader demand for transparency, informed consent, and respect for individual privacy in the deployment of AM. Our findings suggest that without these ethical safeguards, AM risks exacerbating the dehumanization of work and eroding the very values that contribute to a healthy and sustainable organizational culture.

Learning Point 6: The Future of Work and a Proactive Approach

Our research explored the future implications of AM, particularly in the third paper, which employed a forward-looking method to examine how AM might evolve. This exploration raises critical questions about the future of work and the role of technology in shaping it, aligning closely with and contributing to existing literature on how imaginaries and narratives influence technological and organizational development.

Augustine et al. (2019) argue that our future imaginaries, such as those related to geoengineering, significantly influence our current decisions and actions. Building on this, Beckert and Bronk (2019) explore how narratives and calculative technologies shape economic and social outcomes, especially under uncertainty. Gümüsay and Reinecke (2024) further this discussion by advocating for a balance between speculative thinking and rigorous methodology, emphasizing the need to envision futures beyond current limitations. These existing studies collectively underscore the importance of imaginaries and narratives in shaping the future of work.

In the first paper, we utilized vignette design to project and analyze potential future scenarios of AM. This approach is grounded in Augustine et al.'s (2019) idea that future imaginaries influence present decisions. By exploring different scenarios, we aimed to understand how different configurations of future visions of AM could potentially impact employee experiences. The findings revealed that depending on intensity of AM practices and leadership styles (socially close versus socially distant), employee engagement outcomes are significantly different. On the other hand, the third paper adopted a more speculative approach by using theatrical talk performances to simulate future work scenarios involving AM-empowered well-being technologies. This method reflects Gümüsay and Reinecke's (2024) call for balancing speculative thinking with rigorous methodology. By creating immersive future scenarios via theatrical performances, we explored the ethical and emotional dimensions of AM and how it might affect employee well-being. This innovative approach provided deeper insights into the potential impacts of AM, highlighting the need for a thoughtful and proactive stance on integrating these systems.

Together, these studies highlight the importance of proactively shaping the future of work with AM. They illustrate how future imaginaries and narratives influence both organizational decisions and employee experiences. Involving employees in the sensemaking process and addressing both the technological and human aspects of AM are crucial for mitigating risks such as increased stress and burnout. Our research contributes to the broader discourse by emphasizing that a balanced and human-centric approach to AM can contribute to organization flourishing while respecting the full spectrum of employee needs.

Practical Implications

The findings from this research offer significant practical implications for organizations and practitioners involved in the design and implementation of AM systems.

Transparency and Trust

Transparency plays a crucial role in fostering employee trust in AM systems. According to Chowdhury et al. (2022), organizations must communicate clearly how algorithms function, the types of data they collect, and the criteria by which decisions are made. Such transparency is vital to reduce employee anxiety about being monitored or exploited by unseen mechanisms, and it helps employees better understand the purpose and functioning of AM systems. Araujo et al. (2020) support this view, suggesting that transparent AM systems help employees feel more respected and valued by their organizations, enhancing their overall engagement. Without clear communication about AM, employees may perceive these systems as overly controlling or unfair, leading to resistance and reduced engagement.

Fairness and Equity

Ensuring fairness is essential when designing and implementing AM systems. Bankins et al. (2022) emphasize that fairness in task allocation, performance evaluations, and promotions must be built into the algorithms governing AM systems. If AM systems are perceived as biased or discriminatory, they can quickly erode trust and diminish morale within the workforce. Involving employees in the design and implementation phases allows their concerns to be addressed, fostering a sense of ownership and acceptance. Moreover, fairness must be continuously monitored to avoid the development of algorithmic biases that could disadvantage certain groups within the workforce. Fairness is not only about the technical design of the algorithms but also about ensuring that the decision-making processes are equitable and transparent.

Ethical Safeguards

Ethical safeguards are critical to aligning AM systems with broader humanistic and organizational values. As organizations increasingly rely on AM for decision-making, they must establish guidelines to protect employee privacy, autonomy, and well-being. The ethical use of data, particularly sensitive information such as health and performance metrics, must be prioritized (Bankins et al., 2022). This requires a clear data protection policy that outlines how employee data is collected, stored, and used, ensuring compliance with relevant data privacy regulations. Moreover, integrating employee input during the design process can prevent ethical pitfalls, making employees feel more secure about their interactions with AM systems. This approach also aligns with Araujo et al. (2020), who argue that ethical AM design fosters greater trust and acceptance from employees.

Human Oversight

While AM systems are designed to automate many managerial tasks, such as monitoring performance, assigning tasks, and scheduling, maintaining a degree of human oversight is essential. Decisions that impact employee well-being and career development, such as performance reviews and promotions, should involve human managers to ensure fairness and context-specific judgment. The research highlights that fully automated systems, without human intervention, can lead to employees feeling dehumanized, undermining their trust in the organization (Chowdhury et al., 2022). Human oversight provides employees with an avenue to contest decisions they perceive as unfair, ensuring that AM systems do not become overly rigid or punitive. This hybrid approach, where both algorithms and human managers contribute to decision-making, preserves the benefits of efficiency while ensuring fairness and employee engagement.

Customization and Employee Control

To ensure AM systems align with individual employee needs and preferences, it is important to allow a degree of customization. Employees should have the option to control how they interact with these systems, including the ability to opt out of certain forms of monitoring or data collection. This flexibility helps to balance the organization's need for data with employees' rights to privacy and autonomy. Providing employees with some degree of control over AM processes enhances their engagement and satisfaction, reducing feelings of being micromanaged or overly surveilled. This level of customization also addresses the concerns raised by Bankins et al. (2022) about the risk of overreach in AM systems.

Prioritizing Employee Well-being

Finally, AM systems must be designed with employee well-being in mind. While the primary goal of AM systems is often to increase operational efficiency, these systems should also support employee development and mental, emotional, and physical well-being. This can be achieved by integrating features that provide constructive feedback and focus on personal growth rather than solely performance metrics. AM systems that emphasize positive reinforcement and developmental feedback, rather than punitive actions, are more likely to enhance employee engagement and job satisfaction (Chowdhury et al., 2022). Ensuring that AM systems are designed to prioritize employee well-being helps foster a supportive and motivating work environment.

Challenges and Limitations

While the thesis included diverse samples across various studies, the findings may not be fully generalizable to all work settings or industries. For instance, the research may exhibit a bias toward specific sectors, such as the service industry, or geographic regions, particularly Europe and the U.S., which could limit the applicability of the results to other contexts, such as the primary sector or the Global South. Additionally, variations between global and U.S. samples suggest that national and cultural differences may affect the generalizability of the findings. For example, in terms of national culture, U.S. employees, valuing personal autonomy, may resist algorithmic monitoring more than those in collectivist cultures like China, where such technologies might be accepted as tools for enhancing group productivity. Furthermore, the effectiveness and impact of AM systems vary significantly depending on the organizational context, including factors like company size, industry type, and existing management practices. The thesis may have limitations in addressing these contextual differences, which could influence the generalizability of its conclusions.

The shift from quantitative to qualitative methods provided deeper insights but also introduced challenges in balancing, reconciling, and integrating these approaches. Nonetheless, we managed to identify six key learning points across the three papers, finding common ground for discussion despite methodological discrepancies.

The reliance on self-reported data in quantitative paper 1 and paper 2 is subject to biases such as social desirability and recall bias. These biases could affect the accuracy and reliability of findings, particularly in sensitive areas like job autonomy or employee engagement under AM. Future research should consider incorporating more objective measures to enhance robustness in quantitative research such as such as performance metrics, behavioral observations, and data from AM systems.

The studies primarily focused on cross-sectional data, capturing a snapshot in time rather than the evolving impacts of AM over a longer period. While cross-sectional studies offer valuable insights, they may miss the dynamic relationships between AM and employee well-being over time as pointed out by Meijerink & Bondarouk (2021). Longitudinal studies would provide a more comprehensive understanding of these dynamics, but such an approach was beyond the scope of this research. Connecting to this point, the rapid pace of technological change in AM could mean that some findings of the thesis become outdated quickly. As AM technologies continue to evolve, new features or applications may emerge that were not considered in this research, potentially limiting the relevance of the findings over time. For example, recent developments in large language model tools may alter how employees perceive algorithmic management, potentially limiting the relevance of the findings as the scope and intrusiveness of these technologies expand.

Furthermore, the research focused on critical factors like employee engagement, job autonomy, and well-being in general, but other relevant aspects of AM, such as its impact on employee creativity (Jia et al., 2024), team dynamics (Reitz & Higgins, 2024), or broader organizational culture (English, 2023), were less explored. These areas warrant further investigation to provide a more holistic understanding of AM's effects.

Lastly, the inherent complexity and opacity of many AM systems (e.g., Bujold et al., 2022) could limit the ability of the research to fully understand or explain how these technologies operate and impact employees. This could result in an incomplete or overly simplistic interpretation of the relationship between AM and employee outcomes.

Future Research Directions

As AM evolves, this research highlights several key areas for further exploration. To advance our understanding and application of AM, future studies should address the identified limitations and build upon the insights generated by this body of research. We provided several research avenues for future research below.

Long-Term Effects of AM

One of the most critical gaps identified in the current research is the need for a deeper understanding of the long-term effects of AM on employees and organizations. While the existing studies provided valuable insights into the immediate and short-term impacts, longitudinal studies are necessary to examine how these effects evolve over time, especially given how fast AM is being integrated to organizations. Specifically, there is a need to explore how prolonged exposure to AM influences employee well-being, job satisfaction, and career development, and how employees, with time, adapt to the system. Such studies could also investigate whether the benefits of AM are sustainable and if any potential negative impacts intensify or diminish as employees and organizations adapt to these systems.

The Importance of Transparency

Transparency emerged as a critical theme throughout this research, significantly influencing employee perceptions and reactions to AM. Future research should delve deeper into the mechanisms through which transparency—or the lack thereof—impacts trust, engagement, and acceptance of AM systems. Specifically, studies could focus on the development of transparent algorithms that allow employees to understand how decisions are made and what data is being collected. This line of inquiry is crucial for mitigating resistance and fostering a positive relationship between employees and AM systems.

Employee Resistance and Agency

Another area that warrants further exploration is the role of employee resistance and agency in the context of AM. The current research highlighted that employees are not passive recipients of AM directives; rather, they actively engage with and sometimes resist these systems. Future studies should investigate the forms of resistance that emerge in different organizational contexts and how these resistance behaviors can shape the implementation and outcomes of AM. Additionally, research could explore how employees' sense of agency can be supported within AM frameworks to promote more collaborative and less adversarial interactions with these technologies.

Cross-Cultural Comparisons

Given that AM is being implemented in a variety of cultural and organizational contexts globally, cross-cultural research is crucial. Future studies should investigate how cultural differences influence the perception, acceptance, and impact of AM (Mantello et al., 2023). Such research could reveal both universal principles and culturally specific responses to AM, providing valuable insights for the design of systems that are effective across diverse settings. Understanding these cultural dynamics could also inform strategies for more inclusive and equitable AM implementations.

Interdisciplinary Research and Collaboration

The complexity of AM necessitates interdisciplinary research that brings together organizational scholars, system designers, software engineers, ethicists, and end-users. Future research should focus on bridging the technical and social dimensions of AM by fostering collaboration across these fields. Such interdisciplinary efforts could lead to the development of AM systems that are not only technologically robust but also socially responsible and user-friendly. Engaging system designers and software engineers in the research process ensures that ethical considerations and user perspectives are integrated into the design phase of AM systems.

Participatory Research and Quasi-Experiments

Connecting to the previous point is the participatory research approaches that involve employees and other stakeholders directly in the research process. Future studies could also employ quasi-experimental designs to test the effectiveness of different AM interventions in real-world settings. Such research could explore how variations in AM design, implementation, and management practices influence employee outcomes, offering practical insights for organizations seeking to optimize their use of AM.

Developing Frameworks for Humanistic Algorithmic Management

Lastly, there is a pressing need to develop comprehensive frameworks for humanistic algorithmic management that prioritize employee well-being, autonomy, and dignity. Future research should focus on identifying best practices for integrating human-centric values into AM systems and creating guidelines for ethical decision-making. These frameworks could serve as a blueprint for organizations looking to implement AM in ways that are both effective and aligned with broader social and ethical goals.

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