

COMMENTARY

AI-Human Interaction: Insights from Organizational Behavior and AI Ethics in AI Supervision

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Abstract

Purpose - How can we evaluate employee acceptance of AI in lower-level management? Wolf and Stock-Homburg (2025) recommend the Technology Acceptance Model (TAM) and the Expectation-Disconfirmation Theory (EDT) in a study that refers to "managers as robots" (hereinafter "AI managers"). While their study provides useful insights into employee attitudes toward AI managers, we argue that acceptance is not merely a rational or individual evaluation but a socially embedded phenomenon shaped by power relations, organizational culture, and ethical concerns.

Design/Methodology/Approach - We extend the theoretical scope of the original study by integrating insights from organizational behavior, critical management studies, and AI ethics. Drawing on recent literature and empirical findings, we examine how algorithmic opacity, labor dynamics, and cultural factors influence employees' responses to AI managers. We also assess the psychological and well-being implications of AI-driven supervision.

Findings - Our analysis reveals that employee acceptance of AI managers is often driven by coercion or compliance rather than genuine trust. Opaque algorithmic decisions, power distance, and cultural norms—particularly in high power-distance environments—play a significant role in shaping perceptions and behaviors. Additionally, ethical concerns such as algorithmic bias and technostress may undermine employee well-being, leading to resistance rather than sustained acceptance.

Originality/Value - This paper offers a critical and interdisciplinary expansion of AI acceptance models by embedding them within broader organizational, ethical, and psychological contexts. It contributes to both the AI-human interaction and organizational studies literature by challenging assumptions of rational acceptance and proposing new directions for empirical research on AI management. The commentary also provides actionable insights for policymakers and managers seeking to implement AI supervision in just, inclusive, and sustainable ways.

KEYWORDS

AI-human Interaction, AI managers, Robotic managers, Artificial intelligence, Technology acceptance, Cultural norms ethics, Algorithmic bias, Employee well-being, AI-Human interaction.

1 | INTRODUCTION

The study by Wolf and Stock-Homburg (2025) provides an investigation on a contemporary phenomenon related to employees' acceptance of robotic lower-level managers. The main justification for the focus on

robotic management is that the workforce is aging, and skilled workers are not numerous enough to cope with the needs of Western job markets. While the statistics indeed support this statement (McGrath 2021, U.S. Bureau of Labor Statistics 2023ab), rather than promoting the use of robots as lower-level managers, this situation may require organizations and governments to adapt their human resource development and education practices (Packer and Sharrar 2003).

To address labor shortages, governments have increased retirement ages, while organizations need to create age-friendly workplaces (Nagarajan et al. 2019). Effective strategies for supporting older workers

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include targeted training approaches, updating job-related skills, expanding knowledge horizons, and integrating training into recruitment initiatives (Koc-Menard 2009). The simultaneous impact of workforce aging and digitalization necessitates a holistic public policy approach, focusing on high-quality education that develops creative and social skills (Stojković-Zlatanović and Jovanović 2023). This approach should promote decent work conditions and sustainable workplace practices, such as age management mechanisms and age-responsible due diligence. Collaboration between organizations, governments, and educational institutions is crucial for addressing these challenges and ensuring a skilled, adaptable workforce across all age groups. Larger firms may choose to create a Corporate University which, when strategically aligned with their strategy and values (Lissillour et al. 2020), are potent tools to transform into ambidextrous learning organizations (Rodriguez-Escobar and Lissillour 2022).

Corporate social responsibility (CSR) also emerges as a potential solution. CSR can be leveraged to address educational gaps and improve workforce skills (Miller and Akdere 2019, Moreno 2010). Businesses can collaborate with governments and stakeholders to provide education and training, enhance employee competencies, and address labor market mismatches (Markowitsch et al. 2013). For Western economies facing the challenge of integrating migrants, innovative skill-building schemes in countries of origin and destination can help meet skilled worker demand and expedite integration (Tharenou and Kulik 2020). CSR governance can also play a role in migrant integration, addressing security concerns and cultural differences (Schittenhelm and Schmidtke 2011). These approaches can lead to improved employee loyalty, job satisfaction, and productivity (Camilleri 2016). By aligning organizational cultures with government educational policies, businesses can contribute to developing human capital and addressing workforce challenges (Hegyes and Fekete-Farkas 2019).

The study by Wolf and Stock-Homburg adopts a specific focus and extends research on social robots by integrating the Technology Acceptance Model (TAM) and the Expectation-Disconfirmation Theory (EDT) and to examine employees' expectations versus experiences with robotic managers. While these models investigate cognitive and performance-based factors, they consider acceptance as an individual, rational process rather than a structurally embedded phenomenon (as in more critical approach, see Lissillour (2024). However, in information systems literature, robotic managerial acceptance is not merely about individual expectations or performance evaluations—it is deeply shaped by organizational dimensions, resistance to change, power asymmetries, workplace culture, ethical concerns, and psychological reactions to AI-driven supervision. By broadening the scope beyond the individual scope, this commentary reveals where TAM and EDT's assumptions hold, where they fall short, and where they require revision.

This commentary builds upon Wolf and Stock-Homburg (2025)'s findings by integrating insights from concepts related to information systems research, organizational behavior, power dynamics, ethics, and employee well-being. Specifically, while their study identifies distinct acceptance patterns for performance-related and relational factors, we

argue that managerial AI cannot be understood purely through individual perceptions of usefulness or trust. Instead, acceptance is shaped by organizational dimensions and power structures, ethical concerns surrounding algorithmic control, and psychological reactions to AI-driven supervision. To develop this critique, we first summarize the study's contributions and limitations before expanding the discussion in two key areas: (1) the role of power and organizational dynamics in shaping acceptance (or compliance) and (2) ethical and well-being concerns, including algorithmic fairness, transparency, and psychological impacts.

2 | CONTRIBUTIONS AND LIMITATIONS

Wolf and Stock-Homburg (2025) make three significant contributions. First, they offer a theoretical contribution in Human-Robot Interaction (HRI). By applying the Expectation-Disconfirmation Theory (EDT) to robotic management, the authors challenge the prevailing assumption that higher robot capabilities automatically translate into higher acceptance. Their findings—demonstrating an S-shaped curve for performance expectations and a degressive curve for relational expectations—complicate simplistic views of technological acceptance. Second, the study displays empirical strength through its robust experimental design. The authors employ an online vignette-based experiment with 7,061 participants, significantly enhancing the generalizability of the results. This large sample size provides strong statistical power, enabling nonlinear modeling through response surface analysis (RSA)—a methodological advancement in the study of human-robot interactions. Third, the study concludes with practical implications for the workforce integration of AI managers. Specifically, it highlights higher employee acceptance of android robots over humanoid robots. This suggests that organizations aiming to deploy AI-driven management roles should prioritize embodied, yet non-human, robotic designs. Such insights inform AI deployment strategies in organizations facing managerial labor shortages.

Despite its strengths, the study has several limitations. The first limitation is the lack of justification of the theory used in this paper. The authors simply claim that they combine TAM with EDT without any justification or any comparison with any other theory. The point is that TAM is not only one of the oldest theories in information systems (IS), as they quote, starting with Davis (1989), but also one of the most criticized ever. These criticisms were largely published not only in top European journals but also in top American journals such as MISQ. They belong to different tradition against TAM related either to the sociology of work (Rai et al. 2019), the critical social theory in information systems (Lyytinen and Klein 1985, Hirschheim and Klein 1994, Ngwenyama and Lee 1997) but also to behavioral sciences (Boland and Lyytinen 2017).

From a methodology standpoint, this study's experimental design relies on one-time video interactions with robotic managers. This raises concerns about the *novelty effect*: participants may overestimate their acceptance due to the uniqueness of the situation rather than genuine willingness to engage long-term with robotic supervisors (Leite

et al. 2013). Experimentation is also extremely criticized in information systems. The variance approach has been described as not related to organizational phenomenon that can be described only through process approaches or system approaches. In addition, the exclusive focus on quantitative methods is now increasingly criticized also (?). The other totally missing theoretical debate is the main one published only in information systems: automation versus augmentation. Are the robots introduced from a labor substitution perspective or from a complementarity perspective leading to symbiosis or intelligence augmentation (Pavlou 2018)? The focus on robots in supervisory roles simply changes the level of inquiry: are these robots here to replace managers or to augment them? Nothing is said. this debate is simply absent from this paper. The point is that this debate is now the focus of the European Commission which announced the shift from Industry 4.0 based on automation to Industry 5.0 based on augmentation. Numerous cases of robotic augmentations were for instance described in Germany such as Mercedes-Benz or Volkswagen.

Third, the study overlooks the organization. First, the assumption that the business problem is an aging workforce is questionable. According to numerous consulting group reports the first justification of robots is cost reduction, followed by growth, flexibility, or customer satisfaction (Ransbotham et al. 2018, Institute 2017). The consequence is that the managerial recommendations lack the classical contemporary business performance problems that are facing companies and that justify relying on robots. The other missing word is business processes. The word that all companies now use, namely "Robotic Process Automation," is not even mentioned. The justification of robotics is less on the individual level but at the level of the robotization of processes, such as supply chain (Hevner et al. 2004). Management is a process of long-term interactions, where trust and team dynamics evolve. Employees' perceptions in a one-time study do not necessarily reflect actual acceptance over weeks or months. Third, the study arguably lacks behavioral validation. The study measures stated preferences but does not track actual workplace behavior (e.g., how employees respond to robotic managers in high-stakes or stressful situations).

Another limitation is the non-representative sample, which consists of over 70% of participants with prior experience working with robots and over 75% identifying as tech-savvy. This bias is likely a consequence of the study's use of Amazon Mechanical Turk (MTurk), a platform predominantly composed of freelancers, gig workers, and tech-oriented individuals. As a result, the study largely reflects the attitudes of white-collar and remote workers rather than employees in traditional workplaces, such as manufacturing, logistics, or frontline service jobs. In industrial and warehouse environments, AI-driven management is often associated with micromanagement, productivity surveillance, and reduced worker autonomy, leading to higher levels of resistance (Todolí-Signes 2019). Similarly, in unionized workplaces, AI-driven decision-making is frequently contested as a threat to collective bargaining power and fair labor conditions. By relying on a sample with high technological affinity, the study risks overestimating the general level of acceptance among broader workforces.

For instance, the manufacturing sector—one of the largest adopters of automation—has a strong tradition of unionized labor, collective bargaining, and worker protections. Studies show that labor unions and employee advocacy groups often resist AI-driven management due to concerns over worker autonomy, job security, and algorithmic surveillance (Todolí-Signes 2019). If robotic lower-level managers are introduced in these environments, workers may not simply "accept" them based on performance expectations but instead contest their legitimacy as managerial authorities. Similarly, in service-sector jobs that involve emotional labor (e.g., retail, hospitality, healthcare), employees may prioritize social and relational aspects of management over perceived efficiency gains from AI-driven supervision. Future research should therefore expand beyond tech-oriented populations and incorporate longitudinal field studies in diverse workplace settings, including factory floors, logistics operations, and frontline service jobs, where robotic management is likely to face different forms of institutional, cultural, and regulatory resistance. Experimental designs that simulate realistic workplace constraints—such as labor protections, team hierarchies, and job-specific stressors—would provide a more comprehensive understanding of acceptance and compliance dynamics. While the study provides important insights into the mechanisms of employee acceptance, it largely treats this acceptance as a rational, expectation-driven process. However, in real workplaces, power dynamics and organizational structures play a decisive role in whether employees truly 'accept' robotic managers—or merely comply with them. The following section explores these overlooked dimensions.

3 | POWER & ORGANIZATIONAL DYNAMICS

3.1 | Can Robots Truly Be Managers?

The study by Wolf and Stock-Homburg (2025) assumes that lower-level managerial roles are primarily task-oriented, centered on assigning tasks and monitoring performance (Simonet and Tett 2013). However, this narrow definition overlooks critical human-centric functions such as motivation and emotional intelligence (Goleman 1998), conflict resolution and team cohesion (Yukl 2013, Haque and Lissillour 2025), and context-sensitive decision-making (Mintzberg 1973).

If robotic lower-level managers cannot display sufficient emotional intelligence (which is often non-verbal), can they truly replace human managers or merely serve as advanced automation tools? The study overlooks potential employee resentment or resistance when robots lack social management capabilities (Banks et al. 2018). This resistance will necessarily differ within an organization since it is usually composed of diverse groups of employees driven by different organizational subcultures (Lissillour and Wang 2021). Does resistance emerge in jobs where decision-making autonomy is central? Differences may be expected between people from the workers from the research and

development department and those dealing with standardized factory work.

Resistance to change is indeed deeply studied in the Sociology of Work. In IS research, the sociology of work applied to AI and robotics often questions novel forms of control and increased coordination in the workplace (Faraj et al. 2018). The sociology of work also identifies hidden cost, especially working conditions, work organization, coordination, and control issues (Savall et al. 2019). Elaborating on this critical tradition, Habermas' Sociology of Work has been extensively used in media studies for criticizing the effects of AI at work focusing on the social critique of datafication (Haythornthwaite and Wellman 1998, Ball 2010), and commodification (McLean and Wainwright 2009, Bucher 2012).

The authors suggest that future research should incorporate longitudinal studies where robotic managers interact with employees over weeks or months so as to cope with the methodological limitations of the study. Indeed, such study could enable future research to assess the individual and collective trajectory between resistance and acceptance. But other research designs would be appropriate such as behavioral experiments that would observe employees' reactions in real workplace tasks, not just hypothetical video scenarios. This experiment could integrate physiological and neurocognitive measures (e.g., stress indicators) to capture implicit acceptance levels beyond self-reported surveys.

Rather than positioning robots as substitutes for human managers, future research should explore hybrid management models, where human managers focus on relational aspects and use the help of robots as a support for decision-making and data analysis.

3.2 | The Role of Power Dynamics: Do Employees Accept or Comply?

The study assumes that employee acceptance is based on rational evaluations of usefulness and relational features. However, workplace hierarchy and power dynamics (Lissillour 2025) play a crucial role in shaping compliance with robotic managers. Do employees "accept" robots voluntarily, or do they comply because they lack a choice? In Monod et al. (2023)'s study, AI workflow management was imposed by the higher management, so the workforce reacted negatively. Moreover, the AI was defined by the higher management so that it served primarily its interest, i. e. more micro-management capabilities. The study suggests that robotic managers make "fairer" decisions than human managers, referencing studies on algorithmic impartiality (Wu et al. 2024). However, existing research on algorithmic bias (Green and Chen 2019) and automation over-trust (Dietvorst et al. 2018a). suggests that perceived fairness is contingent on transparency and explainability. Further research could explore how transparency in robotic decision-making influences acceptance. Recent studies have found that this transparency is like to be one-sided, with managers benefiting from transparency in terms of more detailed data on workers, but workers suffering from opaque ideas about how the data are used (Lissillour and Monod 2024).

The issue of power dynamics is likely to differ from country to country because of people's cultural preferences. We might then ask how does power distance (Hofstede 2001). influence robotic manager acceptance? Would employees in high power-distance cultures (China, France) accept robotic authority more easily than those in low power-distance cultures (Netherlands, Costa Rica), who might resist it. Literature on AI ethics (Bankins et al. 2022) suggests that attitudes toward robotic authority figures vary not only by power distance but also by uncertainty avoidance (Matsumoto et al. 2020). The study conceptualizes lower-level management as task-focused (Simonet Tett, 2013), assuming that clear task allocation and structured decision-making are sufficient for acceptance. However, the extent to which managers are task-focused or people-focused largely depends on national and corporate culture (Aycan et al. 2000).

The issue in neglecting power dynamics is that the authors simply take for granted the "intention to use" without including a very well-known phenomenon in behavioral sciences of unintended consequences in any attempt at IT development (Boland and Lyytinen 2017), and may therefore be labeled as 'generative', meaning unforeseeable (Rai et al. 2019). Whereas this generativity may be leveraged by AI platforms and lead to positive network effects, value creation, and scalability, it may also lead to improvisation (Boudreau and Robey 2005), shadow systems (Culnan and Bair 1983), or workarounds (Kraut et al. 1999, Azad and King 2008). In addition, AI such as robots reconfigure boundary relations among occupational groups in organizations. This reconfiguration may lead to contradictory consequences for the workers' skills, jurisdictions, status, and visibility. Some groups may benefit from AI while some will suffer from it (Barrett et al. 2012).

While workplace power dynamics influence whether employees accept or simply comply with robotic managers, another critical dimension is ethics and well-being. AI-driven management does not exist in a vacuum—it shapes, and is shaped by, larger concerns about fairness, transparency, and psychological impact. If robotic managers reinforce biases, induce technostress, or create opaque decision-making systems, their acceptance will remain fragile, regardless of performance metrics. The next section examines these ethical and well-being challenges, highlighting the risks and responsibilities associated with AI-driven supervision.

4 | ETHICAL & WELL-BEING CONCERNS

4.1 | Ethical and Algorithmic Bias Concerns: Are Robotic Managers Fair?

The study suggests that robotic managers may improve fairness in decision-making due to their data-driven evaluations. However, existing research on algorithmic bias contradicts this claim (O'Neil 2016, Franklin et al. 2024). Concerns include eventual bias in AI Training Data. If AI systems are trained on biased historical data, robotic managers may replicate human biases, leading to discriminatory task assignments

or performance evaluations. Recent research highlights the importance of addressing biases in artificial intelligence and robot management systems. Diversity training interventions for human-robot interactions have shown mixed results, with perspective-taking potentially backfiring and stereotype suppression proving more effective in reducing negative attitudes towards robots (Wullenkord and Eyssel 2022). AI systems can perpetuate gender, racial, and socioeconomic biases, necessitating responsible AI implementation to mitigate risks (Varsha 2023). In healthcare, machine learning algorithms may propagate biases related to race, ethnicity, gender, age, and socioeconomic status, potentially exacerbating healthcare disparities (Franklin et al. 2024). To address these issues, researchers have developed fairness-aware machine learning interfaces, which aim to discover and mitigate discrimination in decision-making processes (Bantilan 2018). These studies emphasize the need for diverse training datasets, de-biasing techniques, and algorithmic modifications to mitigate biases and promote fairness in AI and robotic systems across various industries.

This ethical perspective has been developed in information systems by the critical perspective considers AI as one more way in which the “haves” use their capital to oppress the working people (the “haves not”). Once again, they see those who have contributed so much to the wealth of the world, having it appropriated from them through the accumulation of the capital holders, whose holdings will expand ever more dramatically through the knowledge power of the AI machine (Boland and Lyytinen 2017). In this way, the value produced by workers becomes the power of capital and the source of their alienation. Especially, the theoretical approach of Habermas (1981) appeared in IS research a few decades ago through his Critical Social Theory (CST) (Lyytinen and Klein 1985) with a focus on emancipation. A critique of instrumental action and teleonomic action is conducted in order to identify the conditions of possibility of communicative action and argumentative action from the perspective of consensus-building (Hirschheim and Klein 1994, Ngwenyama and Lee 1997).

Moreover, users often regret the AI's opacity in decision-making. Indeed, AI-driven managers often operate as “black boxes,” making it difficult for employees to challenge unfair decisions (Pasquale 2015). If employees should have access to explanations of robotic managerial decisions (e.g., why they received a poor performance review), it is usually not the case since the higher management implemented and defined AI tools (Lissillour and Monod 2024). The use of robots as managers may also lead to automation bias and over-trust. Indeed, employees may blindly trust robotic decisions, even when they make errors (Dietvorst et al. 2018a). Consequently, in addition to training both managers and employees, organizations must ensure ethical oversight mechanisms. AI-driven management should include human review processes to correct algorithmic biases during the system's creation, implementation, and use (Sahut et al. 2023a). Rather than a linear process, Sahut et al. (2023b) suggest that all stakeholders must have the opportunity to engage in unbiased and constructive debate at all key stages of the AI system's life. Indeed, if some stakeholders are marginalized or if the organizational

power structure does not give some social groups a real influence, it will undermine the ethical use of the AI system.

4.2 | The Psychological Impact: Does AI Management Undermine Employee Well-Being?

The study does not consider the psychological effects of robotic supervision on employee stress, motivation, and well-being. Studies indicate that AI integration can potentially reduce burnout, but its effectiveness depends on implementation strategies involving comprehensive training, personalization, and regular feedback (Meduri et al. 2024). However, recent research suggests that AI-driven management may increase workplace anxiety. Employees may feel constantly monitored and evaluated, leading to heightened stress and burnout (Sewell and Taskin 2015).

In addition to lacking empathy and emotional support, employees perceive highly competent robotic managers negatively as they may fear job displacement (Frey and Osborne 2017). Indeed, the increasing prevalence of AI and robots in workplaces also raises concerns about job insecurity among employees. Humanlike features of robots can exacerbate these concerns by triggering social comparison (Wang et al. 2023). In digitalized workplaces, particularly call centers, emotional labor, and AI anxiety can negatively impact employees' psychological well-being (Konuk et al. 2023). The rapid adoption of AI applications is creating new stressors for employees, and their response - whether to lead or flee - will influence the success of AI implementation projects (Zhu et al. 2020). As AI governance frameworks evolve, it is crucial to balance technological advancements with ethical and human-centered approaches. Without transparent, inclusive, and fair implementation strategies, robotic managers risk deepening workplace inequalities rather than enhancing productivity. The final section summarizes the study's key contributions and outlines directions for future research.

5 | INTEGRATIVE ANALYSIS: EXTENDING EDT AND TAM

While Wolf and Stock-Homburg (2025) provide valuable insights into how employees evaluate robotic managers, their findings focus largely on rational, cognitive decision-making based on expectations and perceived usefulness. However, by integrating perspectives from power dynamics, ethics, and well-being, this commentary reveals deeper structural and psychological factors that reshape the organizational reception of robotic managers. In some areas, these new perspectives refine the study's conclusions (e.g., by adding a cultural dimension to acceptance); in others, they contradict core assumptions (e.g., showing how AI supervision may increase stress and resistance rather than fairness).

The table below synthesizes the original theoretical models—Expectation-Disconfirmation Theory (EDT) and Technology Acceptance

Model (TAM)—with new perspectives introduced in this commentary, highlighting points of alignment, refinement, and contradiction.

As shown in the table, this expanded analysis both enriches and challenges Wolf and Stock-Homburg (2025)'s conclusions. In certain domains, EDT and TAM remain useful—especially in capturing the role of expectations and usability during early exposure to AI managers. However, these models fall short when structural inequalities, organizational culture, or ethical controversies are considered. Compliance should not be mistaken for genuine acceptance, and the implementation of robotic management systems cannot be divorced from the broader social and legal contexts in which they operate.

Ultimately, robotic managers are not neutral tools—they are embedded actors within organizations, whose legitimacy, effectiveness, and fairness are continually negotiated by stakeholders (Lissillour and Sahut 2022). The next section summarizes these insights and outlines a future research agenda.

6 | CONCLUSION

Wolf and Stock-Homburg's study marks an important step in understanding how employees perceive robotic lower-level managers. By integrating EDT and TAM, they offer a useful but partial explanation for AI acceptance in managerial roles. However, their model remains narrowly focused on cognitive evaluations, overlooking the power structures, ethical dilemmas, and psychological stressors that fundamentally shape how AI-driven management is experienced in real workplaces. Our analysis suggests that robotic managers are not merely accepted or rejected based on expectations—rather, their integration is negotiated within complex systems of hierarchy, agency, fairness, and resistance. As AI governance frameworks (e.g., the EU AI Act) and corporate AI strategies evolve, it is imperative that research moves beyond technology acceptance models and include managerial performance evaluation, robotic process automation, resistance to change, organization change and power dynamics. Longitudinal field studies tracking actual workplace interactions with robotic managers—not just hypothetical scenarios—are needed to uncover how acceptance shifts over time. Cross-cultural comparisons can clarify how power distance, worker protections, and labor traditions influence AI supervision across industries. Policymakers and corporate leaders must also move beyond efficiency narratives, ensuring that AI-driven management is not simply imposed but co-designed with employee agency and ethical oversight in mind. Ultimately, the future of AI in management is not just a question of technological optimization—it is a question of organizational justice. Will robotic managers empower employees, enhance transparency, and support human decision-making? Or will they reinforce asymmetries, increase stress, and reduce worker autonomy? Whether AI-driven management succeeds will not be decided by technology alone—but by the managerial methods and principles that guide its implementation.

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CONFLICT OF INTEREST

The authors declare no potential conflict of interests.

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TABLE 1 Comparison of Theoretical Perspectives on Robotic Manager Acceptance

Key Factor	EDT (Wolf & Stock-Homburg)	TAM (Wolf & Stock-Homburg)	Power & Organizational Dynamics (New)	Ethical & Well-being Concerns (New)
Performance-Related Factors (Usefulness, Efficiency, Task Assignment)	Employee acceptance follows an S-curve: slight over-fulfillment of expectations enhances willingness to work with robotic managers, but excessive performance can create resistance.	Perceived usefulness drives initial acceptance, but sustained acceptance depends on continuous alignment with work expectations.	Contradicts: PoWolf and Stock-Homburg assume employee acceptance is based on performance, but workplace power structures may force compliance rather than genuine acceptance. Unionized workplaces may resist robotic managers, regardless of performance.	Refines: Over-reliance on algorithmic decision-making risks unfair task distribution due to biased AI models. Employees may develop automation bias, trusting flawed AI decisions over human judgment.
Relational Factors (Trust, Social Presence, Team Interaction)	Relational factors follow a degressive curve: positive experiences improve acceptance, but diminishing returns appear with excessive relational expectations.	Human-like (android) robots foster higher acceptance than humanoid robots, but expectations matter less than actual interactions.	Refines: Employees may comply with robotic managers out of necessity rather than genuine acceptance, particularly in high power-distance cultures. Power distance and cultural factors significantly shape acceptance beyond individual expectations.	Contradicts: Lack of emotional intelligence in robots may increase employee stress and reduce workplace cohesion. Wolf and Stock-Homburg focus on rational acceptance, but psychological responses (anxiety, alienation) may create long-term resistance.
Contextual Factors (Workplace Culture, Job Role, Industry)	Refines: Expectations and experiences differ based on industry and job function; managerial automation is more acceptable in standardized work environments.	Refines: Technology adoption varies by sector; industries with high automation exposure show higher acceptance.	Refines: Power distance affects robot acceptance: High power-distance cultures (China, Japan) may favor robotic managers more than low power-distance cultures (Western Europe). However, unionized workplaces and high-autonomy jobs will resist AI-driven management.	Contradicts: The transition to robotic managers must be ethically regulated, ensuring transparency in decision-making and preserving human oversight. Wolf and Stock-Homburg do not account for the one-sided transparency issue—AI managers monitor workers, but workers lack insight into AI's decision-making process.
Psychological Factors (Job Security, AI Trust, Perceived Autonomy)	Refines: Over-performance by robotic managers may trigger job insecurity, reducing employee willingness to work with them.	Refines: Employees trust robotic managers if they perceive them as transparent and easy to use. Modifiability of AI decisions reduces "algorithm aversion."	Refines: Employees in highly autonomous jobs (creative industries) may resist AI managers more than those in routinized jobs. Unionized workplaces may push back against robotic management. The fear of job displacement shapes acceptance beyond rational performance expectations.	Contradicts: Algorithmic control may heighten technostress, leading to workplace anxiety and resistance. AI-driven surveillance may reduce employee well-being, contradicting the assumption that relational interaction alone determines acceptance.

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SUPPORTING INFORMATION

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