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Confronting and alleviating AI resistance in the workplace: An integrative review and a process framework

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ABSTRACT

This study involves an integrative literature review and a process framework explaining the mechanisms to confront and alleviate employee Artificial intelligence (AI) resistance in organizations. First, we conceptualize AI resistance as a three-dimensional concept embodied in employees' fears, inefficacies, and antipathies toward AI. We advance that experiencing mistrust, existential questioning, and technological reflection are key individual mechanisms to confronting AI resistance connected to organizational mechanisms to alleviate AI resistance through the continuous interaction and unfolding of anxiety and introspection. We also explain the alleviation of AI resistance as an organizational process consisting of AI accessibility, human-AI augmentation, and AI-technology legitimation, each of which maps into one of the dimensions in the employee-level confrontation mechanisms. Overall, our conceptual framework provides an overarching and granular understanding of AI resistance, how employees confront it, and how it can be alleviated in the workplace.

1. Introduction

Artificial intelligence (AI) has emerged as a general-purpose technology that can significantly improve organizational tasks and societal outcomes (Basu, Majumdar, Mukherjee, Munjal, & Palaksha, 2023); Pereira, Hadjielias, Christofi, and Vrontis (2023). AI helps organizations and individuals reap new benefits as it augments (Seeber et al., 2020) human tasks, sometimes even replacing them completely (Davenport, Guha, Grewal, & Bressgott, 2020; Gligor, Pillai, & Golgeci, 2021). Recent advances in generative AI, including widely-accessible conversational chatbots such as ChatGPT, have further accelerated this development while bringing new challenges, hesitation, and confusion (Agrawal, Gans, & Goldfarb, 2022; Ritala, Ruokonen, & Ramaul, 2024). Indeed, AI-driven augmentation and automation both involve the potential for tensions and contradictions among employees (Raisch & Krakowski, 2021), which can contribute to employee hesitancy and resistance to interacting with AI.

While generative AI has brought a lot of new affordances of AI technology visible to the workplace (see e.g., Ramaul, Ritala, & Ruokonen, 2024), most workers still view AI tools with suspicion and hesitation. For instance, in a recent survey done in Argentina,

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Denmark, France, Japan, the UK, and the USA during 2024, significant differences were found among internet users regarding knowledge and use of generative AI based on age, with 56 % of 18–24 s say they have used generative AI tools such as ChatGPT at least once, compared to 16 % of those aged 55 and over (Fletcher & Nielsen, 2024). Moreover, knowledge of other forms of AI and their applications was found to be very limited. Thus, many employees who are required or enabled to engage with AI tools in the workplace might be inherently resistant to such tools. Relatedly, the increasing use of AI tools for further control and tracking is another major factor contributing to worker suspicions (e.g., Monod, Mayer, Straub, Joyce, & Qi, 2024). Hence, hesitancy and resistance to AI are real issues in the workplace context despite the visibility and usage of generative AI tools during the last couple of years.

Resistance to information technology (IT) has been recognized as a critical issue for managers and employees (Ali, Zhou, Miller, & Jeromonachou, 2016; Craig, Thatcher, & Grover, 2019; Rivard & Lapointe, 2012). However, AI is distinct from conventional IT for several reasons. AI systems can mimic, match, and even surpass human cognitive tasks in specific domains (Dwivedi et al., 2023; Kaplan & Haenlein, 2019), and they are distinguished from previous IT systems via their black-boxed performance, inscrutability, and autonomy (Berente, Gu, Recker, & Santhanam, 2021; Vanneste & Puranam, 2024). AI, based on machine learning and deep learning technologies, can learn from data, identify patterns, and make autonomous decisions based on these patterns without being pre-programmed (Basu et al., 2023; Davenport et al., 2020). Thus, unlike rule-based conventional IT systems, machine learning and deep learning-based AI can solve complex, uncertain, and ambiguous problems (Agrawal et al., 2022), as well as create new types of content and outputs based on users' prompts (Ramaul et al., 2024; Retkowsky, Hafermalz, & Huysman, 2024). AI systems also raise unique ethical concerns, e.g., accountability, bias, or privacy, and may impact new ethical considerations in the workforce (Kushwaha, Pharswan, Kumar, & Kar, 2023), which may be less prevalent with conventional IT systems. Based on these unique differences, we argue that we are witnessing a new underexplored phenomenon – *AI resistance* – that creates unique and novel challenges for organizations and their employees. For these reasons, we believe there is a need for a better understanding of what AI resistance constitutes, why it arises, and how it could be alleviated.

In this regard, several streams of literature have pointed out a variety of perspectives on AI resistance, including fear of AI (Sindermann et al., 2022; Zhan, Molina, Rheu, & Peng, 2024), algorithmic aversion (Mahmud, Islam, Ahmed, & Smolander, 2022; Schaap, Bosse, & Hendriks Vettehen, 2024), and AI identity threat (Mirbabaie, Brünker, Möllmann, & Stieglitz, 2022). Likewise, the literature has identified several drivers of employee AI resistance, including AI-driven job insecurity (Nam, 2019), technological complexity (e.g., Vrontis et al., 2022), and technology stress (Ayyagari, Grover, & Purvis, 2011). However, despite interesting insight accumulated thus far, past research fails to draw a holistic, processual picture of the connections between critical dimensions of AI resistance and how AI resistance is confronted and alleviated in the workplace. In particular, despite the increasingly visible recognition of AI resistance in the workplace and its potential sources, little is known about how managers and employees face and rise above this challenge. Indeed, employees play a critical role in effectively applying and leveraging new technologies in the workplace, but their resistance to new technology and change is overlooked as a research topic (Walsh, O'Reilly, Gleasure, McAvoy, & O'Leary, 2021). Furthermore, despite the growing research on human-AI interaction and the challenges associated with daily business activities (Fosso Wamba, Queiroz, Guthrie, & Braganza, 2022; Seeber et al., 2020), scant attention has been paid to how employees confront and alleviate AI resistance and the potential managerial interventions and practices that would help employees to align, accept, and work with AI in business practice.

To address the challenge of dispersed evidence and arguments on AI resistance, we adopt an integrative review approach, which is a feasible method to integrate theoretical and empirical insights across multiple communities of practice (Cronin & George, 2023) and can potentially help establish a conceptual framework that synthesizes different core mechanisms and their interrelationships related to a particular phenomenon (Post, Sarala, Gatrell, & Prescott, 2020). For our study, this means collecting, bridging, and integrating evidence and arguments across different schools of thought and the theoretical camps to explain and understand AI resistance. By virtue of this approach, we develop a conceptual process framework – and related research propositions – to explain the mechanisms intended to confront and alleviate AI resistance as a multilevel, multi-step process consisting of employees' distinct experiences and activities with AI over time and organizational mechanisms helping to alleviate the related tensions. Hence, we respond to the calls by human resource management (HRM) scholars focusing on AI influences on workplace outcomes (Pereira et al., 2023) who have stressed the need to incorporate the process approach and dynamic interactions among key factors to enrich this emergent research area (Basu et al., 2023). To achieve a comprehensive picture of different aspects of AI resistance, we conceptualize employee resistance to AI as a *refusal or unwillingness by employees to engage, adopt, and work with artificial intelligence systems in the workplace, which is embodied by employees' fear, inefficacy, and antipathy toward these systems*. Our conceptual approach follows the process approach to theoretical contributions explaining the dynamic unfolding of phenomena over time (Cloutier & Langley, 2020). This approach is particularly useful when explicating how phenomena emerge, evolve, or terminate over time through activities and events (Langley, 2007), as in the case of our framework that explains not only the sources of AI resistance but also how it is alleviated over time. The framework portrays employees as active agents who undergo the experience of working alongside AI and can engage in an interactive process within an organizational workplace setting to confront and alleviate AI resistance.

Our paper offers several contributions to HRM and AI in the workplace literature streams by bridging employee- and organizational-level mechanisms and processes into an integrated framework. In line with Renkema, Meijerink, and Bondarouk (2017), it explicates the complex interplay between individual behaviors and organizational practices within the domain of confronting and alleviating AI resistance in the workplace. Firstly, we provide useful clarity around AI resistance by conceptualizing it as a three-dimensional concept embodied by employee fear, inefficacy, and antipathy toward AI. Consequently, we argue that AI resistance is a multifaceted, intricate phenomenon that defies linear and easy solutions, such as relying solely on training or counseling (Condliffe, 2019). Secondly, we enrich the understanding of workplace AI resistance by highlighting issues concerning mistrust toward AI, existential questioning, and technological reflection (by the employees). We demonstrate how these issues simultaneously lead to

both anxiety and deeper introspection, involving contrasting interpretations of how organizations work to alleviate employee AI resistance. Finally, the current paper stresses the alleviation of AI resistance as an organization-level process consisting of AI accessibility, human-AI augmentation, and AI-technology legitimation. Each of these dimensions taps into one of the three dimensions of employee-level AI resistance mentioned previously, thus providing a balanced view of confronting AI resistance and potential mechanisms for overcoming it.

2. Integrative review methodology and process approach

Review approaches such as systematic reviews (Tranfield, Denyer, & Smart, 2003) and meta-analyses (Borenstein, Hedges, Higgins, & Rothstein, 2009) seek to adjudicate existing bodies of literature with formal search criteria and documentation and pursue a thorough documentation of evidence. In contrast, our conceptual model is based on an integrative review approach that aims to *redirect* rather than *adjudicate* evidence (Cronin & George, 2023). In so doing, integrative reviews bridge different conversations together and often produce novel sensemaking in the form of conceptual frameworks, propositions, or arguments (Huff, 2009; Torraco, 2005). In particular, our study seeks to identify evidence and arguments across different literature streams and schools of thought to provide insights into various dimensions of confronting and alleviating AI resistance in the workplace. We do this by synthesizing diverse literature sources on this topic and developing a process model and related propositions where we conceptualize the key dimensions of AI resistance in workplace settings, as well as individual and organizational determinants of how such resistance arises and how it is potentially alleviated.

Following the suggestions of Cronin and George (2023), we started our literature search from our home discipline (organization and management) and broadened the search to other relevant disciplines, most prominently, information systems (IS) and IT. Given that our aim is not to formally adjudicate a complete catalog of evidence in a domain (which is the strong point of systematic reviews), we did not follow a formal protocol with inclusion and exclusion criteria of literature, nor did we come up with formal search queries. However, we utilized a triangulation approach within a multidisciplinary author team composed of scholars from strategy, human resources management, international business, and IS to conduct a broad search for literature on AI resistance. This included different search approaches to find relevant literature, including keyword searches, snowballing, and reverse snowballing, to ensure the relevant literature was initially covered. Then, after the initial search phase, we moved into the thematic-synthesis process (Cronin & George, 2023), the outcome of which is depicted in a process model and propositions drawn from our integrative review that bridges different literature streams on the topic.

Our approach to bridging different communities of practice and schools of thought is also made visible in Appendix 1, where we document the different dimensions and concepts of our “polytheoretical” and multidisciplinary framework, the key sources for the main insights, as well as the related theoretical foundations. With our approach, we join other HRM scholars who have conducted conceptual studies leading to the presentation of an integrated framework in recent years, including those published in HRMR. For example, Bell, Brown, and Weiss (2018) developed a conceptual framework for leveraging team decisions for building human capital, while Küpper, Klein, and Völckner (2021) presented an integrated framework for gamifying employer branding. In another recent study, Del Giudice, Scuotto, Orlando, and Mustilli (2023), in their conceptual framework, highlighted the criticality of a human-centered approach to individual acceptance of AI in organizations. We build on prior work and expand the dialogue by addressing the unique challenges and opportunities presented by AI resistance in organizations by situating our study within this landscape of conceptual scholarship. In line with this integrative approach, our process model complements the polytheoretical framework by offering a dynamic lens to understand how AI resistance unfolds and evolves.

Accordingly, our conceptual framework follows a process approach to theoretical contributions (Cloutier & Langley, 2020) by creating a “process model that lays out a set of mechanisms explaining events and subsequent outcomes” (Cornelissen, 2017, p. 3). A process model explains how phenomena emerge, evolve, or terminate over time through interconnected and path-dependent activities and events, and it captures the richness of lived experiences (Cloutier & Langley, 2020). Furthermore, there is an emphasis on change and dynamism (i.e., recognizing that most phenomena are not static but involve a series of dynamic and interconnected events), holism (i.e., giving a comprehensive account of complicated issues by considering many interacting parts as opposed to focusing on single variables or factors), and narrative (i.e., describing the unfolding of events and the interplay of factors over time) (Cloutier & Langley, 2020; Cornelissen, 2017).

3. AI in the workplace: a new domain for technology resistance

While AI in the workplace is a source of a lot of excitement, we are also witnessing a renewed and potentially unique instance of resistance to AI. Indeed, tools such as ChatGPT, Gemini, and Microsoft Copilot increase the amount of potential human-AI augmentation but also replace “white collar” knowledge jobs and tasks that used to be strictly under the domain of human ingenuity (Dwivedi et al., 2023; Ritala et al., 2024). This potential resistance adds up to the previous generation of machine learning-based AI models that have also driven automation of human labor but also involve algorithmic control and other contested uses of AI in the workplace (see e. g., Kellogg, Valentine, & Christin, 2020). Consequently, there are growing instances of employee resistance to applying AI in their organizations and teams (Arslan, Cooper, Khan, Golgeci, & Ali, 2022) as the new AI systems challenge the employees’ self-perceptions of their identity, work, and autonomy (Mirbabaie et al., 2022; Pachidi, Berends, Faraj, & Huysman, 2021). Therefore, in this section, we introduce the concept of technology resistance and then link it with AI.

IS research on technology resistance has a large focus on workforce (users) resistance to IT implementation (Helliwell & Fowler, 1994). User resistance is defined as “behavior intended to prevent the implementation and use of new systems, or to prevent system

designers from achieving their objectives” (Ali et al., 2016) and has its roots in personal, task-related, and social factors of IT resistance behaviors (Craig et al., 2019). For example, users may perceive unfavorable technological changes, resulting in resistance (Joshi, 1991). Other types of user resistance include passive resistance, based on user cynicism about a system’s future use (Selander & Henfridsson, 2012). The level of user resistance may also arise from the psychological contract employees have with their organization and is related to individual, system, organizational, and process issues (Klaus & Blanton, 2010). Furthermore, user resistance may arise within the mandatory adoption of IT within organizations. Therefore, previous literature has shown that effective management strategies are required, with the most desirable strategies for users being top-down communication, management expertise, and clear management plans (Klaus, Wingreen, & Blanton, 2010). Resistance may lead to organizational disruptions (Rivard & Lapointe, 2012), and therefore it is important to address the potential resistance both before and after IT implementation (Meissonier & Houzé, 2010).

In the current study, we examine AI as a new domain in IS that involves distinctive features that play a role in workplace dynamics and resistance to this new technology. AI is defined as programs, algorithms, systems, and machines that learn from processing data and mimic intelligent human behavior (Davenport et al., 2020; Grover, Kar, & Dwivedi, 2022). AI has further been referred to as the ability of a system to learn from external data correctly and apply the lessons learned to achieve the desired objectives or undertake the assigned tasks (e.g., Kaplan & Haenlein, 2019). AI combines “sophisticated hardware and software with elaborate databases and knowledge-based processing models to demonstrate characteristics of effective human decision making” (Kumar & Thakur, 2012, p. 65), and it relies on major new technologies, such as “machine learning, natural language processing, rule-based expert systems, neural networks, deep learning, physical robots, and robotic process automation” (Davenport et al., 2020, p. 26). The application of AI has an array of implications for organizational processes and outcomes and employee behavior in the workplace context (Pereira et al., 2023; Seeber et al., 2020). Since AI is characterized as a new generation of technologies capable of interacting with the environment and aiming to simulate human intelligence (Glikson & Woolley, 2020), it can help by both augmenting and automating many human tasks and even creative work (Raisch & Krakowski, 2021; Ritala et al., 2024).

First, AI is increasingly applied to *general and routine tasks* across organizations. In particular, it has found widespread applications in organizations and increasing acknowledgment of such applications in the extant literature (Fosso Wamba et al., 2022; Grover et al., 2022). For example, Amazon employs intelligent robots in its warehouse operations to minimize errors; DHL implements the IDEA algorithm in route optimization and staff allocation to improve its order-picking processes, minimize costs, and optimize its e-fulfillment activities; and Nestlé applies augmented reality on remote production and assistance and to connect suppliers, people, and factories to improve its operational efficiency, reduce response times, and minimize CO₂ emissions (Fosso Wamba et al., 2022). Other examples include the use of AI for customer relationship management (Chatterjee & Chaudhuri, 2023) and job recruitment (Rodney, Valaskova, & Durana, 2019). Likewise, popular AI algorithms, such as federated AI with smart contracts, swarm intelligence, algorithms for analyzing unstructured data, smart manufacturing, and cognitive computing, are increasingly applied in high-tech operations (Cagliano, Canterino, Longoni, & Bartzzaghi, 2019). AI may surpass humans, with “old jobs” disappearing, new jobs emerging, and knowledge workers forced to upskill.¹ The risk is especially high for those doing routine jobs like accounting and financial transactions (Zarifhonarvar, 2023) or relatively standard customer service (Ferraro, Demsar, Sands, Restrepo, & Campbell, 2024).

Second, AI can increasingly reason, plan, and solve *complex organizational tasks*, thereby handling complex functions, including managerial and planning tasks (Basu et al., 2023; Davenport et al., 2020; Kaplan & Haenlein, 2019) as well as creative and design tasks (e.g., Ramaul et al., 2024; Retkowsky et al., 2024). Scholars are already postulating that the rapid developments in AI are increasingly resulting in these machines displaying scientific creativity, social skills, and general “wisdom”, which has been associated thus far with humans (Davenport et al., 2020; Grover et al., 2022). This progression in AI capabilities can generate resistance at both the employee and organizational levels. At the employee level, concerns about job displacement (Moore, 2018), reduced autonomy (Mirbabaie et al., 2022), and a perceived erosion of human value in decision-making processes (Mahmud et al., 2022) may foster resistance. At the organizational level, the integration of AI into job roles may provoke resistance due to concerns about over-reliance on AI (Spatola, 2024), ethical implications (Varma, Dawkins, & Chaudhuri, 2023), and the potential misalignment with established corporate cultures and human-centered operational frameworks, which may impact human values, ethics (Heyder, Passlack, & Posegga, 2023), innovation (Farndale, Horak, Piyanontalee, Puffer, & Vidović, 2025), and employee well-being (Zhang, Li, Li, Chang, & Zhang, 2024).

4. A conceptual framework for confronting and alleviating AI resistance

Based on the integrative review approach, we develop a conceptual framework that depicts AI the key cognitive dimensions of AI resistance in the workplace, the mechanisms via which AI resistance is confronted at the individual employee level, and finally, the organization-level processes for potentially alleviating AI resistance (Fig. 1).

Furthermore, in line with the integrative review approach that we follow in this paper, Appendix 1 summarizes the key concepts, definitions, key literature sources, and theoretical foundations of each dimension – i.e., fear, inefficacy, and antipathy as constituting cognitive dimensions of AI resistance, experiencing mistrust toward AI, existential questioning, and technological reflection as individual-level mechanisms of confronting AI resistance, and AI accessibility, human-AI augmentation, and AI-technology legitimation as organization-level processes of alleviating AI resistance.

Following the process approach, our conceptual framework explains the multilevel steps involved in confronting and eventually alleviating AI resistance. We argue that AI resistance is not a singular event but an ongoing, recursive interaction in which the

¹ <https://theconversation.com/ai-and-the-future-of-work-5-experts-on-what-chatgpt-dall-e-and-other-ai-tools-mean-for-artists-and-knowledge-workers-196783>

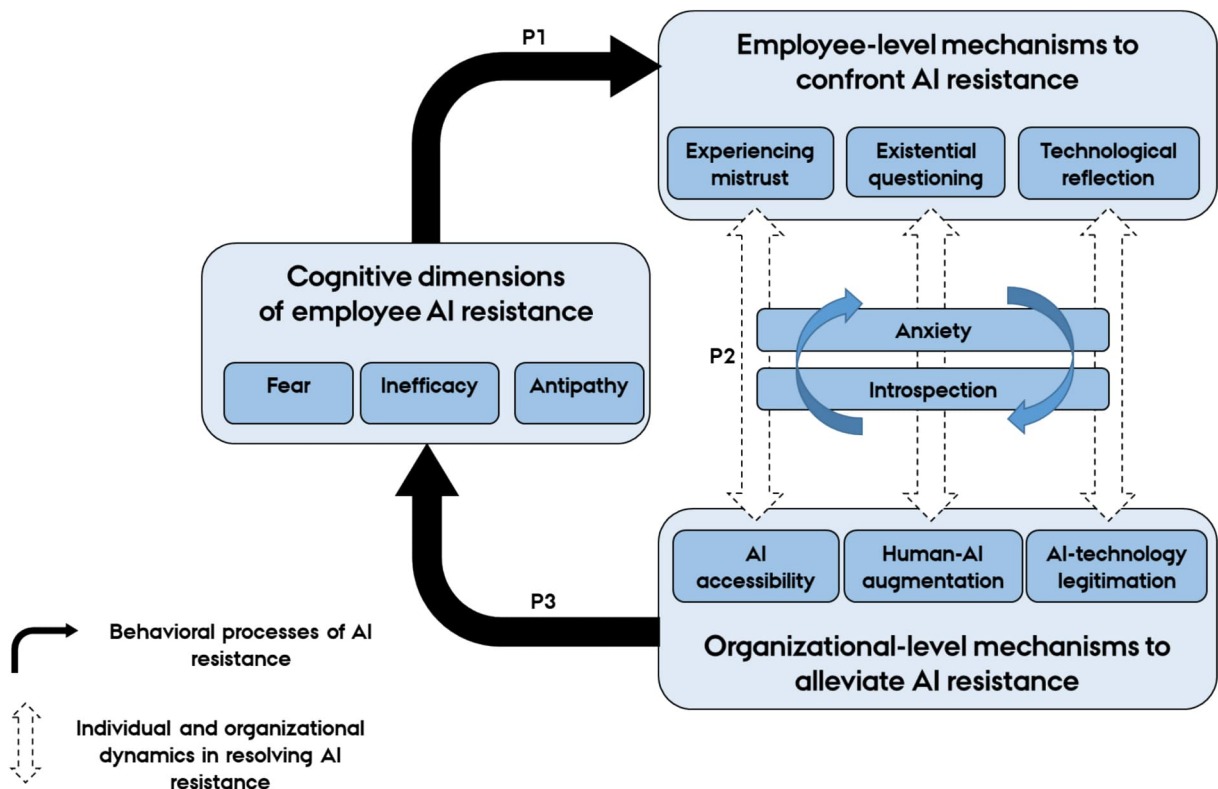


Fig. 1. Conceptual framework for AI Resistance.

connections are more important than the sequence between different individual- and organizational-level processes. Our approach highlights that AI resistance is not an end state but an evolving, recursive, and dynamic process. For instance, as depicted in the model, different cognitive dimensions of AI resistance may trigger or intensify employee-level confrontation mechanisms of mistrust toward AI, existential questioning, and technological reflection as employees grapple with the implications of AI on their roles and identities. Relatedly, organizations might either proactively or reactively employ organizational mechanisms such as AI accessibility to alleviate such tensions. The following sections will discuss different dimensions and related arguments of our conceptual model.

4.1. Conceptualizing AI resistance: three cognitive dimensions

In today's rapidly evolving technological landscape, employees are increasingly confronted with complex tools and emerging technologies like AI (Brendel, Hankerson, Byun, & Cunningham, 2016; Mohanta, Nanda, & Patnaik, 2020). However, this surge in technological complexity and the swift pace of technological change may breed resistance and negative sentiments toward AI (Brendel et al., 2016; Mohanta et al., 2020). Concurrently, concerns surrounding AI-driven job insecurity are rising (Moore, 2018). As such, contemporary environmental characteristics like technological complexity and job insecurity are among the important sources of AI resistance that entail further clarification and conceptualization.

Given the major changes recent rapid technological improvements mean for employees, the adoption of AI is unsurprisingly meeting a variety of resistance, including cognitive aspects such as fear (Sindermann et al., 2022) and identity issues (Mirbabaie et al., 2022), but also more or less active behavioral issues, such as aversion and hesitancy (Mahmud et al., 2022). Based on the accumulating evidence (Arslan et al., 2022; Choudhury, Asan, & Medow, 2022; Demir, McNeese, & Cooke, 2020; Kros, Jaspers, & van Zalk, 2021; Sindermann et al., 2022), we contend that there are three major constituent cognitive dimensions of AI resistance among employees – fear, inefficacy, and antipathy. We intend to delineate these cognitive dimensions to provide a comprehensive conceptualization for understanding the multifaceted nature of employees' AI resistance in the workplace. We also delineate AI resistance dimensions of employee fear, inefficacy, and antipathy with attention to exploring cognitive, rather than extrinsic, factors for employees interacting with AI in the workplace. Even though the labeling in different literature streams might vary slightly, these three dimensions clearly constitute the major cognitive elements of how AI resistance is experienced and manifested. As shown in Appendix 1, the foundations of our conceptual framework start with understanding individual-level emotional and cognitive responses to AI technologies, namely fear, inefficacy, and antipathy. Each of these concepts helps explain the diverse cognitive states underlying AI resistance. Behavioral processes, in turn, highlight the importance of addressing employee perceptions and emotions, as unresolved fear, inefficacy, or antipathy can serve as barriers to successful AI applications in the workplace. The theories supporting these concepts, such as the

critical theory of technology (Feenberg, 1991), the psychological theory of alienation (Ollman, 1976), the reflective practice theory (Schön, 1983), and the technology acceptance model (Davis, 1989), provide a theoretical foundation for understanding why employees resist change and fear technological advancements. We delve deeper into each dimension below.

Fear, denoting distress or apprehension driven by the perceived side effects of and threats from advanced technologies, is a common emotional response associated with new technologies, especially those perceived as disruptive or transformative (Sindermann et al., 2022). Decades ago, Bowen (1966, p. 9) posited: “Technology eliminates jobs, not work.” For employees, however, whether performing processes or operations in a factory setting or working in more strategic functions, the threat of the elimination of “their own job” is one of the fundamental cognitive dimensions associated with the implementation of any new technology, particularly AI (e.g., Arslan et al., 2022). The fear of the perceived elimination of jobs by AI can be pervasive among employees (Willcocks, 2020). Nonetheless, this fear extends beyond job security to encompass concerns about the challenges of adapting to and effectively utilizing new technologies. As highlighted similarly by Willcocks (2020), retooling employee skills can, in fact, be the real challenge associated with interacting with AI in the near future. Hence, fear associated with working with new technology, i.e., adopting AI in the workplace, is also relevant. To this end, the fear of working with new technologies, including AI, is well-documented in the extant literature (e.g., Ayyagari et al., 2011; Bawden & Robinson, 2009).

Furthermore, fear of AI may also arise from health and safety concerns, as the integration of AI technologies into various domains can impact human well-being and safety, and individuals may perceive AI systems as potential risks to their health, safety, and overall livelihood (Cebulla, Szpak, Howell, Knight, & Hussain, 2023). AI-based systems like industrial robots may impact physical safety (Martinetti, Chemweno, Nizamis, & Fosch-Villaronga, 2021). Concerns may arise regarding AI algorithms’ reliability, accuracy, and robustness in critical situations, leading to fears of accidents, injuries, or fatalities. Likewise, employees may perceive AI systems as harmful to their physical and psychological health, as their adoption may lead to stress, anxiety, or psychological distress due to uncertainty, loss of control, or perceived threats posed by AI technologies (Kellogg et al., 2020; O’Connor & DeMartino, 2006). Thus, health and safety concerns may play a critical role in shaping employees’ fear of AI in relation to its adoption and use.

Inefficacy is associated with a (real or perceived) inability of employees to interact with AI systems, leading to an employee being unable or unwilling to work in such contexts (Demir et al., 2020) or adopt AI (Choudhury et al., 2022). Employees may feel overwhelmed or inadequate in mastering AI systems, leading to frustration and self-doubt. This dimension represents the cognitive and skill-related barriers that impede employees’ ability to effectively engage with AI tools and platforms. The potential for negative experiences with AI (Chong, Zhang, Goucher-Lambert, Kotovsky, & Cagan, 2022) and the trustworthiness of AI (Gillath et al., 2021) can be closely linked to inefficacy as a cognitive dimension of AI resistance. The increasingly accelerating pace of technological change (Brendel et al., 2016; Mohanta et al., 2020) means that skills involved in operating or interacting with new technologies quickly become obsolete, amplifying employee inefficacy in handling AI and possibly engendering AI resistance along with it. Thus, employee upskilling in AI is important (Willcocks, 2020). Inefficacy can also be linked to cynicism, stress, and burnout among employees, especially in technology-intensive contexts (Selander & Henfridsson, 2012). As such, while inefficacy is not at its core about employee feelings toward AI, it may nonetheless be a central cognitive element of AI resistance, given the negative experiences it may generate in AI interactions.

Antipathy is referred to as a mental state of disliking someone or something, which ultimately results in the urge to avoid any association with that particular person or object (Kros et al., 2021). This dimension encompasses skepticism, distrust, or resentment toward AI, stemming from concerns about privacy, ethics, or the potential negative impact on job security and human relationships. In the context of organizational change, scholars have highlighted how antipathic behavior among employees becomes more visible when they feel alienated from changes and when changes are not sufficiently communicated (Lok & Willmott, 2013). Studies specifically focusing on new technology introductions in organizations, including AI, have also referred to emotions and attitudes similar to employee antipathy (Grint & Woolgar, 2013). More recent research has explored the negative attitudes toward AI arising from security or privacy concerns (Kushwaha et al., 2023) or that AI can be dehumanizing (Al-Amoudi, 2022). Thus, employees may harbor antipathy toward AI for various reasons, which may constitute a major cognitive dimension of their AI resistance.

The inability of employees to constantly adapt their skills and fully understand and use the changing technologies often propagates feelings of fear, inefficacy, and antipathy toward AI. For example, in October 2024, dockworkers along the East and Gulf Coasts of the United States, represented by the International Longshoremen’s Association (ILA), commenced strikes to oppose the rising automation within port operations. The union called for a complete prohibition on automating functions like gate operations, crane usage, and container transport vehicles, arguing that these changes pose risks to job security and could lead to worker displacement. As a result, the strikes caused notable interruptions in shipping activities and underscored the escalating conflict between labor forces and management regarding technological progress (Bussewitz, 2024). In May 2024, the advocacy organization PauseAI coordinated demonstrations in thirteen nations, including the USA, UK, Brazil, Germany, Australia, and Norway. Protesters demanded a stop to the advancement of sophisticated AI technologies, highlighting concerns about potential existential threats and significant job losses. The protests took place outside government offices and headquarters of AI companies, calling on lawmakers and industry executives to suspend AI development until safety and ethical issues are thoroughly evaluated (Gordon, 2024). As such, “the biggest barrier to getting technology rolled out is the organizational (workforce) resistance to adoption,” according to Erik Brynjolfsson, director of the Initiative on the Digital Economy at the Massachusetts Institute of Technology (Condliffe, 2019).

Based on the conceptual discussion above, together with practical examples, we define employee resistance to AI in the context of our paper as *a refusal or unwillingness by employees to engage, adopt, and work with artificial intelligence systems in the workplace, which is embodied by employees’ fear, inefficacy, and antipathy toward these systems.*

4.2. Employee-level mechanisms to confront AI resistance

Nowadays, the sheer scale and complexity of technological transformation pose unprecedented challenges for employees. However, although plenty of literature documents the challenges associated with technological change (Brendel et al., 2016; Mohanta et al., 2020), no adequate work focuses deeply on the behavioral, employee-level mechanisms to confront AI resistance. Particularly, while much of the extant research has focused on how employees drive change or achieve peak performance (e.g., Hill, Seo, Kang, & Taylor, 2012; Peterson, Walumbwa, Byron, & Myrowitz, 2009), less is known about what they do to confront AI resistance and, in the meantime, maintain their sanity amidst daunting challenges imposed by the growing prevalence of AI and the transformative changes it engenders in the workplace. In our framework, AI resistance is composed of cognitive mechanisms that lead to deeper mistrust, existential questioning, and reflection on the role of technology. As depicted in Appendix 1, these three mechanisms represent individual-level cognitive processes for confronting AI resistance. As such, we argue that resistance should be seen as a recursive feedback loop rather than a one-way outcome of pre-existing beliefs. Resistance may, for example, arise from a general sense of unease or uncertainty about AI's role, which can then catalyze specific responses, such as mistrust or existential questioning. Against this backdrop, we delve deeper into the individual means of confronting AI resistance (i.e., experiencing mistrust, existential questioning, and technological reflection), which we do not necessarily view as a negative phenomenon, as it may involve both negative and positive experiences.

First, *experiencing mistrust* of AI refers to a lack of confidence, skepticism, or wariness toward AI systems, technologies, and applications in the workplace (Schepman & Rodway, 2023). It encompasses feelings of doubt, suspicion, or apprehension regarding the reliability, safety, intentions, or ethical implications of AI-driven solutions (Starke & Ienca, 2022). It is rooted in the diffusion of innovations theory (Rogers, 1995), the technology acceptance model (Davis, 1989), the trust model (Mayer, Davis, & Schoorman, 1995), and the social exchange theory (Cropanzano & Mitchell, 2005) (see Appendix 1). Experiencing mistrust of AI is a natural direct confrontational mechanism for employees with AI resistance. Trust is an instrumental glue of sociotechnical systems, enabling humans to manage and reduce complexity in their surrounding environments (Abbass, 2019). Recent trust research in information technologies has designated trust as a "primary predictor of technology usage and a fundamental construct for understanding user perceptions of technology" (Li, Hess, & Valacich, 2008, p. 39), and by extension, an important indicator of employee use of AI (Glikson & Woolley, 2020).

Mistrust of AI can stem from various factors, including concerns about data privacy and security, fears of job displacement or automation, skepticism about the accuracy and fairness of AI algorithms, and apprehensions about unintended consequences of AI technologies. As stated earlier, AI is often perceived to be associated with job insecurity (Moore, 2018). Such a negative association attributed to AI will likely lead to mistrust that tends not to be grounded in experience but more in employees' instincts or gut feelings toward AI. As such, employees may resist AI due to initial fear and antipathy, which may subsequently lead to heightened mistrust as they process the implications of the technology on their roles. The fundamental principle of AI accessibility when employees interact with technology in organizations is familiarity with the technology, reduced/eliminated uncertainty concerning the advantages and disadvantages of the focal technology, and perceived assurance that the technology will not harm the human party to the interaction (Abbass, 2019; Lankton, McKnight, & Tripp, 2015; Li et al., 2008). In fact, the right mixture of benevolence, integrity, and ability (i.e., drivers of affective trust based on faith in trustworthy intentions) together with helpfulness, reliability, and functionality (i.e., drivers of cognitive trust based on confidence in competence and dependability) are essential for employees to build trust in new technology (Lankton et al., 2015). On the other hand, since AI has gained rapidly increasing popularity and application recently, with many uncertainties associated with its advantages and disadvantages (Gligor et al., 2021), most employees who are less familiar with AI are likely to mistrust it when confronting it. Therefore, the experience of mistrust is likely to be a major element in employees' confronting AI resistance.

Existential questioning is related to employees' fundamental self-doubt and the feeling of uneasiness concerning work identity and usefulness amid the rise of AI in the workplace (Skrbiš & Laughland-Booÿ, 2019). It is rooted in the ideas stemming from existentialism -focusing on questions of existence, authenticity, and freedom (Sartre, 1973) - the psychological theory of alienation that highlights existentialist notions of alienation from self, others, and work (Ollman, 1976), and critical theory of technology that critiques the alienating and dehumanizing effects of technological rationality (Feenberg, 1991) (see Appendix 1). As AI technologies are increasingly prevalent in organizations (Davenport et al., 2020), they exert an increasingly prevalent influence on how people feel and behave while performing various tasks. With the growing presence and impact of AI in organizations, employees can question their work identity and their place in the workplace (Petriglieri, Ashford, & Wrzesniewski, 2019). When interacting with AI in organizations, the combination of profound forces will likely provoke employees to question the meaning of their work and their positioning/function within the organizational task environments. For example, AI-based text analysis systems and their applications at Google have generated a contentious work environment, as biases inadvertently built into its AI systems have become apparent and created commotion among Google employees (Metz, 2021). Some employees felt dehumanized due to the biased and hasty application of AI in their workplace and questioned their position in the firm. In turn, this has generated an existential questioning of the role of AI and the ethical implications of AI high-tech firms (such as Google) in particular (Metz, 2021). Existential questioning may manifest itself in different stages of questioning the self, new sense-making amid rapid technological change, and disrupting and revamping the work identity in response to technological turbulence in the workplace. Thus, we expect that one of the fundamental mechanisms that employees deploy when interacting with AI in organizations will be existential questioning to adapt to AI-driven changes in their work and embark upon a new journey as the technological revolution gathers pace in the commentary business environment.

Finally, while experiencing mistrust of AI related to an individual's perception of AI and existential questioning of their self-perception, *technological reflection* combines these perspectives to reflect on the technologies they interact with and their

implications for the workplace and society. Technological reflection denotes comprehensive and thorough reflection on both positive and negative aspects of technology and its implications for society and employees (Schweitzer, Rau, Gassmann, & van den Hende, 2015). It is related to a “cognitive, inquisitive and introspective effort using experiences and reflections for an understanding, judgment, and evaluation of the impact of a novel artifact or a new technological release” (Andrade-Valbuena & Torres, 2018, p. 85). It is grounded in reflective practice theory, which explores how individuals learn from their experiences and critically reflect on their actions (Schön, 1983), sociotechnical systems theory that emphasizes the interconnectedness of technology, work practices, and organizational structures (Trist & Bamforth, 1951), critical theory of technology (Feenberg, 1991), and technology acceptance model (Davis, 1989) (see Appendix 1). Employees working and interacting with AI in their workplace may have both the opportunity and responsibility to reflect upon its potential positive and negative implications. Technologically reflective employees have, therefore, the possibility to analyze AI-driven technologies and the interactions between them and their work when interacting with AI (Schweitzer et al., 2015). In fact, properly interacting with AI cannot be fully realized without holistically contemplating the meaning and impact of such technologies and considering their benefits vis-à-vis caveats for the organization and the employee. As employees resist AI, their initial discomfort or unease may solidify into more structured beliefs, creating a recursive effect where resistance reinforces reflection. Hence, we suggest confronting AI resistance involves technological reflection and diligently weighing the positives and negatives of AI in the workplace. Thus, we develop the following proposition:

P1: *Employee AI resistance leads to employee-level confrontation mechanisms of a) experiencing mistrust toward AI, b) existential questioning, and c) technological reflection.*

Our framework distinguishes individual-level mechanisms to confront AI resistance from organization-level mechanisms to alleviate it, and it connects these two mechanisms through simultaneous processes of anxiety and introspection among employees. This position is based on the notion that AI-based technologies are increasingly profound phenomena with widespread and intricate implications for people (Davenport et al., 2020), and human–technology interaction is a complicated, multifaceted, rigorous process that entails in-depth path-dependent examination rather than treating it at as a one-stop phenomenon (Arslan et al., 2022). Therefore, we argue that rising above AI resistance starts with a better understanding of how employees confront it in the first place and how mechanisms to confront it are connected with distinct organizational mechanisms to alleviate it. Because AI resistance is a strong, emotion-based multidimensional phenomenon, alleviating it may entail facing this resistance and learning from the experience of confronting such resistance. That said, due to the multifaceted mechanisms to confront AI resistance, we expect connections between confronting and alleviating it to manifest in both negative and positive aspects.

On the negative side, we argue that employees confronting AI resistance experience *anxiety*, that is, a cognitive-affective response “characterized by apprehension about an impending, potentially negative outcome that one thinks one is unable to avert” (Schlenker & Leary, 1982, p. 642). Given the often-overwhelming experience of interacting with AI, employees may inevitably experience anxiety in their work life. Anxiety is part of a range of human emotions, which have been specifically stressed in some recent studies to be significantly linked to (and influenced by) AI (e.g., Freed, 2019).

Anxiety has been found to lead to mistrust (e.g., Brauner et al., 2023) and existential questioning (Passmore, Lutz, & Howell, 2023) by behavioral scholars. Existential questioning harbors positive and negative aspects that can interact and manifest unpredictably (Petriglieri et al., 2019). Hence, reflecting deeper on technology can reveal, along with its positive aspects, unexpected negative aspects of technology that can intensify anxiety among employees linked to AI resistance. The collective accumulation of sources of AI resistance, coupled with the negative aspects of confronting it, can overwhelm employees and accelerate their feelings of anxiety.

In turn, the collective experiences of individual anxieties associated with confronting AI resistance can hinder organizational mechanisms to alleviate it. Employees experiencing anxiety because of multifaceted individual mechanisms to confront AI may accumulate negative experiences that can limit the viability and effectiveness of organizational mechanisms to alleviate AI resistance. Anxiety is often associated with the absence/hindrance of positive forces and the presence/amplification of negative forces (Bawden & Robinson, 2009; Brendel et al., 2016). We argue that anxiety can amplify the negative aspects of confronting AI resistance and potentially jeopardize organizational mechanisms to alleviate AI resistance.

On the positive side, confronting AI resistance may give rise to opportunities to achieve greater levels of *introspection* and store energy for individuals to better leverage organizational mechanisms to alleviate AI resistance. In simple terms, introspection denotes examining one’s own beliefs, judgments, and practices (Mutch, 2007). It involves reflecting on one’s own thoughts, feelings, and beliefs, as well as considering how AI technologies may affect one’s professional identity, skills, and prospects. Introspection is fundamentally grounded in examining and reconstituting practices and behavior when facing new (or fundamentally changed) life circumstances (Lumma, Hackert, & Weger, 2020). We argue that AI is such a major change, triggering employees’ introspection to develop resistance through behavioral and emotional mechanisms to address it. Accordingly, employees confronting AI resistance may utilize this experience as a learning experience and engage in introspection. In turn, introspection allows employees to delve deeper into their thoughts and emotions, leading to a more nuanced understanding of their resistance to AI. For example, existential questioning and technological reflection may trigger introspection among employees and enable them to deeply contemplate both the positive and negative aspects of AI, which may, in turn, help reduce their concerns about, mistrust of, and fear of AI.

Employees confronting AI resistance will likely develop positive residuals from their challenging and equally rewarding confrontation experience and channel it toward increased introspection as a means to enhance organizational mechanisms to alleviate it. In other words, employees enduring mistrust toward AI and existential questioning and technological reflection stemming from their experiences with it will likely stimulate introspection within them, enabling mechanisms to alleviate AI resistance. Thus, introspection is argued to be an instrumental enabler of positively, recursively, and innately engaging with new positive phenomena and tackling negative phenomena (Easterby-Smith & Malina, 1999). It also involves actively considering the implications of what has

been observed/experienced for the observers' own practice and is a fundamental ingredient of effective sense-making (Easterby-Smith & Malina, 1999). Consequently, introspection can arguably serve as a constructive connective process through which employees can explore potential solutions or coping strategies to address their AI resistance in the workplace.

For example, BMW has been using numerous AI devices in multiple operations since 2018, including automated image recognition, nameplate checks, and dust particle analysis in the paint shop. Employees initially demonstrated negative opinions or judgments about how AI would take away their jobs, and they would be unable to keep up with and understand efficient AI systems. These perceptions propagated negative emotions toward AI, such as mistrust. Over time, however, employees realized that AI has supported them in completing complex production tasks that are difficult to accomplish manually. Considering the opportunities or benefits of interacting with AI, they confronted personal beliefs about or perceptions of AI, reflecting on the pertinence and usefulness of AI in production processes. Today, BMW is one of the leading organizations in terms of productive interaction between humans and AI for numerous operations (BMW Group, 2021).

Thus, we propose the following proposition to connect mechanisms to confront and alleviate AI resistance.

P2: *Anxiety and introspection are two complementary processes of sensemaking among employees when their AI resistance is subjected to organizational-level mechanisms to alleviate that resistance.*

4.3. Organization-level mechanisms to alleviate AI resistance

One of the fundamental challenges for organizations is facilitating and leveraging human–technology interaction in the workplace (Arslan et al., 2022). Regarding AI resistance, examining and developing a better understanding of organizational mechanisms to alleviate this resistance is highly relevant. This is because while confronting AI resistance can be more of an individual experience, mechanisms to alleviate it are more effective when they are collective (i.e., organizational rather than individual and fragmented). Below, we propose three major organization-level mechanisms -AI accessibility, human-AI augmentation, and AI-technology legitimation- explaining how organizations can actively reduce resistance by implementing supportive processes. The three mechanisms represent different approaches identified in the literature and practice and, importantly, represent different organizational responses to the three dimensions in the employee-level confrontation mechanisms identified earlier (see proposition one and the vertical dotted-line arrows). As depicted in Appendix 1, These organizational interventions build upon employees' cognitive confrontation by ensuring that there is a structural and cultural environment that supports the alleviation of resistance. Theories such as anthropomorphism (Blut, Wang, Wunderlich, & Brock, 2021), inclusive design framework (Persson, Åhman, Yngling, & Gulliksen, 2015), conjoined agency (Murray, Rhymer, & Sirmon, 2021), sociotechnical systems theory (Trist & Bamforth, 1951), legitimacy theory (Suchman, 1995), and discursive legitimation (Vaara & Tienar, 2008) provide frameworks for understanding how organizations can foster trust and confidence in AI.

AI accessibility refers to different organizational mechanisms that make AI more accessible to employees at cognitive, as well as concrete and pragmatic levels (Goldenthal, Park, Liu, Mieczkowski, & Hancock, 2021). It is rooted in anthropomorphism -the attribution of human characteristics, behaviors, emotions, or intentions to non-human entities- and AI Humanization (Blut et al., 2021), technology acceptance model (Davis, 1989), and inclusive design framework that advocates for designing products and environments that are easily accessible and usable by as many people as possible (Persson et al., 2015) (see Appendix 1). Making AI more accessible aims to address the initial mistrust among employees. Indeed, extant research acknowledges that the success of integrating AI into organizations critically depends on employee trust in AI (Glikson & Woolley, 2020). To alleviate the suspicion and resistance against AI and work effectively with it, employees must fully trust AI's benevolence, ability, and utility (Lankton et al., 2015). Likewise, AI's tangibility, transparency, reliability, and anthropomorphism are critical in AI accessibility (Blut et al., 2021; Glikson & Woolley, 2020). Interactive processes involved in building more accessible AI include management communicating with workers to learn the specifics of the objections and reanalyzing the software to ensure that such problems are addressed. Accordingly, human–technology interaction follows similar norms to human-human interaction (Gillath et al., 2021). In particular, trust-building processes, such as making AI systems transparent, explainable, and ethical, assessing and mitigating employee bias against AI, and preventing unfair outcomes, could be especially relevant (Varma et al., 2023) – and are often conceptualized under the umbrella of “explainable AI” (see Rai, 2020). Furthermore, to improve trust in AI, managers could ensure that AI shares the same goals with employees (Gillath et al., 2021).

Beyond making AI more accessible by building trust in the technology and making it more transparent, organizations can also pursue improved accessibility by “humanizing AI”; that is, involving human-like qualities in the AI systems and their interfaces. As noted earlier, people are more likely to trust in and work with relatable systems, displaying human-like characteristics (Gillath et al., 2021). When AI systems are designed to be relatable to human employees—easy to understand or feel sympathy for—they are more likely to be perceived as “co-workers” than as substitutes or threats. Conversely, positioning AI as emotionless, dry, and callous systems in the constant pursuit of strict applications of logic and efficiency without any concern for human welfare may result in a vicious cycle of disdain and mistrust toward AI – as demonstrated in the discussions about downsides of algorithmic control (Kellogg et al., 2020). AI systems that show human-like characteristics, such as greater and more authentic displays of emotions, humor, and social presence, are often perceived to be easier to deal with and more sympathetic (Blut et al., 2021). Since many employees could find the technological complexity of new technologies like AI to be overwhelming (Brendel et al., 2016; Mohanta et al., 2020; Vrontis et al., 2022), humanizing those systems not only gives them human-like qualities but also makes it easier for human employees to interact with AI. Thus, organizational processes concerning AI accessibility can reduce fears and antipathies against AI, alleviate AI resistance, and make interacting with AI easier for employees.

Another organizational mechanism to alleviate AI resistance, *human-AI augmentation*, relates to how the organization can integrate human and AI workflows in a way that involves synergy, mutual support, and complementary (rather than supplementary) roles (Raisch & Krakowski, 2021). It entails the integration of AI technologies with human capabilities to enhance productivity, decision-making, and performance in the workplace. It is grounded in research on organizational integration (Tsai & Hsu, 2014), conjoined agency, i.e., multiple agents jointly pursuing a shared endeavor (Murray et al., 2021), sociotechnical systems theory (Trist & Bamforth, 1951), and psychological empowerment theory that stresses the role of meaning, competence, self-determination, and impact in the sense of empowerment in the workplace (Zimmerman, 1995). As such, rather than replacing humans with machines/algorithms, human-AI augmentation seeks to empower individuals by leveraging AI to augment their skills, knowledge, and capabilities. Thus, human-AI augmentation addresses the existential concerns of employees by demonstrating how AI can complement human agency rather than undermining or destroying it (Murray et al., 2021). It may also help align and integrate employees and AI systems in the workplace, enhance human efficacy in dealing with AI systems and AI-based robots, and help reduce operational friction when producing goods and services. Such integration is a fundamental precursor to enabling synergies between different actors and systems in the workplace (Tsai & Hsu, 2014).

In the case of interactions between employees and AI systems in the workplace, integration is a fundamental pillar (Abbass, 2019). Despite being built on different foundations and displaying different characteristics (Gligor et al., 2021; Rodney et al., 2019), AI technologies can complement human skills by automating routine tasks, processing large volumes of data, identifying patterns, and performing complex calculations quickly and accurately, freeing human workers to focus on higher-level tasks that require creativity, critical thinking, emotional intelligence, and interpersonal skills (Abbass, 2019). As such, organizational processes exhibiting high levels of human-AI interaction with employees (e.g., Sainato, 2019) entail greater attention to breaking down processes into their smallest components and developing new process maps in which humans and AI systems are efficiently incorporated at their finest levels. Such an organizational integration process requires attention to detail, a holistic and in-depth understanding of AI-based and human-based processes, and advanced analytical capabilities to break down segregated algorithms and rebuild them in a consolidated manner (Akter, Wamba, Mariani, & Hani, 2021) such that employees can work better with AI and utilize AI systems more effectively. Integrating artificial, intelligence-based, and human-based processes can, thus, be vital to alleviating employee AI resistance in the workplace. For instance, “co-bots” (collaborative robots) are a concrete example of human-AI augmentation in a physical context (Simões, Soares, & Barros, 2020). At the Ford Motor Company, employees and AI-driven co-bots work together on various operations.² The co-bots help employees to fit shock absorbers more precisely in Fiesta cars and to access hard-to-reach places in the assembly line. Also, instead of manually handling heavy shock absorbers and related installation tools, co-bots enable employees to lift and automatically place the shock absorber into the wheel arch. Co-bots also help employees perform ergonomically difficult and technically challenging tasks. As such, Ford employees feel that collaboration with co-bots helps make their tasks much safer, easier, and quicker than working alone.

Finally, *legitimizing AI technology* is an important organizational process whereby managers and other key members of organizations use different means to legitimate AI technology in the eyes of organizational members (Korneeva, Salge, Teubner, & Antons, 2023). It is grounded in legitimacy theory (Suchman, 1995), discursive legitimation (Vaara & Tienar, 2008), and issue selling (Dutton, Ashford, O’Neill, & Lawrence, 2001). This mechanism is particularly related to employees’ technological reflections, where the pros and cons of AI technology are weighted and iterated. If AI is deemed legitimate, reflections on its appropriateness are more likely to turn positive. In general, legitimacy is defined as “a generalized perception or assumption that the actions of an entity are desirable, proper, or appropriate within some socially constructed system of norms, values, beliefs, and definitions” (Suchman, 1995, p. 574). Radically new technologies involve major uncertainty and ambiguity (O’Connor & DeMartino, 2006), meaning that institutional norms about and perceptions of technologies such as AI are often missing when first introduced. This is true for all AI technologies, particularly for the rapidly emerging generative and conversational AI solutions expected to affect a major range of occupations, workflows, and work roles (Agrawal et al., 2022; Ritala et al., 2024). Managers must, therefore, engage in processes such as “issue selling” (Dutton et al., 2001) or “discursive legitimation” (Vaara & Tienar, 2008) inside the organization. Issue selling and discursive legitimation processes for AI occur via intra-organizational communication, persuasion, and rhetoric that help employees understand what AI fundamentally means for the organization, which norms it complies with, and how it should be perceived. Furthermore, pragmatic legitimation mechanisms (Suchman, 1995) are also likely to be useful when the utility of AI is displayed in everyday interactions and experiences in the workplace. Indeed, several scholars have noted how making the results of AI algorithms more understandable and transparent improves the legitimacy and acceptance of AI in the workplace (e.g., Martin & Waldman, 2023; Shin, 2021). Thus, we propose the following:

P3: Organization-level mechanisms to alleviate AI resistance reduce employee AI resistance by a) increasing AI accessibility, b) human-AI augmentation, and c) legitimizing AI technology.

5. Discussion and conclusions

Our goal in this section is to discuss an overarching and granular understanding of AI resistance, how employees confront it, and how it can be alleviated in the workplace. AI technologies involve black-boxing of algorithms and features of automated decision-making that make them different from previous-generation IT systems (Berente et al., 2021). Therefore, with the growing presence

² <https://media.ford.com/content/fordmedia/feu/en/news/2019/09/26/ford-choreographs-robots-to-help-people-and-each-other-on-the.html>

of AI in the workplace, employees are not only excited about the new affordances and productivity potential of AI (Raisch & Krakowski, 2021), but there is also increasing hesitation, confusion, and resistance among employees to utilize the technology (Agrawal et al., 2022; Ritala et al., 2024). In the current study, we adopted the integrative review approach (Cronin & George, 2023), which allowed us to bridge different literature streams into a process model describing the nature and the mechanisms via which employee AI resistance unfolds and the organizational mechanisms that can be used to alleviate such resistance. Our main contribution to the literature on AI in organizations is the unbundling of the interactive process of employee-level and organizational-level phenomena via which AI resistance is both realized, processed, and potentially alleviated. The integrative review and the related process approach demonstrate that AI resistance is a multifaceted and multidisciplinary field, with different literature streams and approaches contributing to understanding the phenomena (see Appendix 1). Therefore, we believe our study helps management research on AI identify various approaches to the phenomenon of AI resistance, enabling the building of further, more targeted empirical and conceptual studies from different viewpoints. In what follows, we discuss our study's theoretical and practical implications.

5.1. Theoretical implications

Based on the integrative review and the developed processual model of confronting and alleviating AI resistance in the workplace, our paper offers several implications for theory development in HRM and AI literature streams. For relevant HRM literature (Arslan et al., 2022; Basu et al., 2023; Pereira et al., 2023; Varma et al., 2023; Vrontis et al., 2022), the first theoretical implication relates to specifying the dynamic interaction among cognitive, individual, and organizational elements in the context of resistance to AI implementation. Such a dynamic process approach has been stressed as being vital for HRM theory development in the context of AI influences on workplace outcomes in a recent study published in HRM (Pereira et al., 2023). Moreover, by specifying both the cognitive dimensions of AI resistance as well as individual and organizational processes that are critical in resolving AI resistance, our process framework strengthens both human resource planning and training and development theorization in the larger HRM field. Incorporating aspects highlighted in our framework is also expected to enrich the emergent AI-HRM interactions and outcomes literature stream (Basu et al., 2023). We further advance a grounded definition of interacting with AI and explain its three distinct dimensions that characterize AI resistance as a unique type of IT resistance that draws from the specific features of AI as adaptable and learning (Kaplan & Haenlein, 2019), but also inscrutable and black-boxed systems (Berente et al., 2021). Hence, our processual model also contributes to the configuration explanation of AI-HRM interaction and outcome literature stream (Basu et al., 2023). Finally, in HRM literature, scholars have stressed an increasingly personalized rather than generic approach to applying AI and associated technologies (e.g., Malik, Budhwar, Patel, & Srikanth, 2022). Our process framework strengthens the theorization of personalized HRM application in relation to AI, as it postulates individual employee behavioral processes, which are critical in developing and implementing any personalized HRM model.

Along with HRM, our process framework enriches extant AI (and its application in the workplace context) literature stream (Glikson & Woolley, 2020; Kaplan & Haenlein, 2019; Mirbabaie et al., 2022; Willcocks, 2020) in several ways. Firstly, we discuss particularly the experience of mistrust toward AI, existential questioning, and technological reflection mechanisms for confronting AI resistance in organizations. Our examination of confronting AI resistance reveals how such confrontation encompasses both positive and negative experiences and activities and is a necessary step in the journey toward alleviating it. For example, it is possible to better understand how employees can build trust by recognizing that confronting AI resistance includes mistrust toward AI. Likewise, our paper shows that the journey toward AI-technology legitimation passes through the technological reflections of employees in the first place. We also explain how these confronting experiences and activities lead to both anxiety and deeper introspection, which result in contrasting influences on how organizations alleviate AI resistance. Examining the connections between confronting and alleviating AI resistance sheds some light on the interface between these two major processes. It helps distinguish actors who alleviate it from those who merely confront it. As such, our paper goes beyond a reductionist examination of confronting AI resistance and explains how employees move forward from the individual confronting stage to the collective alleviating stage.

We also explain the alleviation of AI resistance as an organizational reflective and reframing process consisting of AI accessibility, human-AI augmentation, and AI-technology legitimation. We highlight these three processes as instrumental elements in alleviating AI resistance. Nonetheless, we also stress how these processes are reflective and reframing processes that require individuals to confront AI resistance in the first place. Organizational mechanisms to alleviate such resistance may be unsuccessful without such confrontation and a thorough understanding of employee AI resistance. As such, alleviating AI resistance is a path-dependent process that requires understanding the sources of this resistance and mechanisms to confront it and how such confrontation is connected to the subsequent alleviation stage. This contribution is particularly relevant to the literature stream on technology acceptance (Davis, 1989) and resistance (Ali et al., 2016; Longoni, Bonezzi, & Morewedge, 2019; Rivard & Lapointe, 2012) in organizations, as well as organizational change management (Davenport et al., 2020; Dutton et al., 2001).

Our framework highlights how processes that alleviate AI resistance are not insulated activities but are in constant and recursive interaction with the sources and mechanisms to confront it. As such, our conceptual framework makes a process-based theoretical contribution (Cloutier & Langley, 2020; Langley, 2007) to the nascent research field on AI in the workplace. We shed light on contingent interactions of AI resistance via interweaving various organizational relations (cf. Cloutier & Langley, 2020). Importantly, our theoretical framework *contextualizes* employee AI resistance in the workplace and demonstrates how confronting and alleviating AI resistance is a process whereby employee-level and organizational mechanisms interact in various ways. Ultimately, we argue that alleviating AI resistance is not a "one-size-fits-all" type of exercise but rather a process wherein multiple types of resistance are constantly being re-considered and reframed. Resolving AI resistance is, therefore, not a one-time affair. Rather, as our framework shows, it is a continuous process whereby existing issues are resolved, and new issues arise in response to the emergence of new AI

technologies and their adoption in the workplace.

5.2. Managerial and policy implications

Our paper also offers several managerial and policy implications. First, AI resistance is not a simple phenomenon but a multifaceted, socially constructed, and interdependent set of practical and normative perceptions (Longoni et al., 2019; Mou, Xu, & Hu, 2023; Walsh et al., 2021). HR managers should recognize that AI resistance arises from diverse and interconnected concerns, both practical (e.g., fears of job displacement and skill obsolescence) (Moore, 2018) and normative (e.g., ethical concerns, threats to identity or professional values) (Varma et al., 2023). Therefore, managers and employers must understand that AI resistance is not just about employees being resistant to technology—it is far more complex. People may feel uneasy because AI works differently from traditional tools; it is smart, often hard to understand, and can raise concerns about job security or ethical issues. Managers need to address practical concerns, like fears of job loss, and value-based concerns, like ethical use and alignment with the company's goals. Open and clear communication about AI and its role in the organization is important. Managers should tailor their messaging to different teams, focusing on what matters most to them—whether it is efficiency, ethics, or alignment with company values.

Second, HRM professionals and other leaders can promote collaboration between employees and AI systems by demonstrating how AI can augment human capabilities, improve decision-making, and reduce routine tasks. This synergetic – rather than supplementary – approach fosters a sense that AI will complement rather than replace human roles, reducing fear of job loss and resultant antipathy toward AI. By promoting AI as a supportive tool – rather than mystifying it as a source of disruption – HR managers can emphasize its role in enhancing creativity, problem-solving, and other human-centric skills while at the same time helping replace mundane, boring, or repetitive work. HR initiatives like workshop sessions and hands-on training can be organized where employees directly interact with AI systems, witnessing firsthand the potential synergies and challenges in adopting AI in daily work. Such experiential learning can debunk myths, dispel misconceptions, and reduce inherent biases or fears against AI. Over time, as employees observe tangible benefits from their collaboration with AI, such as reduced workloads or quicker task completion, their trust and acceptance of the technology will likely grow. Moreover, managers can create mentorship programs, “clubs”, and best practice groups where AI enthusiasts or early adopters within the organization guide their peers, sharing success stories and concrete everyday tips.

Third, a critical HRM implication is the need for clear career development pathways that show employees how they can grow within the organization (Skrbiš & Laughland-Booÿ, 2019), even in the context of AI integration. In this regard, organizations could also invest in reskilling and upskilling (Willcocks, 2020) to equip employees with the skills needed to work alongside AI. Employees need to see how they can thrive in an AI-integrated workplace. This means offering training programs that help them build the skills needed to work effectively with AI. Managers should be upfront about their organization's AI plans and what they mean for employees' roles and futures. Clear pathways for career growth should be demonstrated, including new roles that emerge with AI integration. Leaders should regularly engage with their teams to address their concerns, answer questions, and show that the company is committed to their development.

Finally, from a policy standpoint, policymakers should work with industry stakeholders to offer various resources, guidelines, and support to help with a sustainable shift to human-AI collaboration. With an emphasis on addressing employees' anxieties, inefficacies, and antipathy toward AI, policymakers should specifically support initiatives promoting AI literacy and training. These programs can be specifically designed to address the antecedents mentioned in the study, such as mistrust, existential doubt, and technological reflection. This will guarantee that AI technologies are implemented in a way that encourages employee trust and reduces anxiety. The ethical standards, data privacy regulations, and other legal requirements pertaining to the deployment of AI should be regularly audited and inspected by policymakers to verify compliance – in this regard, the developments regarding the AI Act in the European Union might be helpful, for instance. Moreover, policymakers can mandate organizations to develop guidelines and standards for the usage of AI, which could drive AI legitimation among the organization's employees and stakeholders. Such policy interventions are naturally more likely with the “big tech”, as we have seen recently; however, more broadly adopted and enforced best practices and standards can also be helpful broadly. Organizations could also be supported and incentivized to establish Human-AI augmentation programs, for instance, by providing tax benefits or grants to businesses that fund similar initiatives or by funding university-industry research projects that push forward the frontier in this regard.

5.3. Future research directions

Despite being a conceptual piece, our paper addresses a relevant and under-researched area, which opens several avenues for scholars to explore. Firstly, future studies should undertake quantitative and qualitative assessments in different contexts to analyze resistance to working with AI in the workplace. Extant literature would also benefit from comparative empirical studies analyzing issues like fear, antipathy, and inefficacy in different contexts. Such studies can highlight the potential differences based on culture and the level of development of the context (e.g., country) being studied. To strengthen the theoretical basis of the role of AI in various organizational functions, it is important to specify the differences in the role of the above-mentioned factors for different employees (i. e., white-collar vs. blue-collar employees) and how strategies differ when addressing (alleviating) the hesitation of employees to work alongside and together with AI at different organizational levels.

Second, future research can further explore the sources of resistance, as well as confronting and alleviating mechanisms, to see which factor is more powerful and deserves to be addressed first in organizations. It will also be insightful to examine if the sources of resistance impact or drive each other and, if so, which source is more influential in driving others. Likewise, different confronting and alleviation mechanisms might involve distinct and interactive dynamics. Studying the nuances of these mechanisms and their

interactions can help decision-makers deal with each factor more systematically and orderly and better utilize the key resources of firms working to cultivate useful human-AI interaction.

Third, future studies can undertake a longitudinal analysis to see the evolutionary changes in employee attitudes toward AI at different stages (introductory stage, before relevant training, after relevant training, and later stages). Similarly, for alleviation strategies, mechanisms like AI accessibility may likely appear more important in the early stages, but empirical research is needed. Also, such longitudinal assessment is expected to produce useful insights, particularly into human-AI augmentation and AI-technology legitimization strategies, as these aspects are expected to mature as time passes, leading to more streamlined business processes and possibly some new challenges.

Fourth, unique challenges and barriers might arise when implementing AI systems and technologies in specific fields or industries. Exploring domain-specific sources of AI resistance can provide valuable insights into understanding how AI adoption varies across different sectors and contexts. For example, some industries, like the medical industry (Longoni et al., 2019), deal with highly complex systems or processes that may present challenges for AI implementation and may involve unique ways of AI resistance in the workplace. Likewise, beyond employees, consumers may fail to recognize the distinct capabilities, benefits, or risks associated with AI technologies and resist AI in unique ways. In particular, they may exhibit uniqueness neglect -cognitive bias where individuals overlook or underestimate the unique features or characteristics of a particular situation or object when making judgments or decisions- as a way of resisting AI (Mou et al., 2023). Thus, future research should account for unique aspects of industry and context-specific AI resistance.

Finally, future research could also explore the cognitive and emotional aspects of human-AI collaboration, including the interplay between positive and negative perceptions and emotions. AI resistance could be seen as a counterforce for “AI engagement,” excitement, or similar positive psychological or emotional phenomena. Interestingly, individuals might also feel ambivalent—simultaneously positive and negative—toward AI systems. Examining such issues is outside the scope of our current study but would be an interesting future research topic.

Confronting and alleviating AI resistance in the workplace

An integrative review and a process framework.

Declaration of competing interest

None.

Appendix A. Literature sources and theoretical foundations of confronting and alleviating AI resistance in the workplace

Framework dimension	Key explanatory concepts	Definition	Key literature	Theoretical foundations
Behavioral dimensions of employee AI resistance	<i>Fear</i>	Distress or apprehension driven by the perceived side effects of and threats from advanced technologies (Sindermann et al., 2022)	Sindermann et al. (2022) Arslan et al. (2022) Willcocks (2020) Ayyagari et al. (2011) Bawden and Robinson (2009)	<ul style="list-style-type: none"> • Diffusion of Innovations (Rogers, 2003) • Status Quo Bias (Samuelson & Zeckhauser, 1988) • Technological Determinism (Smith & Marx, 1994) • Technology Aversion (Brosnan, 1998) • Resistance to change (Dent & Goldberg, 1999)
	<i>Inefficacy</i>	A (real or perceived) inability of employees to interact with AI systems, leading to an employee being unable or unwilling to work in such contexts (Demir et al., 2020)	Demir et al. (2020) Choudhury et al. (2022) Chong et al. (2022) Kaur, Uslu, Rittichier, and Durrezi (2022) Brendel et al. (2016) Mohanta et al. (2020) Jaiswal, Arun, and Varma (2022) Pradhan and Saxena (2023) Tang, Ren, Chadee, and Yuan (2020)	<ul style="list-style-type: none"> • Technology Acceptance Model (Davis, 1989) • Unified Theory of Acceptance and Use of Technology (Venkatesh, Morris, Davis, & Davis, 2003) • Self-Efficacy Theory (Bandura, 1977) • Technological Frames of Reference (Orlikowski & Gash, 1994) • Job Insecurity Theory (Shoss, 2017) • Resistance to change (Dent & Goldberg, 1999)
	<i>Antipathy</i>	A mental state of disliking someone or something, which ultimately results in the	Lok and Willmott (2013)	<ul style="list-style-type: none"> • Technophobia (Brosnan, 1998) • Technology Aversion (Brosnan, 1998)

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Framework dimension	Key explanatory concepts	Definition	Key literature	Theoretical foundations
Employee-level mechanisms to confront AI resistance		urge to avoid any association with that particular person or object (Kros et al., 2021).	Grint and Woolgar (2013) Kushwaha et al. (2023) Budhwar, Malik, De Silva, and Thevisuthan (2022) Al-Amoudi (2022)	<ul style="list-style-type: none"> • Technostress (Ragu-Nathan, Tarafdar, Ragu-Nathan, & Tu, 2008) • Resistance to change (Dent & Goldberg, 1999)
	<i>Experiencing mistrust</i>	A lack of confidence, skepticism, or wariness toward AI systems, technologies, and applications in the workplace (Schepman & Rodway, 2023)	Li et al. (2008) Lankton et al. (2015) Glikson and Woolley (2020) Schepman and Rodway (2023) Starke and Ienca (2022)	<ul style="list-style-type: none"> • Technology Acceptance Model (Davis, 1989) • Diffusion of Innovations (Rogers, 2003) • Trust Model (Mayer et al., 1995) • Social Exchange Theory (Cropanzano & Mitchell, 2005) • Critical Theory of Technology (Feenberg, 1991)
	<i>Existential questioning</i>	Employees' fundamental self-doubt and the feeling of uneasiness concerning work identity and usefulness amid the rise of AI in the workplace (Skrbiš & Laughland-Booÿ, 2019)	Petriglieri et al. (2019) Davenport et al. (2020) Skrbiš and Laughland-Booÿ (2019)	<ul style="list-style-type: none"> • Existentialism (Sartre, 1973) • Technological Determinism (Smith & Marx, 1994) • Psychological Theory of Alienation (Ollman, 1976) • Sociology of Work (Grint, 2005) • Critical Theory of Technology (Feenberg, 1991)
	<i>Technological reflection</i>	Comprehensive and thorough reflection on both positive and negative aspects of technology and its implications for society and employees (Schweitzer et al., 2015).	Schweitzer et al. (2015) Andrade-Valbuena and Torres (2018) Stephanidis et al. (2019)	<ul style="list-style-type: none"> • Work Identity (Walsh & Gordon, 2008) • Reflective Practice Theory (Schön, 1983) • Sociotechnical Systems Theory (Trist & Bamforth, 1951) • Technology Acceptance Model (Davis, 1989) • Critical Theory of Technology (Feenberg, 1991)
Organizational-level mechanisms to alleviate AI resistance	<i>AI accessibility</i>	Different organizational mechanisms that make AI more accessible to employees at cognitive, as well as concrete and pragmatic levels (Goldenthal et al., 2021)	Glikson and Woolley (2020) Gillath et al. (2021) Lankton et al. (2015) Schanke, Burtch, and Ray (2021) Goldenthal et al. (2021)	<ul style="list-style-type: none"> • Explainable AI (Rai, 2020) • AI Alignment (Gabriel, 2020) • Anthropomorphism and AI Humanization (Blut et al., 2021) • Technology Acceptance Model (Davis, 1989) • Inclusive Design Framework (Persson et al., 2015)
	<i>Human-AI augmentation</i>	Integrating human and AI workflows in a way that involves synergy, mutual support, and complementary (rather than supplementary) roles (Raisch & Krakowski, 2021)	Abbass (2019) Aker et al. (2021) Simões et al. (2020) Raisch and Krakowski (2021)	<ul style="list-style-type: none"> • Organizational Integration (Esper, Ellinger, Stank, Flint, & Moon, 2010) • Conjoined Agency (Murray et al., 2021) • Sociotechnical Systems Theory (Trist & Bamforth, 1951) • Automation–Augmentation Paradox (Raisch & Krakowski, 2021) • Psychological Empowerment Theory (Zimmerman, 1995)
	<i>AI-technology legitimization</i>	Different means to legitimate AI technology by managers and other key actors in the eyes of organizational members (Korneeva et al., 2023)	Martin and Waldman (2023) Shin (2021) Korneeva et al. (2023) Dutton et al. (2001) Vaara and Tienar (2008)	<ul style="list-style-type: none"> • Legitimacy Theory (Suchman, 1995) • Discursive Legitimation (Vaara & Tienar, 2008) • Issue Selling (Dutton et al., 2001) • Social Influence Theory (Deutsch & Gerard, 1955)

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