



A taxonomy framework and process model to explore AI-enabled workplace inclusion[☆]

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ABSTRACT

This study develops a taxonomy framework and a process model to explain how artificial intelligence (AI) reshapes workplace inclusion through human resource management (HRM) practices. We analyze 25 empirical studies using a hybrid inductive–deductive method informed by Nickerson et al.'s (2013) taxonomy development framework. The resulting taxonomy classifies AI-enabled HRM practices according to their strategic goals, types of human-AI interaction, inclusion typologies, evaluation methods, and mitigation strategies. We extend this taxonomy with a process model that illustrates how different forms of AI agency – ranging from assisting to automating – shape inclusion outcomes and require differentiated mitigation strategies. Our analysis reveals three interconnected dimensions of AI-enabled workplace inclusion emerge in such contexts: inclusion in work (individual experiences), inclusion at work (organizational climate), and inclusion of work (human-AI interaction). Each dimension demands distinct context-sensitive mitigation strategies depending on the level AI agency involved. By linking AI agency to differentiated forms of inclusion and tailored mitigation strategies, this study advances theoretical understanding of AI-enabled inclusion. It also offers actionable guidance for organizations implementing AI in HRM practices while safeguarding workplace inclusion.

1. Introduction

The intersection of artificial intelligence (AI) and workplace inclusion is an area that is critical yet underexplored in contemporary organizational research. Despite the anticipated improvements in how organizations manage their staff, research suggests that AI tools in human resources management (HRM) often strengthen existing biases rather than eliminate them. These systems may reproduce existing human prejudices which lead to increased marginalization of already excluded groups (Kelan, 2023; Kellogg et al., 2020; von Krogh, 2018), thus pushing marginalized groups further away from workplace consideration (Ferrer et al., 2021).

The proper analysis of AI impact on workplace inclusion requires defining diversity and inclusion as distinct yet connected concepts. Workforce diversity represents organizational composition and demographic characteristics (Peretz, Levi, and Fried 2015), yet inclusion extends beyond legal requirements to include voluntary international efforts (Winters, 2013). Diversity is therefore centered more around the

“what” – namely, different identities and perspectives – while inclusion concerns “how” these differences are integrated and celebrated in the workplace. Creating an inclusive workplace involves fostering the belonging of all employees, regardless of social identity group affiliations, by establishing a culture of access and accessibility (Georgiadou et al., 2024). To this end, it is necessary to implement managerial and organizational practices offering fair access to valuable opportunities (Bell et al. 2011; Roberson 2006).

Despite substantial advances in inclusion research, the impact of AI on inclusion efforts remains largely unexamined (Kim et al., 2021; Georgiadou et al., 2024). The existing literature focuses narrowly on recruitment and minority demographics, overlooking the broader organizational and technological factors that influence both positive and negative inclusion outcomes (Hunkenschroer & Luetge 2022; Köchling & Wehner 2020; Will, Krpan, & Lordan 2022). Moreover, the current models are inadequate in capturing the influence of AI on inclusion across the different levels of individual experiences, organizational aspects and human-AI interactions. Beyond specific HRM practices such as

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hiring (Kelan, 2023), the concept of AI-enabled workplace inclusion remains theoretically underdeveloped. By AI-enabled workplace inclusion, we refer to the systematic integration of AI technologies within organizational processes to foster workplace inclusion across multiple levels, from individual experiences to organizational structures.

To address these gaps and contribute to theory development on the impact of AI on workplace inclusion, our study develops a novel taxonomy and a process model. The taxonomy offers a systematic classification of AI-enabled HRM practices, focusing on their strategic goals, types of human-AI interaction, inclusion typologies, evaluation methods, and mitigation strategies. It is developed using a hybrid inductive–deductive method informed by Nickerson et al.'s (2013) taxonomy development framework. The purpose is to structure the fragmented empirical landscape, providing researchers and practitioners with a coherent lens through which to interpret the implications of AI for workplace inclusion. Our taxonomy is then extended through a process model that maps how different types of AI agency (from assisting to automating) affect inclusion outcomes and the mitigation strategies required at each stage. The two provide a framework for analyzing how AI adoption shapes workplace inclusion, offering a common language for researchers and practitioners and enabling the identification of patterns not apparent when examining individual cases. This framework serves as a foundation for redirecting future research, helping to address AI-related biases in ways traditional frameworks cannot and push research into this underexplored arena (Cronin and George 2023).

This study advances theory on AI-enabled workplace inclusion through three interconnected contributions. First, we reconceptualize inclusion through a multilevel framework that distinguishes between individual experiences (inclusion in work), organizational climate (inclusion at work), and human-AI interaction (inclusion of work). This reconceptualization reveals how different dimensions of inclusion require fundamentally different mitigation strategies and cannot be addressed through universal approaches. The framework moves beyond binary questions of whether AI helps or hinders inclusion to examine how different forms of conjoined agency create distinct inclusion challenges that demand tailored responses.

Second, we demonstrate how the level of AI agency fundamentally shapes inclusion outcomes in ways that current literature has failed to recognize. Our taxonomy reveals that the progression from assisting to automating AI creates escalating inclusion risks that require increasingly sophisticated mitigation strategies. This finding challenges prevalent assumptions that AI implementations can be evaluated independently of their agency characteristics and suggests that inclusion outcomes are intrinsically linked to the degree of autonomy organizations delegate to their AI systems.

Third, we provide the first systematic framework for matching mitigation strategies to specific AI implementations, offering both theoretical insight and practical guidance for navigating the complex terrain between algorithmic efficiency and inclusive outcomes. Rather than advocating for or against AI adoption, our framework enables organizations to implement AI systems thoughtfully, with clear understanding of inclusion implications and concrete strategies for promoting positive outcomes across multiple organizational levels.

2. AI and HRM

2.1. Conjoined human-AI agency in HRM

AI, encompassing a range of different technologies, is defined as “the ability of machines to perform human-like cognitive tasks, including the automation of physical processes such as manipulating and moving objects, sensing, perceiving, problem solving, decision making and innovation” (Benbya et al., 2020, p. 9). The increasing data generation has resulted in the application of AI in various industries and jobs (Pachidi et al. 2021; Shobana & Kumar 2015; Collins et al. 2021).

Our AI-enabled inclusion taxonomy is centered on two primary

HRM-relevant technologies: Machine Learning (ML) and Deep Learning (DL). ML, which learns from training data to perform specific tasks (Benbya et al., 2020), is the most widely used AI technique in HRM (Sofian et al., 2022). DL, a specific class of ML, uses artificial neural networks to learn and make decisions without human supervision. The two technologies are the foundation of the “AI Technology” dimension of our taxonomy, which classifies HRM practices according to the type of AI technology applied.

In view of this, it is imperative to discuss the technology as well as the human-AI interactions in the organizational context in order to understand AI-enabled workplace inclusion. This interaction is crucial for understanding how AI influences workplace inclusion. For our analysis of how AI influences workplace routines and decisions, we use Murray et al.'s (2021) “conjoined agency” concept, defined as “a shared capacity between humans and nonhumans to exercise intentionality” (Murray et al., 2021, p. 555). Organizational routines consist of two key components: protocol development, which involves establishing activity guidelines, and action selection, which entails making decisions and interactions that impact the routine (Piezunka & Dahlander 2019). Viewing these components as the locus of agency, Murray et al. (2021) explore the shared agency between humans and agentic technologies (e.g., AI applications), observing how these technologies “shift the locus of agency away from humans in protocol development and action selection” (p. 555).

Based on technology's role in conjoined agency and its ability to act intentionally in protocol development and action selection, we identified four different forms of technology for the “human-AI interaction” dimension of our taxonomy: assisting AI technologies, which support human decision-making without exercising independent agency; arresting AI, which automatically executes tasks under specific conditions which are then verified, allowing humans to develop protocols but imposing constraints on routine practices; augmenting AI, which develops protocols or recommendations but leaves the final decisions to humans; and automating AI, which develops protocols and makes decisions independently. The impacts of AI on inclusion can be analyzed following this classification. For example, assisting AI may standardize initial candidate screenings and reduce bias in recruitment, while, without careful oversight, automating AI could perpetuate existing biases. Regarding arresting technologies (e.g., blockchain in smart contract management), such applications are rare in HRM, as AI-imposed constraints typically operate alongside protocol development in automating technology.

The spectrum of AI involvement in HRM tasks ranges from enhancement to full automation, directly influencing inclusion outcomes. Understanding these different levels of conjoined agency helps analyze how different forms of AI affect inclusive practices and outcomes in organizations. Given AI's applicability across organizational functions and decision-making tasks (Huang & Rust 2018), it is crucial to undertake a granular analysis of AI's effects on workers and HRM practices (Benbya et al., 2021).

The intersection of AI and HRM represents a critical juncture for understanding technology's impact on workplace inclusion. To develop an integrated concept of AI-enabled workplace inclusion, we need to examine how AI technologies are specifically applied to HRM practices and the resulting implications for inclusivity.

The increased digitalization and datafication of the HRM function have boosted the development and application of AI tools in HRM decisions, processes and practices (Kim, Wang & Boon 2021). The topic has received growing scholarly interest and it is raising new questions on the opportunities and risks related to the growing use of AI in HRM (Cheng & Hackett 2021). Indeed, an increasing number of organizations are adopting AI-powered HRM solutions, where a broad range of software algorithms execute HRM activities that would normally require human cognition and intervention (Kim et al., 2021; Za et al., 2023).

Previous research has indicated potential advantages of AI in HRM, including enhanced efficiency and data-driven decision-making.

However, deeper scrutiny has uncovered substantial obstacles, particularly regarding workplace inclusion (Georgiadou et al., 2024). For example, several studies demonstrate that AI recruitment platforms might perpetuate and even intensify existing prejudices, potentially worsening discrimination faced by marginalized groups (Köchling & Wehner, 2020; Köchling et al., 2021). This paradox – the notion that AI simultaneously improves HRM practices while potentially undermining workplace inclusion – creates a fundamental tension within the integrated concept of AI-enabled workplace inclusion.

Contemporary applications of advanced AI systems in HRM reveal the complexity of inclusion challenges that organizations now face. Beyond the chatbots handling routine queries from job applicants or employees seeking policy information, some organizations are now implementing emotion-detecting video interview platforms that promise to reduce interviewer bias but could systematically disadvantage, for example, candidates whose emotional expressions differ from predominantly Western training datasets (Rhue, 2018; Köchling et al., 2021). Automated performance management systems aggregate productivity metrics, communication patterns, and task completion rates to generate ratings that could influence promotion decisions, yet these potentially undervalue employees whose contributions might be more collaborative or contextual in nature (Newman et al., 2020; Tong et al., 2021). ML algorithms now recommend employees for promotion opportunities and personalize career development pathways, however these frequently rely on historical advancement patterns that embed past biases whilst appearing objective (for a review, see Vrontis et al., 2022).

Therefore, it is of paramount importance that AI systems do not replicate or amplify discriminatory behaviors (Mehrabi et al. 2021). Indeed, when applied to specific problems, AI algorithms could worsen the situation by threatening rights, opportunities and wealth, not only the creating new inequalities but also amplifying existing ones (Hoffmann 2019). Moreover, as a large number of organizations are increasingly adopting AI applications, the decisions of such systems could simultaneously influence many people, increasing the scope of potential problems related to ethics, fairness and algorithmic bias (Zuiderwijk, Chen & Salem 2021) and undermining organizational inclusion.

2.2. AI and workplace inclusion

The scope of inclusion has evolved from its initial focus on enhancing the demographic representation of underrepresented groups in recruitment and retention (Ely & Thomas, 2001) to addressing contemporary challenges of digital discrimination and algorithmic bias (Ferrer et al., 2021). Hence, organizations must now balance traditional inclusion factors with emerging technological facets (Georgiadou et al., 2024).

The current state of AI deployment in HRM reflects a kind of inclusion blindness; an implementation of advanced technological solutions without adequate consideration of their differential impacts on workplace inclusion. This blindness manifests across multiple domains of contemporary practice. For example, HR chatbots designed to handle employee queries about various institutional approaches and advancement opportunities, often struggle with non-native speakers or employees less comfortable with digital interfaces, effectively creating a two-tier system of HR service delivery. Also, ML algorithms that advise employees for promotion opportunities or assess their potential, frequently rely on historical advancement patterns that reflect past biases, essentially automating discrimination whilst appearing objective and data-driven (Speer, 2021; Zhang et al., 2023).

Scholars have established that diversity alone cannot guarantee positive organizational outcomes without well-designed inclusion management approaches (Joshi et al., 2011; Williams & O'Reilly, 1998). While diversity emphasizes demographic representation, inclusion focuses on employee involvement and integrating diversity into HRM practices to optimize HR and enhance employee contributions (Georgiadou & Antonacopoulou, 2021; Roberson, 2006).

The recent academic discourse has emphasized integrating AI to foster inclusion and equity, building on organizational inclusion frameworks (Budhwar et al., 2022; Robert et al., 2020; Georgiadou et al., 2024). However, by reflecting biased data, these technologies often perpetuate historical biases (Angrave et al., 2016; Eubanks, 2018). Successful implementation therefore requires an understanding of both the social attribution processes and technological structures shaping the inclusion outcomes (Georgiadou et al., 2024).

Perhaps most concerning is how these technologies reshape the fundamental nature of workplace inclusion itself. When promotion decisions are mediated by algorithms that prioritize merely quantifiable achievements, employees whose contributions might be more interactive or contextual may find themselves repeatedly underrated (Tong et al., 2021). The concept of inclusion “of work” – that is, how humans and AI collaborate in shaping inclusive workplaces – becomes critical here, as these systems don't merely affect individual experiences but fundamentally define the terrain on which inclusion is challenged and realized. This transformation requires attention to both the technical capabilities of AI systems and how individuals within organizations interpret and interact with these technologies. In line with Kossek and Pichler's approach (2006), we propose that effective inclusion management in AI-enabled contexts must address selecting for inclusion, reducing workplace discrimination and enhancing financial performance, but these traditional goals now require new strategies adapted to algorithmic mediation.

Nishii et al.'s (2008) attribution framework revealed how employees' perceptions and behaviors are shaped by their interpretations of the management's HRM practices. These attributions become very important in AI-enabled HRM practices, particularly when staff face unfamiliar or potentially threatening changes. Newman et al. (2020) found that employees view AI-based HRM decisions as less fair than those made by humans, especially when they believe AI has been implemented to cut costs rather than to enhance fairness.

As Mor Barak (2010) emphasized, the organizational context drastically affects workplace inclusion outcomes. Employees' perceptions of AI systems vary based on the existing inclusion climate, leadership communication and past technological experiences. The institutional context frames what the organizations value (Georgiadou & Syed, 2021) and provides legitimizing narratives (Baumeister et al., 2013).

The technological perspective of adaptive structuration theory (AST; DeSanctis & Poole, 1994) explains how cognitive, social and cultural dynamics shape human-AI interaction. How effective the adoption of technology is, depends on how people utilize the existing norms and communication processes (Leonardi & Barley, 2010). This sociological framework suggests that identical AI systems may produce different inclusion outcomes depending on the organizational context and employee attributions.

The synthesis of attribution theory and AST demonstrates that the successful implementation of AI requires attention to both technical capabilities and social interpretations. When employees perceive algorithmic decision-making in HRM, their satisfaction and commitment may decrease even in the face of objectively fair outcomes (Newman et al., 2020). This highlights the necessity of managing both the technical and social aspects of AI implementation to promote genuine workplace inclusion.

Recent management scholarship has highlighted the paradoxical relationship between automation and augmentation in AI applications. Raisch and Krakowski (2021) argue that rather than representing a simple trade-off, automation and augmentation exist in a paradoxical tension where they are both contradictory and interdependent. Whilst automation removes humans from the process, augmentation keeps them 'in the loop', creating opposing organizational demands. However, these approaches also enable one another across time and space. This paradox proves particularly relevant when examining how different forms of AI agency create distinct inclusion challenges. Assisting AI technologies may appear to preserve human agency whilst subtly

shaping decision-making through the information they surface or suppress. Augmenting AI systems create tensions between algorithmic recommendations and human judgment, often in contexts where the basis for algorithmic suggestions remains obscure to decision-makers. Automating AI presents perhaps the utter paradox – promising to eliminate human bias whilst potentially embedding systematic exclusion that becomes invisible within apparently objective processes.

Our approach extends recent taxonomic work in AI research, particularly frameworks developed within innovation contexts. [Mariani et al. \(2023\)](#) provided a comprehensive taxonomy of AI applications in innovation research, whilst [Gama and Magistretti \(2025\)](#) developed taxonomic approaches for AI in innovation management more broadly. However, these frameworks focus primarily on technological capabilities and innovation outcomes, without addressing the inclusion implications that prove central to AI enabled workplace. Our work redirects attention toward the inclusion dimensions these studies overlook and categorizes AI by its impact on inclusion. This shift from innovation-focused to inclusion-focused taxonomic development reflects the urgent need for frameworks that can navigate the complex terrain between algorithmic efficiency and inclusive outcomes ([Georgiadou et al., 2024](#)).

Building on these insights, we develop a comprehensive taxonomy framework and process model. Our approach integrates attribution theory’s insights on employee perceptions with AST’s understanding of technology adoption, while incorporating [Murray et al.’s \(2021\)](#) concept of conjoined agency. Drawing on [Pratt and Ashforth’s](#) meaningfulness typology (2003), we advocate for a reconceptualization of inclusion across three interconnected dimensions: inclusion *in* work (individual experiences), *at* work (organizational climate), and *of* work (human-AI interaction). This integrated framework enables analysis of AI-enabled workplace inclusion, examining how different forms of AI agency interact with workplace inclusion and the mitigation strategies organizations employ to promote inclusive outcomes.

3. Method

Due to the lack of direct evidence in published research, we aim to redirect scholarly attention toward previously overlooked dimensions of workplace inclusion in AI adoption and opening new theoretical avenues for future research ([Cronin & George 2023](#)). To achieve this, we conducted a taxonomy-based exploratory study ([Nickerson et al. 2013](#)) using an iterative inductive (reviewing literature based on available evidence) and deductive (grounded in existing theoretical framework) analytical approach.

Our research objectives require a thorough analysis of the dimensions and interrelationships influencing AI adoption and workplace inclusion outcomes. Utilizing a taxonomy approach allows to identify the key variables – referred to as dimensions – and their relationships, contributing to a nuanced understanding of how AI-enabled HRM practices influence workplace inclusion.

Taxonomies structure and classify empirical evidence, enabling scholars to analyze and theorize complex domains ([Bailey, 1994](#)). Specifically, taxonomies describe and categorize subjects by highlighting commonalities among discrete observations ([Fawcett & Downs 1986](#)), which facilitate deeper analysis of selected studies based on these shared characteristics ([Cipriano & Za 2022](#)).

In this research, we systematically coded these commonalities to develop a taxonomy that captures central themes concerning the debate on the impact of AI on inclusion ([Gregor 2006](#)). Based on the taxonomy method proposed by [Nickerson et al. \(2013\)](#), we implemented three sequential stages, detailed in the following sections. The resulting taxonomy provides a robust foundation for our process model, which clarifies the relationships among identified dimensions in AI-enabled workplace inclusion.

3.1. Step 1: Locating relevant research

The first step in our research protocol consisted of identifying studies following the PRISMA guidelines that could be considered relevant to our taxonomy. [Table 1](#) presents an overview of the data collection and selection criteria, providing a summary of the screening, eligibility and inclusion process.

Two of the authors independently reviewed all the papers and together reached a final agreement on the dataset for the study. As a result, the literature search yielded a set of 25 contributions (last update February 2024).

3.2. The taxonomy development process

As a second step, once the dataset was defined, we started constructing the taxonomy through the iterative development process suggested by [Nickerson et al. \(2013\)](#).

The iterative taxonomy development process ([Nickerson et al., 2013](#)) represents the core of this study (see [Fig. 1](#)). This process starts with the definition of the *meta*-characteristics (key objects relevant to a taxonomy) and the ending condition (criteria for concluding the iterative analysis). Then, two iterative approaches are used for analyzing the papers in the dataset (empirical-to-conceptual and conceptual-to-empirical) in order to reshape and validate the dimensions and their values through a compatibility check with the papers until the ending condition is met. The empirical-to-conceptual approach (inductive) begins by analyzing empirical data or existing evidence to identify common characteristics among objects or phenomena. Researchers start from empirical observations or specific examples and progressively group these into categories, subsequently abstracting these commonalities into broader conceptual dimensions. The dimensions and their characteristics emerge directly from empirical evidence. In contrast, the conceptual-to-empirical approach (deductive), begins conceptually,

Table 1
Description of the steps followed to define the final dataset.

Step	Process	Result	
Term search to identify the initial dataset by performing a query on the Scopus platform	Definition of the adopted technologies (based on the title, abstract and authors’ keywords)	“artificial intelligence” OR “robot” OR “chatbot” OR “cobot” OR “machine learning” OR “deep learning” OR “neural network” OR “algorithm”	304 papers
	Definition of the context in which the technology is used (based on the title, abstract and authors’ keywords)	“Human resource” OR “HR” OR “workplace” OR “worker” OR “employee”	
	Definition of the aspects to be investigated (based on the authors’ keywords)	“inclusion” OR “inclusiv*” OR “equity” OR “diversity” OR “discrimination” OR “fairness” OR “bias”	
Expansion of the dataset	Following a search for publications (published and unpublished) in scientific networks, reference lists and by authors active in the field, 7 additional papers were added to the dataset.	311 papers	
Automatic refining	Exclusion of papers not in English (9), not scientific (1) or duplicated (1).	300 papers	
Manual refining	Removal of 275 papers for the following reasons: –AI used as a research method: 20 papers –focus of the AI adoption not in HRM practices or organizational contexts: 123 papers –focus not on AI: 16 papers –focus not on inclusion: 58 papers –no primary data (e.g., systematic literature reviews, conceptual papers, commentaries): 58 papers	25 papers	

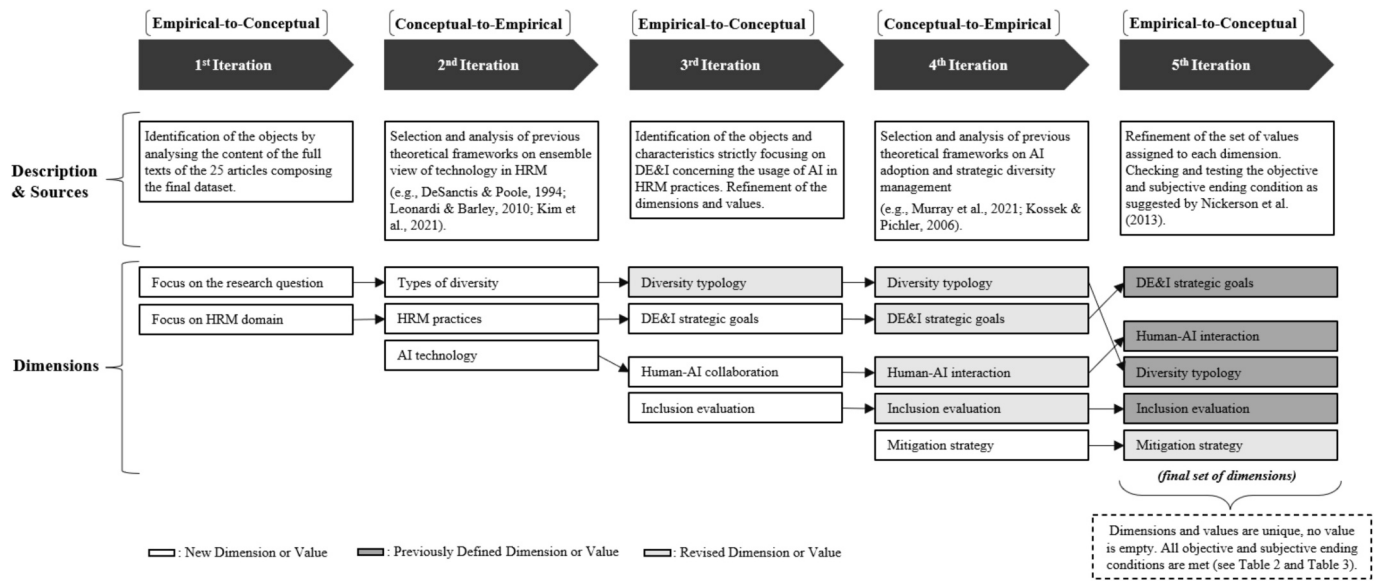


Fig. 1. Summary of the taxonomy development process.

with researchers using existing theories or frameworks to propose dimensions and their characteristics deductively. These theoretically derived dimensions are then tested empirically against available evidence to validate or refine their relevance and accuracy.

The aim is to achieve mutual exclusiveness and collective exhaustiveness (objective ending condition). This ensured that each contribution is assigned exactly one value for every dimension. Therefore, no contribution could acquire two different values for the same dimension. Finally, the characteristics of the dimensions and their values should also meet Nickerson et al.'s (2013) subjective ending condition: dimensions and values must be concise, robust, comprehensive, extendible and explanatory. Thus, every dimension helps investigate the nature and scope of each paper while keeping track of the specific issue under debate. In other words, to meet the ending condition, exhaustive dimensions and their respective values have to be defined (Kutzner et al., 2018; Nickerson et al., 2013).

In our study, all the authors engaged in multiple iterations resolving disagreements through discussion until achieving consensus on categorization (Gregor, 2006; Miles & Huberman, 1994). In the taxonomy development process, we used a combination of approaches, which allowed us to systematically code the gathered contributions (McKelvey, 1982; Za et al., 2018). We conducted five iterations.

The first iteration employed an empirical-to-conceptual approach to gain an initial understanding of the subjects directly aligned with our dataset. We systematically analyzed the full texts of the 25 selected articles in order to clearly define our research domain and formulate a clear research question. Our research domain focused on papers investigating the adoption of AI-enabled HRM practices aimed at enhancing workplace inclusion. This analysis allowed us to formulate the following research question: How can AI adoption foster workplace inclusion, particularly regarding the potential exacerbation or alleviation of inequalities among marginalized groups?

In the second iteration, adopting a conceptual-to-empirical approach, we selected and examined previous theoretical frameworks on the integration of technology within HRM contexts (Kim et al., 2021; Leonardi & Barley, 2010; DeSanctis & Poole, 1994). This theoretical review helped us establish three initial dimensions: 1) types of inclusion, 2) HRM practices, 3) AI technology.

The third iteration, again empirical-to-conceptual, further refined the dimensions based on a detailed analysis and coding of the papers. As a result, we fine-tuned the previous dimensions, adding a fourth one: (i) Inclusion typology, (ii) Inclusion strategic goals, (iii) Human-AI

collaboration, and the newly introduced (iv) Inclusion evaluation. However, further refinement was necessary to precisely define each dimension's specific values.

In the fourth iteration, employing a conceptual-to-empirical approach, we conducted another theoretical examination focusing on previous frameworks related to AI adoption and strategic diversity management (Murray, Rhymer & Sirmon 2021; Kossek & Pichler 2006). With theoretical consolidation as our goal, we refined existing dimensions and introduced a fifth dimension, (v) "Mitigation strategy", explicitly designed to capture actions aimed at addressing potential inclusion-related issues arising from AI adoption.

Finally, the fifth iteration, again empirical-to-conceptual, involved a comprehensive and collaborative refinement of all dimensions and their respective values, ensuring clarity, eliminating overlaps, and rigorously checking against both the objective and subjective ending conditions outlined by Nickerson et al. (2013). Upon meeting these conditions – ensuring dimensions and values were unique, exhaustive, and clearly defined – the taxonomy development process concluded.

More specifically, in the empirical-to-conceptual (inductive) iterations of the taxonomy development process, as suggested by Roy et al. (2025), we followed the guidelines provided in the literature (Miles & Huberman, 1994) and three independent coders carefully analyzed and coded the dataset according to these predefined themes and subthemes, ensuring accuracy and reliability throughout the coding process. Fig. 2 illustrates how the coding led to the taxonomy.

Subsequently, we applied the finalized taxonomy framework to systematically classify the selected dataset papers.

3.3. Step 3: process model development

The resulting taxonomy framework served as the basis for our process model on AI-enabled workplace inclusion. We used a causal network approach to evaluate which conditions, factors and patterns lead AI to achieve workplace inclusion (Miles & Huberman, 1994). We created a within-case processual matrix in which each row represented a study in our dataset and each column represented the dimensions resulting from the taxonomy development process. This matrix thus provided a summary of the types of dimensions that were consistent with or constrained other dimensions and revealed underlying themes and patterns. The final step was to connect specific variables and relations in an overarching model. To move to this cross-study level of analysis, we created meta-causal network sequences of the variables

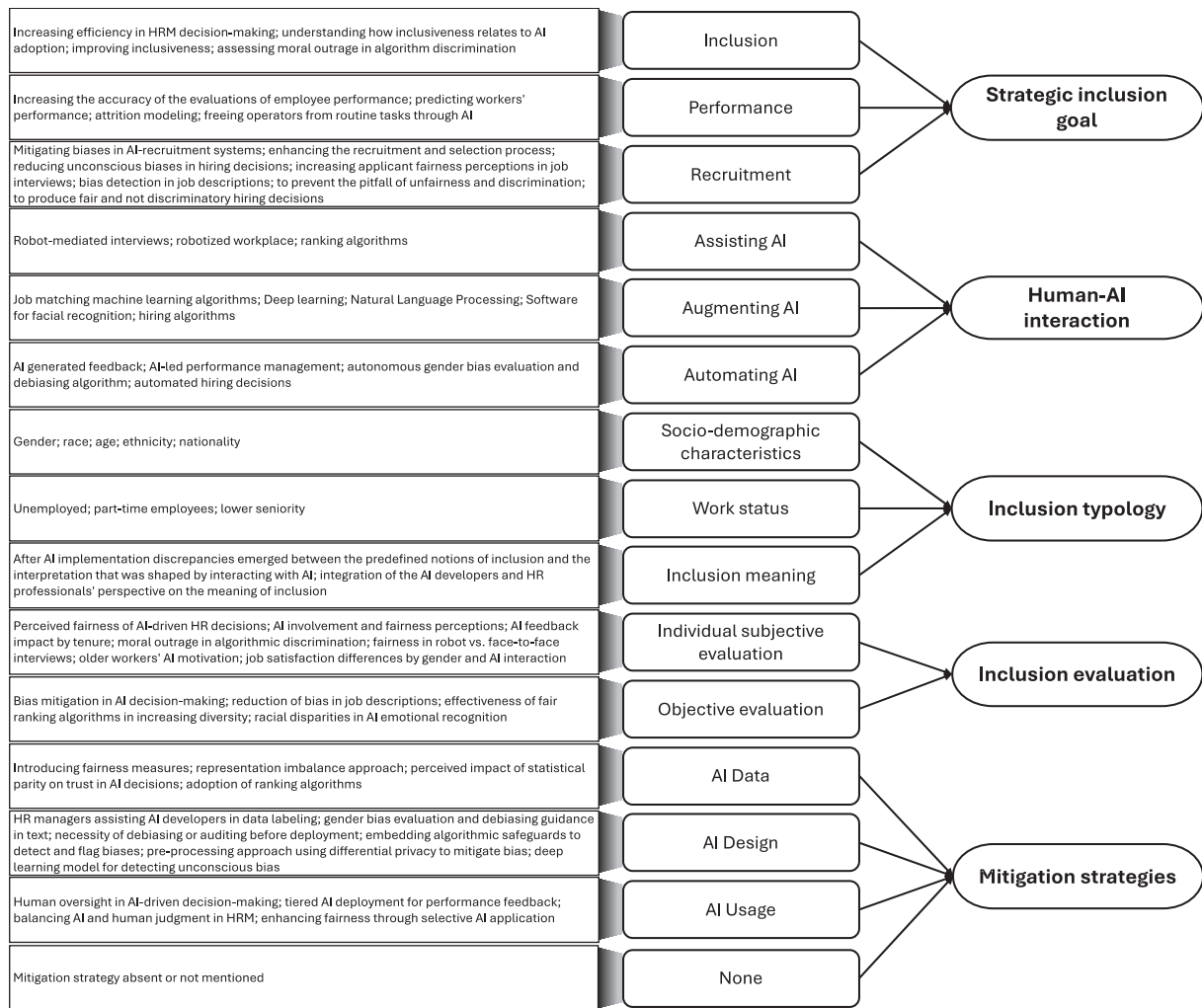


Fig. 2. Sample coding.

identified in each study. Using a compare-and-contrast exercise at the cross-case study level (Miles & Huberman, 1994), we matched each case-specific causal network to determine how specific relations performed across the complete set of studies. To ensure the validity of these relations, all the researchers conducted this analysis jointly. Divergent judgments regarding potential relations were assessed and resolved to capture the relevant issues emerging from the different studies.

4. Findings

4.1. The taxonomy-based framework

A synthesis of the dimensions and values of the taxonomy framework is presented in Table 2. Table 3 presents the taxonomy dimensions and their codes for each paper in our dataset.

As mentioned in the previous section, the taxonomy consists of five dimensions, namely the strategic goal of the implemented AI-led HRM practice, human-AI interaction, inclusion typology, inclusion evaluation and mitigation strategies. Below, we describe and provide examples for each dimension and the related values.

4.1.1. The strategic goal of the implemented AI-led HRM practice

The strategic goals dimension identifies the underlying reasons for AI adoption in HRM practices, specifically focusing on the management's motivations for using AI to manage workplace inclusion. Following Kossek & Pichler's (2006) framework, these goals encompass

recruitment, inclusion and performance outcomes.

The literature has so far been mainly concerned with the implementation of AI in inclusive recruitment practices (Kelan 2023). Existing research shows that the use of AI in recruitment primarily aim to support decision-making and to prevent unfair treatment and prejudice (Delecraz et al. 2022; Rhue 2018; Sühr, Hilgard & Lakkaraju 2021; Zhou et al. 2021; Köchling et al. 2021; El Ouadrhiri & Abdelhadi, 2021; Kubiak et al. 2023). Other studies have investigated bias reduction in hiring decisions (Soleimani, Intezari & Pauleen 2022; Hofeditz et al. 2022), the detection of bias (Bashar et al. 2021; Ramezanzadehmoghadam et al. 2021; Zhang et al. 2023) and the enhancement of applicants' fairness perceptions during job interviews (Nørskov et al. 2022; Bedemariam & Wessel 2023).

In the inclusion subdomain, the use of AI was intended to reduce workplace discrimination. For example, several studies (Bigman et al. 2020; Newman, Fast & Harmon 2020) explored the fairness perceptions of those affected by decisions made by algorithms, which in turn could challenge the notion of inclusion *per se* as AI shaped what came to be understood as inclusive in the physical (van den Broek et al., 2019) and virtual (Cutler et al. 2021) workplace.

With regard to performance, the use of AI was intended to create value from inclusion and generate financial effectiveness. This strategic goal highlighted the potential tension between the reasons for AI adoption (such as the promise of improved performance) and the actual outcomes (such as improvements in both performance and inclusion).

Several papers focused on the effect of AI on certain categories in the

Table 2
AI-enabled workplace inclusion taxonomy dimensions.

Dimension	Value	Value description
Strategic inclusion goal	Inclusion	AI employed to promote and support inclusion among employees
	Performance	AI employed to improve performances
	Recruitment	AI employed in order to attract and hire a more diverse workforce
Human-AI interaction	Assisting AI	Non-agentic technologies wielded by humans in both protocol development and action selection
	Augmenting AI	Agentic technologies which exercise intentionality over protocol development but not over action selection
	Automating AI	Agentic technologies which exercise intentionality over both protocol development and action selection
Inclusion typology	Socio-demographic characteristics	Groups of people positively or negatively impacted by AI according to their individual characteristics
	Work status	Groups of people positively or negatively impacted by AI according to their work status
	Inclusion meaning	Challenges to the meaning of inclusion shared within the organizational context due to AI adoption
Inclusion evaluation	Individual subjective evaluation	Subjective perceptions related to the adoption of AI-technologies for HRM purposes
	Objective evaluation	Intended and actual outcomes that AI adoption implies for diversity, equity and inclusion
Mitigation strategy	AI data	Mitigation strategies to remove systematic bias and account for skewed representation of individual or work characteristics in the trained dataset
	AI design	Mitigation strategies to reduce risk of discrimination by introducing discrimination checks and debiasing strategies or including more diversity in the AI development stage
	AI usage	Mitigation strategies involving managers and HR practitioners to increase sense of AI usage in HRM
	None	No mitigation strategies adopted

Table 3
AI-enabled workplace inclusion taxonomy dimensions and codes for each study.

Paper	Strategic goal	Human-AI interaction type	Inclusion typology	Inclusion evaluation	Mitigation strategy
01. Bashar et al. (2021)	Recruitment	Augmenting AI	Socio-demographic characteristics	Objective	Design
02. Bedemariam & Wessel (2023)	Recruitment	Automating AI	Socio-demographic characteristics	Subjective	Usage
03. Bigman et al. (2020)	Inclusion	Automating AI	Socio-demographic characteristics	Subjective	Usage
04. Blagoev et al. (2022)	Performance	Assisting AI	Socio-demographic characteristics	Subjective	None
05. Cutler et al. (2021)	Inclusion	Assisting AI	Work status	Objective	None
06. Delecraz et al. (2022)	Recruitment	Augmenting AI	Socio-demographic characteristics	Objective	Design
07. Harris (2022)	Recruitment	Augmenting AI	Socio-demographic characteristics	Objective	Data
08. Hofeditz et al. (2022)	Recruitment	Augmenting AI	Socio-demographic characteristics	Objective	Usage
09. Hu et al. (2022)	Recruitment	Automating AI	Socio-demographic characteristics	Objective	Design
10. Köchling et al. (2021)	Recruitment	Augmenting AI	Socio-demographic characteristics	Objective	Data
11. Kubiak et al. (2023)	Recruitment	Augmenting AI	Socio-demographic characteristics	Objective	Data
12. Newman et al. (2020)	Inclusion	Automating AI	Socio-demographic characteristics	Subjective	Usage
13. Nørskov et al. (2022)	Recruitment	Assisting AI	Work status	Subjective	None
14. El Ouadrhiri & Abdelhadi, 2021	Recruitment	Automating AI	Socio-demographic characteristics	Objective	Design
15. Ramezanzadehmoghadam et al. (2021)	Recruitment	Automating AI	Socio-demographic characteristics	Objective	Design
16. Rhue (2018)	Recruitment	Augmenting AI	Socio-demographic characteristics	Objective	Design
17. Soleimani et al. (2022)	Recruitment	Augmenting AI	Inclusion meaning	Objective	Design
18. Speer (2021)	Performance	Augmenting AI	Socio-demographic characteristics	Objective	Design
19. Sühr et al. (2021)	Recruitment	Assisting AI	Socio-demographic characteristics	Objective	Data
20. Tong et al. (2021)	Performance	Automating AI	Work status	Subjective	Usage
21. Toyoda et al. (2021)	Performance	Augmenting AI	Socio-demographic characteristics	Objective	Design
22. Turja et al. (2022)	Performance	Assisting AI	Socio-demographic characteristics	Subjective	None
23. van den Broek et al. (2019)	Recruitment	Augmenting AI	Socio-demographic characteristics	Subjective	Data
24. Zhang et al. (2023)	Recruitment	Augmenting AI	Socio-demographic characteristics	Objective	Design
25. Zhou et al. (2021)	Inclusion	Augmenting AI	Inclusion meaning	Subjective	Usage

evaluation of employee performance ([Tong et al. 2021](#); [Toyoda, Lucas & Gratch 2021](#)) or on reducing the potential for group discrimination when predicting turnover ([Speer 2021](#)). In other cases, AI was adopted in order to improve organizational effectiveness, thus impacting certain groups' motivation ([Blagoev, Shustova & Protas 2022](#)) or job satisfaction ([Turja et al. 2022](#)).

This threefold categorization of the strategic goals provides a comprehensive framework for understanding the motivations for AI adoption in HRM. The framework enables a nuanced analysis of how varying strategic objectives influence workplace inclusion outcomes, contributing to an integrated understanding of AI-enabled workplace inclusion. The taxonomy specifically allows the examination of potential disconnects between intended and realized outcomes across these strategic dimensions. Consider, for instance, how organizations implementing emotion-detecting video interview platforms typically frame their adoption around recruitment goals – seeking to eliminate interviewer bias and create fairer selection processes. However, when these systems systematically misinterpret emotional expressions from candidates with different cultural backgrounds, the intended recruitment fairness transforms into exclusion by design, revealing the gap between strategic theoretical intentions and inclusion pragmatic outcomes.

4.1.1.2. *Conjoined agency: human-AI interaction*

The human-AI interaction dimension encompasses both technology types and the conjoined agency of humans and agentic technologies. This framework enables the categorization of AI applications in HRM based on their level of conjoined agency and inclusion impacts. We identified three key values – *assisting AI*, *augmenting AI* and *automating AI* – drawing from [Murray et al. \(2021\)](#). Note that *arresting AI* did not emerge in our analysis. These distinctions prove crucial in practice. An HR chatbot that simply provides information about practices and policies (assisting AI) creates minimal inclusion risks, primarily affecting employees with potential language barriers. However, an algorithmic performance management system that independently generates employee ratings (automating AI) could disadvantage employees whose work styles and patterns (i.e. different approach to time – see [Georgiadou & Damianidou, 2025](#)) don't align with algorithmic expectations, creating profound inclusion implications that require complicated mitigation strategies.

These categories of human-AI interaction provide a framework for

understanding how different levels of conjoined agency in HRM practices may influence workplace inclusion. By including this concept in our taxonomy, it is possible to analyze the complex interplay between AI technologies and human decision-makers in shaping inclusive workplace environments.

Assisting AI is non-agentic technology in which humans control both protocol development and action selection. These tools enhance efficiency while maintaining human control over decision-making processes. Examples in the literature included AI-mediated job interviews (Nørskov et al. 2020), routine task automation (Turja et al. 2022) and recruitment ranking algorithms (Sühr, Hilgard & Lakkaraju 2021).

Augmenting AI technologies exercise intentionality in protocol development but not in action selection. These systems provide recommendations while preserving human decision-making authority. Examples included job-matching ML algorithms for fair recruitment decisions (Delecraz et al. 2022), employee turnover prediction (Speer 2021), facial recognition for performance predictions (Köchling et al. 2021; Toyoda, Lucas & Gratch 2021) and bias detection in job descriptions (Bashar et al. 2021; Ramezanzadehmoghadam et al. 2021).

Finally, *automating AI* exercises intentionality in both protocol development and action selection. These systems independently gather data, formulate rules and make decisions, effectively substituting human decision-making. Notable applications included state-of-the-art DL neural network-based performance evaluation systems (Tong et al. 2021) and bias evaluation algorithms for job descriptions (Hu et al. 2022; El Ouadrhiri & Abdelhadi, 2021).

Critical examination of these technologies has revealed complex implications for workplace inclusion. For instance, Bedemariam & Wessel (2023) conducted a study testing an AI-based selection tool that autonomously declined candidates. Their findings indicated that Black applicants rejected by the AI algorithm reported more negative procedural justice reactions compared to those rejected by human evaluators. Furthermore, a pairwise comparison revealed that Black participants accepted by the AI algorithms reported stronger procedural justice reactions than those accepted by human HRM. However, the condition (AI vs. HRM) had no significant effect on the general fairness reactions of White applicants, regardless of the outcome (acceptance or rejection). These findings highlighted the complex and potentially differential effects of automating AI on workplace inclusion, particularly for marginalized groups.

The human-AI interaction dimension reveals critical relationships between adoption factors and outcomes. While organizations may implement assisting AI to support decision-making and reduce bias, its success depends on the human utilization of the AI insights. Similarly, automating AI aimed at eliminating human bias requires careful design and monitoring to prevent its adoption perpetuating or amplifying existing biases. This framework enables the analysis of the complex interplay between AI technologies and human decision-makers in creating inclusive workplace environments.

4.1.3. Inclusion typology

The inclusion typology dimension relates to how inclusion is understood and put into practice in the literature examining how AI adoption affects inclusion in HRM decision-making. This part of our taxonomy is vital as it helps us categorize and analyze the various aspects of diversity and inclusion that AI-enabled HRM practices try to address. Including this dimension gives us a more detailed understanding of how AI affects different elements of workplace inclusion.

Most studies in our dataset mentioned inclusion in terms of special groups of people who may be either positively or negatively influenced by the AI adoption based on *socio-demographic characteristics* like race, gender, and age. This focus on demographic characteristics of diversity and inclusion tradition, although important, may not capture the whole picture of the workplace inclusion when AI is used in HRM practices.

Gender and race were the most frequent characteristics explored in relation to AI adoption (Zhang et al. 2023; Hofeditz et al. 2022;

Bedemariam & Wessel 2023; Kubiak et al. 2023; Zhou et al. 2021; Delecraz et al. 2022; Toyoda, Lucas & Gratch 2021), followed by age (Bigman et al. 2020; Harris 2022; Blagoev, Shustova & Protas 2022). These findings highlighted the potential of existing or even worsening biases in the application of AI and the ability to tackle more implicit forms of exclusion.

A number of studies considered *work status* as a source of inclusion and more specifically how aspects like tenure, unemployment and part time work impacted people's perceptions of AI in HRM decisions (Tong et al. 2021; Cutler et al. 2021; Nørskov et al. 2022). This extended the view of inclusion to factors that are not demographic in nature, but rather derive from the organization and its employment relationships.

Interestingly, a few studies questioned what inclusion actually *means*, highlighting how using AI for HRM purposes challenged the shared understanding of inclusion within specific organizational settings (Soleimani et al., 2022; van den Broek et al., 2019).

The inclusion typology dimension of our taxonomy allows the examination of both the intended targets of AI-enabled inclusion efforts (adoption factors) and the actual impact on different groups (outcome). For instance, an organization might adopt AI-powered recruitment tools with the intention of increasing gender diversity (adoption factor targeting socio-demographic characteristics). However, the outcome of this initiative would be evaluated by the actual change in gender representation and the experiences of women in the organization's post-adoption phase.

4.1.4. Inclusion evaluation

The inclusion evaluation dimension considers whether the effect of AI on inclusion is measured according to individual subjective perception or objective gauges. This dimension of our taxonomy is crucial as it captures the multifaceted nature of inclusion outcomes in AI-enabled HRM practices, acknowledging that the impact of AI on workplace inclusion can be assessed from different perspectives.

Individual subjective evaluation has been adopted, for example, in laboratory studies to measure if people affected by algorithmic decisions (e.g., employees, job candidates) felt these decisions were less fair than those made by humans, even when the results were exactly the same (Bedemariam & Wessel 2023; Newman, Fast & Harmon 2020). This approach showed how important perceived fairness is in AI-enabled HRM practices, which can greatly affect how included employees feel and how committed they are to their organization.

Research examining AI's impact on inclusion has employed various methodological approaches. Tong et al. (2021) conducted field experiments examining how employees responded to AI-generated versus human-manager performance feedback. In recruitment contexts, Nørskov et al. (2022) investigated the fairness perceptions of robot-mediated job interviews from both the applicants' and HRM professionals' perspectives, while Zhou et al. (2021) studied perceptions of AI fairness when gender-focused fairness measures were introduced.

The evidence regarding AI's effect on inclusion presents a complex picture. Some studies have indicated positive outcomes: unemployed job candidates viewed AI-led selection processes as fairer (Nørskov et al. 2022) and recruitment process demonstrated improved gender fairness when specific measures were adopted (Zhou et al. 2021). Hofeditz et al. (2022) found that AI-based systems reduced discrimination against older and female candidates, though notably, the same system selected fewer candidates from foreign backgrounds.

However, research has also uncovered potential problems. Newman et al. (2020) found that people viewed algorithmic HRM decisions as less fair than identical decisions with more human involvement, regardless of gender, ethnicity or age. Interestingly, Bigman et al. (2020) found that discriminatory outcomes caused less moral outrage when blamed on algorithms rather than human decision-makers, suggesting that AI might accidentally normalize certain types of discrimination.

Objective evaluation is related to the analysis of intended and actual outcomes on inclusion implied by AI adoption, mainly through DL

models that detect unconscious bias in content (Bashar et al. 2021; Ramezanzadehmoghadam et al. 2021) or algorithmic analysis for facial recognition on a real dataset of videos or pictures (Rhue 2018; Köchling et al. 2021). As positive consequences on inclusion, objective evaluation has shown that fair ranking algorithms increased female candidates (Kubiak et al. 2023; Sühr, Hilgard & Lakkaraju 2021) and that recruitment biases were mitigated when AI was adopted, thereby keeping the recruitment process fairer (Bashar et al. 2021; Ramezanzadehmoghadam et al. 2021; Hu et al. 2022). On the flip side, several studies have shown that AI repeated existing inequalities and bias in the recruitment process and negatively affected the inclusion of female, older and dark-skinned workers (Zhang et al. 2023; Toyoda, Lucas & Gratch 2021; Speer 2021).

Including both subjective and objective evaluation measures in our taxonomy fits with the theoretical concept of organizational justice (Colquitt et al., 2013), which covers both perceived (subjective) fairness and actual (objective) fair treatment. This dual approach allows for a more thorough evaluation of AI's impact on workplace inclusion, capturing both the lived experiences of employees and measurable changes in organizational diversity and inclusion metrics.

4.1.5. Mitigation strategies

Given the potential negative impact that AI can have on inclusion, the last dimension refers to strategies to mitigate the effects analyzed by the papers in our dataset. This dimension is crucial for our integrated concept of AI-enabled workplace inclusion as it acknowledges the proactive measures organizations can take to ensure that AI implementation helps rather than hinders inclusion. The subset of values for this dimension consists of *AI data*, *AI design* and *AI usage*.

Mitigation strategies focusing on *AI data* aimed to remove systematic bias and account for skewed representation of individual or work characteristics in the trained dataset that the AI relies on. For example, underrepresentation of a certain gender or ethnicity in the training dataset may lead to an unpredictable overestimation and/or underestimation of the likelihood of inviting representatives of these groups to a job interview. Ways to help reduce such a risk were: using gender-blind data (Kubiak et al. 2023); introducing to the dataset fairness measures such as statistical parity to represent fairness or implementing calibration and correction methods to tackle class imbalance problems (Köchling et al. 2021; Zhou et al. 2021).

Another set of mitigation strategies referred to *AI design*. These were initiatives undertaken in the design stage of the AI system in order to reduce discrimination risk. This was done by introducing discrimination checks and debiasing strategies or by including more diversity in the AI developing teams. Some examples of AI design strategy were: adopting a pre-processing approach that used differentiated privacy properties to mitigate sensitive attribute bias by introducing a randomized response mechanism to reduce inequity and avoid discrimination resulting from the training dataset (El Ouadrhiri & Abdelhadi, 2021); embedding safeguards in the AI-based automation process algorithm that flagged possible biases and measured them in order for the decisions made by the ML algorithm matching job applicants with job offers to be as fair as possible (Delecraz et al. 2022); auditing and adjusting algorithms (e.g., removing variables, changing variable weights) to remove bias (Speer 2021; Toyoda, Lucas & Gratch 2021). Interestingly, collaboration between the HRM department and AI developers was advocated in the design phase of AI for HRM decision-making in order to reduce discrimination risks (Soleimani, Intezari & Pauleen 2022).

The *AI usage* mitigation strategy was more related to creating a sense and vision around the adoption of AI for HRM decision-making and increasing awareness of discrimination risks and debiasing strategies. According to the papers in our dataset, some companies considered training HR practitioners to deploy AI in a differentiated rather than uniform approach where the level of AI use varied based on employees' characteristics or roles. For example, companies could consider using AI to provide performance feedback to veteran employees thanks to their

familiarity with the organizational context, but using managers to provide performance feedback to novices who lacked information about the context and the overall reasons for AI adoption in the HRM systems (Tong et al. 2021). Moreover, HRM managers could reduce the employees' perceptions that AI-led HRM decision-making was reductionistic and therefore less fair by emphasizing that the algorithm was just one factor human decision-makers had the option of considering when selecting which actions to implement (Newman, Fast & Harmon 2020) or providing job candidates with information about the functionality of an AI-based system (Hofeditz et al. 2022).

The mitigation strategies dimension of our taxonomy aligns with the theoretical concept of responsible AI, which emphasizes the need for ethical considerations in the development and deployment of AI systems. By categorizing mitigation strategies into data, design and usage-related approaches, our taxonomy provides a comprehensive framework for implementing responsible AI-based practices in HRM.

Moreover, this dimension helps reconceptualize inclusion in the context of AI-enabled HRM by highlighting the proactive measures organizations can take to ensure AI promotes inclusivity. It shifts the focus from merely avoiding discrimination to actively fostering an inclusive environment through thoughtful AI implementation.

4.2. The AI-enabled workplace inclusion process model

In order to answer our research question on how AI adoption can help or hinder a company's efforts to promote inclusion, we modelled a sequence of events based on the underlying patterns present in the studies included in our dataset. Indeed, in addition to Table 3, which summarizes the variables identified in each paper on the effect of AI adoption on inclusion, we put together a pattern of sequencing variables considered meaningful across all studies. From this, we built a meta-causal network (Miles & Huberman, 1994) describing what happens when companies adopt AI in order to achieve inclusion goals. Fig. 3 summarizes the sequence of events involved in the AI adoption process model leading to workplace inclusion. The grey boxes represent the stages in AI adoption, moving from non-agentive to agentive technologies that influence what kind of mitigation strategies are needed in order to overcome discrimination risks and lead to inclusion. Moreover, the solid arrows in Fig. 3 point to mainly technology-related sequences of events, while the broken lines indicate the themes related to the notion of inclusion that emerge when AI is adopted.

The genesis of an AI process for all stages of HRM decision-making is contingent upon the organizational impetus to incorporate AI to boost inclusion in HRM decision-making. Our findings suggest that these factors can be broadly categorized into three principal types, as per Kossek & Pichler's (2006) model: recruitment, inclusion and performance. In line with this taxonomy, strategic inclusion goals may be geared towards current employees with contextual knowledge of the organization, for example, in initiatives to foster inclusivity and performance. Conversely, initiatives to amplify inclusion in recruitment may target prospective employees who possess a limited understanding of the company's context. In the absence of other pertinent information, these may make use of peripheral cues from the AI technology adopted to infer the company's inclusiveness.

While the outcomes of AI adoption to promote inclusion may be either positive or negative, the link between AI adoption and its consequences appears to depend on the capacity of the AI technology adopted to exercise intentionality. More specifically, when non-agentive assisting technologies are adopted (e.g., robots, ranking algorithms), there seems to be a lower risk of AI exacerbating discrimination since the impact of these technologies on inclusion is highly dependent on the humans who wield them. Indeed, most of the studies on the effect of adopting assisting AI on inclusion have reported positive outcomes, such as an increase in female candidates due to fair ranking algorithms (Sühr, Hilgard, and Lakkaraju 2021), increased fairness perceptions among the unemployed when teleoperated robots are adopted for job interviews

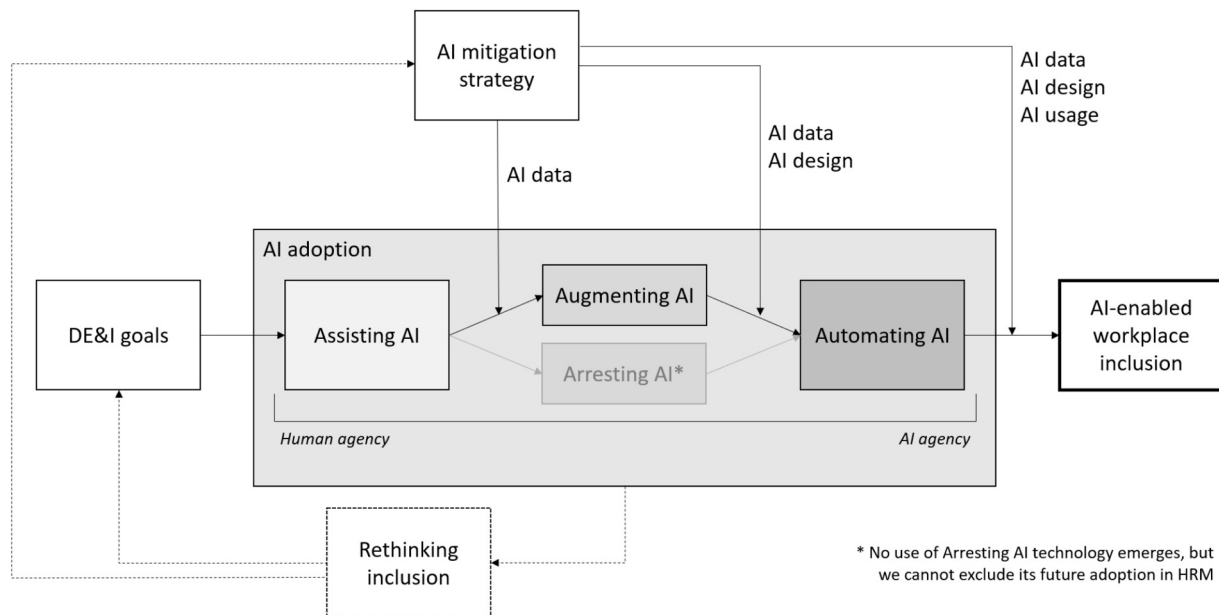


Fig. 3. The AI-enabled workplace inclusion process model.

(Nørskov et al. 2022) and improved inclusiveness of part-time employees (Cutler et al. 2021). Notably, only one case – among older workers in the bank sector – showed the adoption of robots leading to lower motivation (Blagoev, Shustova & Protas 2022). Therefore, in order to achieve workplace inclusion, it seems that no mitigation strategies are needed when assisting AI is involved.

However, the situation is slightly more nuanced when organizations move towards adopting more agentic AI technologies. In this respect, the situation becomes more complicated upon the adoption of augmenting AI that develops protocols and predictive recommendations, thus complementing humans. In this situation, several papers have suggested that ML systems promote gender fairness in the recruitment process (Kubiak et al. 2023; Zhou et al. 2021) or that DL models decrease bias in job descriptions, therefore keeping the recruitment process fairer (Harris 2022; Bashar et al. 2021; Ramezanzadehmoghadam et al. 2021). On the opposite side, the likelihood of augmenting AI having an adverse impact on women, older and dark-skinned workers, thus replicating existing inequalities and bias in the recruitment process, has been found to be high (Toyoda, Lucas & Gratch 2021; Speer 2021). Interestingly, the findings have shown that AI data mitigation strategies need to be adopted in order to move from assisting AI to augmenting AI adoption without undermining inclusion efforts. For example, in the case of systems that use historical recruiting data to train a ML model and predict whether a candidate would be hired, systematic information (Kubiak et al. 2023) or bias needs to be removed from the trained dataset, in order to promote fairness in the recruitment process (Zhou et al. 2021). Therefore, augmenting AI may lead to more inclusion if AI data mitigation strategies such as fairness measures or calibration and correction methods are adopted in advance (Köchling et al. 2021; Zhou et al. 2021). Interestingly, the meaning of inclusion within the specific organizational context is called into question when companies start delegating the development of protocols and recommendations to augmenting AI, for example (Soleimani et al., 2022; van den Broek et al., 2019). Indeed, if no agentic technology is adopted, the meaning of inclusion is considered unproblematic and shared among members. But the delegation of inclusion responsibilities to agentic technologies leads stakeholders to rethink what comes to be understood as inclusive under the AI umbrella and to reconsider and negotiate the inclusion goals as well as the mitigation strategies that need to be put in practice to keep the AI system inclusive. Thus, the notion of inclusion needs to be rethought to adapt to the new circumstances of AI adoption in HRM decision-making.

Also, the transition towards the most agentic stage, namely the adoption of automated AI that substitutes humans in HRM decision-making, requires specific mitigation strategies to reduce the risk of discrimination. More specifically, the objective outcome of automating AI adoption seems to be positive since it seems to mitigate recruitment biases, but this can only be achieved if AI design mitigation strategies such as pre-processing or debiasing algorithms are adopted (Hu et al. 2022; El Ouadrhiri & Abdelhadi, 2021). Moreover, studies on the effect of automating AI on inclusion have mainly been focused on exploring how algorithm-driven HRM decisions are perceived by current employees. For example, AI feedback disclosure (namely informing employees that feedback is AI produced) seems to produce a less severe negative effect among employees with longer tenure (Tong et al. 2021). Interestingly, in some cases, HRM decisions taken by automating AI were perceived to be less fair than identical decisions featuring more human involvement (Newman, Fast & Harmon 2020). In other cases, people were less morally outraged when age, race and gender discrimination was perpetrated by an algorithm rather than by humans (Bigman et al. 2020). Therefore, only when the organization internally adopts automating AI for inclusion and performance goals an AI usage mitigation strategy is needed to create a sense and vision among employees around inclusion-oriented AI adoption for HRM decision-making.

5. Discussion

5.1. Theoretical implications

When examining AI-enabled workplace inclusion through a multi-level lens (Georgiadou et al., 2024), we can identify three distinct but interrelated level of analysis (Fig. 4): inclusion *in* work (individual level), inclusion *at* work (organizational level) and inclusion *of* work (human-AI interaction level). Each level requires specific consideration of how different forms of AI agency interact with workplace dynamics.

At the individual level, inclusion *in* work focuses on personal experiences and engagement with AI-enabled HRM systems. Our process model reveals that as organizations progress from assisting to augmenting AI, individual experiences of inclusion become increasingly dependent on AI data mitigation strategies. For example, when implementing AI-enabled performance management systems, organizations must ensure that individual work styles and contributions are fairly recognized. This calls for specific strategies to address data problems,

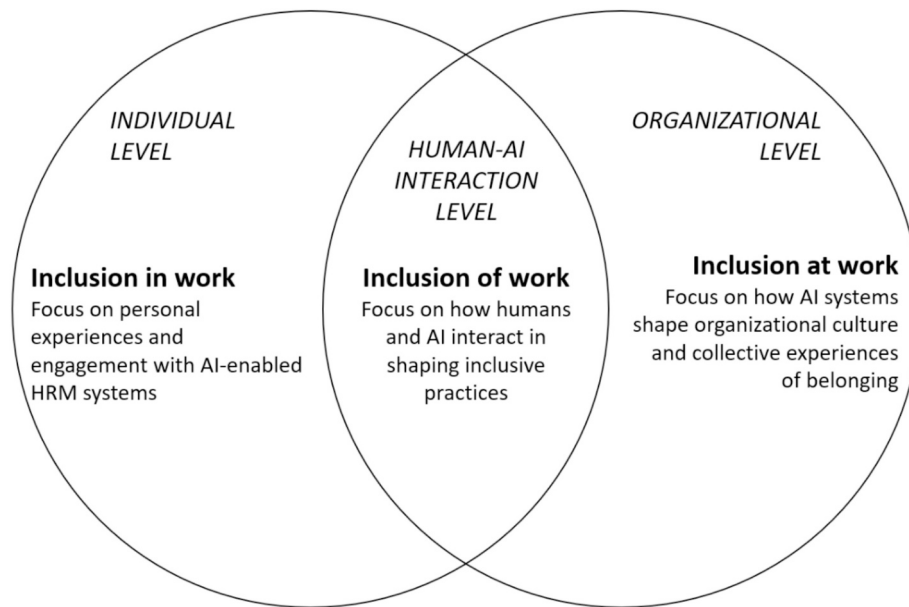


Fig. 4. Reconceptualization of workplace inclusion in the context of AI adoption.

like cleaning systematic bias from the datasets used for training and putting in place fairness measures for AI-based systems.

Whether these strategies work depends on keeping distributive fairness (Colquitt et al., 2013); that is making sure that when AI makes decisions about resources and opportunities, these are shared fairly among all staff members. This individual dimension is especially critical as employees come to interpret the AI systems, with what they attribute to these systems significantly influencing their sense of inclusion (Newman et al., 2020; Nishii et al., 2008). Therefore, to address inclusion *in* work, a focus is needed on individual experiences and the personal implications of AI technologies.

Inclusion *at* work examines how AI systems shape organizational culture and collective experiences of belonging. Our process model illustrates that as organizations adopt more agentic AI technologies, there is an increasing need for organizational-level mitigation strategies. This dimension requires careful consideration of how AI systems influence the organizational climate, group dynamics and shared understanding of inclusion.

For the successful implementation of automating AI, there are specific mitigation strategies that should be used at the organizational level, starting from the idea of a shared meaning of AI adoption and trust in AI-based decisions. These organizational level strategies are consistent with procedural fairness concept (Colquitt et al., 2013), which deals with the issues of openness and regularity of the AI enabled processes within the organization. The effectiveness of AI in this level depends on the general organizational context in which it is applied because the same systems can lead to different inclusion outcomes in different organizations (Mor Barak, 2010). In order to achieve workplace inclusion, the focus has to be on the collective experiences and shared perceptions that are influenced by AI systems.

Inclusion *of* work concerns the meta-level integration of AI into workplace systems, emphasizing how humans and AI interact in shaping inclusive practices. The process model shows that this dimension becomes increasingly important as organizations move towards more agentic AI technologies. The model indicates that to achieve inclusion of work, specific design-related mitigation strategies are needed, particularly when implementing augmenting or automating AI. These strategies focus on interactional fairness (Colquitt et al., 2013); namely they address how staff members interact with and experience AI systems in their everyday work.

The human-AI interaction dimension shows how important

collaborative approaches are when implementing AI, involving different stakeholders in designing and deploying the system. This aligns with AST (DeSanctis & Poole, 1994), which posits that the effectiveness of technological systems largely depends on how people utilize existing norms and communication processes to structure their interactions with technology.

The interaction between inclusion *in* work, *at* work and *of* work is crucial to understanding the complexities of AI implementation in organizations. Our process model provides a nuanced perspective by connecting these levels of inclusion, which are often addressed separately in the existing research, highlighting their interdependence and collective impact on workplace dynamics.

First of all, this model builds on the existing theoretical frameworks in several critical ways. In relation to attribution theory, it increases our knowledge about how employees interpret the meaning of AI-enabled HRM practices, particularly with respect to how these attributions affect their perceptions of inclusion across the individual, organizational and interactive levels (Nishii et al., 2008). For instance, based on their beliefs, employees may consider AI systems to be more unbiased and more transparent than human driven systems, which would impact their sense of inclusion *in* work, or may consider them as impersonal and detached and, therefore, may have a different perception of inclusion *at* work. These interpretations can shape how AI is received and trusted across different organizational layers, demonstrating that attribution is not a uniform process but one deeply influenced by the specific type of AI technology and its role in the HRM strategy. Moreover, our model builds on AST (DeSanctis & Poole, 1994), revealing the dynamic relationship between technology and social systems by illustrating how various forms of AI agency influence workplace inclusion. AST posits that technology use in organizations is shaped by both existing norms and the way individuals and groups adapt to new systems. Our findings indicate that AI adoption, from assisting to automating technologies, can redefine organizational norms and practices around inclusion. As employees adapt and respond to AI interventions, they either reinforce or transform organizational practices and structures, with each level of inclusion requiring distinct strategies to align AI use with the organization's inclusion goals.

Secondly, our model suggests that the three dimensions of inclusion are deeply interconnected in ways that become more apparent as organizations adopt more sophisticated AI technologies. For example, individual experiences of inclusion (*in* work) significantly influence and

are influenced by the organizational climate (*at work*), while both dimensions shape and are shaped by the ways in which humans and AI systems interact (*of work*). This interconnectedness suggests that organizations must maintain a balanced focus across all three dimensions to achieve meaningful inclusion outcomes.

When examining assisting AI technologies, we found that inclusion outcomes are highly dependent on human agency, with relatively few discrimination risks requiring mitigation strategies. This suggests that to build trust and understanding, organizations might begin their AI implementation journey with these technologies while developing their inclusion capabilities. The transition to augmenting AI introduces new complexities across all three dimensions of inclusion. At the individual level (*inclusion in work*), our model shows that AI systems can promote gender fairness in recruitment processes but may also replicate existing inequalities if not carefully managed. The dual nature of AI systems demonstrates why data-related mitigation strategies are essential for addressing bias in training datasets (Köchling et al., 2021; Zhou et al., 2021).

The organizational dimension of inclusion *at work* becomes vital when organizations implement AI because employees start to redefine organizational inclusion according to their workplace context (Soleimani et al., 2022). Organizations can develop advanced workplace inclusion strategies through this questioning process which addresses the distinctive characteristics of digital technologies. The transition to automated AI systems creates the most significant barrier to work inclusion which demands advanced design-based solutions to establish fair and transparent decision-making systems.

The model indicates that AI system success during this stage requires stakeholder participation from all organizational levels during both design and operational phases. Research indicates that automated systems can minimize recruitment biases when properly designed (Hu et al., 2022; El Ouadrhiri & Abdelhadi, 2021). Each dimension requires unique mitigation strategies that resolve its particular challenges. Nevertheless, consideration must also be given to how these strategies interact. For example, data-related strategies primarily support inclusion *in work* by ensuring fair treatment at the individual level, while design-related strategies foster inclusion *of work* by promoting positive human-AI interactions. Usage-related strategies promote inclusion *at work* by helping organizations cultivate supportive climates for AI adoption.

Thirdly, our model emphasizes the need for a continuous, iterative approach to AI implementation, wherein organizations pay attention to the evolving organizational climate and employee experiences so as to maintain inclusion outcomes across all dimensions. The progression from assisting to automating AI should not be viewed as a linear path but rather as an iterative process in which organizations may need to move between different forms of AI agency depending on the specific context and inclusion goals. Indeed, our model reveals that the impact of automating AI on inclusion varies significantly depending on the strategic goal being pursued. This dynamic perspective helps explain why similar AI implementations can produce different inclusion outcomes across organizations. When used for recruitment purposes, automated systems might reduce discrimination through objective decision-making processes. However, when applied to internal organizational processes like performance evaluation, these systems need careful attention to usage-related mitigation strategies to maintain employees' trust and perception of fairness.

The model also highlights the critical role of feedback loops in maintaining and enhancing inclusion across all dimensions. As organizations implement AI systems, they must continuously monitor and adjust their approaches based on inclusion outcomes. This ongoing process of assessment and adaptation is particularly important given the rapidly evolving nature of AI technology and its applications in HRM. Our multilevel framework extends paradox theory (Schad et al., 2016) by revealing how the automation-augmentation tension identified by Raisch and Krakowski (2021) manifests differently across levels of

inclusion. At the individual level (*inclusion in work*), the paradox emerges as organizations attempt to reduce subjective bias through automation whilst needing human expertise to ensure fair data strategies. At the organizational level (*inclusion at work*), it surfaces in tensions between standardized, automated processes and the human judgment needed for inclusive climate development. At the interaction level (*inclusion of work*), the paradox appears in the delicate balance between AI's consistent application of rules and humans' contextual understanding. These nested paradoxes suggest that effective AI-enabled inclusion requires organizations to develop capabilities for managing tensions across multiple levels simultaneously.

5.2. Limitations and future research

Although our study has taken the theory on AI adoption in HRM and workplace inclusion forward by drawing up a taxonomy framework and a process model across a diverse set of studies, the following limitations should be considered when evaluating the findings. Even though the sample size of the dataset was aligned with other studies developing process models (e.g., Lazazzara et al., 2020), it was not easy to locate papers relevant to the specific research question addressed in our study, also considering the current early phase of knowledge of the possible pitfalls of AI in HRM and the lack of relevant empirical studies (Köchling & Wehner 2020). Moreover, owing to the novelty and large amount of ongoing research on this topic, it is impossible to guarantee full coverage of the papers empirically dealing with it. In addition, most of the papers in the first iteration of our taxonomy development process were excluded due to the lack of primary data (e.g., conceptual papers, literature reviews). However, this study does not adopt a systematic review approach; rather, it can be defined as a theory development approach based on redirection (Cronin & George 2023). Therefore, future research would benefit from more relevant empirical studies, particularly those that are sensitive to contextual aspects, in order to empirically test the theory we have developed.

An additional particular concern in the search for pertinent research for our investigation was the ambiguity surrounding the concept of inclusion. It is important to acknowledge that inclusion is related to, yet distinct from, non-discrimination and bias. The former centers on the engagement and integration of specific groups in HRM policies and practices that facilitate the complete utilization of human resources and enhance employees' optimum contribution potential (Georgiadou & Antonacopoulou, 2021; Roberson, 2006). To avoid potential concept drift, we limited our final dataset to studies that concurrently examined specific HRM practices and well-defined target groups (e.g., those distinguished by specific demographic or job-related features). Interestingly, our results indicate that the implementation of AI shapes a new interpretation of inclusion. Consequently, further clarification and operationalization of inclusion, especially inclusion *of work*, is necessary to create it within contemporary digital workplaces.

Finally, we acknowledge that, following the classification of human-AI collaboration, there is a lack of evidence of the adoption of one type of conjoined agency, namely arresting technologies, in HRM. Considering the four forms of conjoined agency defined by Murray et al. (2021), the use of AI as arresting technology seems difficult to pinpoint. Indeed, to be classified as arresting technology, its behavior (its decisions or constraints) should be encoded in the algorithm so that it is executed every time specific conditions are satisfied, while nevertheless allowing humans to develop the protocol (guidelines on what to do). Instead, what emerged from this research is that AI technology is often only used to assist humans or develop the protocol, in the latter case also with the possibility of letting AI technology make decisions on behalf of humans. There is no evidence of the adoption of arresting technologies in HRM.

Future research may explore if and how arresting technologies (e.g., blockchain) may be applied to HRM and the related mitigation strategies needed for their adoption in HRM. This represents a significant gap in our understanding of AI applications in inclusion contexts, as blockchain

and similar technologies could offer transparent, immutable record-keeping that potentially fosters trust in algorithmic decision-making whilst still maintaining human oversight. Such research could examine whether arresting technologies might provide a middle ground between full automation and human-intensive augmentation approaches.

Moreover, the three forms of AI technology applied in our process model (i.e., assisting, augmenting and automating) could provide the starting point for defining a maturity model for the adoption of AI and the related mitigation strategies. Such a maturity model would map the progression of AI implementation across different HRM functions, identifying the capabilities, resources, and cultural changes needed at each stage of adoption. It could examine whether organizations necessarily proceed linearly through these forms of AI agency or whether different functions within the same organization might simultaneously operate at different levels of AI maturity. This model could also take into consideration the external factors (e.g., organizational characteristics) potentially helping or hindering the positive effects on inclusive algorithmic HRM. Of particular interest would be longitudinal studies tracking how organizational inclusion cultures evolve in response to different AI implementation approaches, and whether certain organizational characteristics predispose companies toward more or less successful integration of AI into their inclusion strategies.

5.3. Practical implications

Our taxonomy and process model offer actionable guidance for organizations navigating the increasingly complex landscape of AI-enabled workplace inclusion. By classifying AI systems according to their level of agency and corresponding inclusion risks, our framework supports decision-makers in matching appropriate mitigation strategies to specific HRM applications. This is particularly relevant in domains where AI adoption is most pronounced, such as recruitment, performance management, and career development, each of which presents distinct inclusion challenges that must be proactively addressed.

In recruitment, where our dataset reveals the highest concentration of AI applications, the transition from assisting to automating systems illustrates a steep increase in inclusion risk. AI chatbots used to answer applicant questions represent low-agency technologies with limited inclusion implications, aside from accessibility concerns for digitally disadvantaged candidates. However, organizations that deploy automated resume screening systems powered by natural language processing encounter more profound risks. These systems often reproduce historical hiring biases embedded in the training data. Our framework highlights the need for AI data mitigation strategies, such as fairness metrics and dataset debiasing, to avoid systematically excluding underrepresented candidates.

In performance management, AI systems that automatically evaluate employee output—often using email metadata, task completion metrics, or keystroke activity—exemplify high-agency (automating) technologies with significant inclusion consequences. These systems may undervalue less quantifiable yet organizationally vital behaviors, such as mentoring, emotional labor, or collaborative work. Here, AI design mitigation strategies, including algorithmic transparency, human review loops, and inclusive value mapping, become essential for preventing hidden exclusions.

Career development tools present a third, equally critical frontier. AI-powered learning platforms and internal mobility engines increasingly drive decisions about who is recommended for advancement. These augmenting AI systems personalize career pathways, but if trained on historical promotion data, they risk systematically overlooking women, minorities, or employees in non-traditional roles. Our framework's multilevel lens – inclusion in work, at work, and of work – provides a powerful diagnostic tool to understand how such technologies shape not only individual outcomes but broader organizational advancement norms. Mitigation at this level may include user

transparency, participatory system design, and bias-sensitive recommendation engines.

However, the applicability of our framework is not universal. It depends on several key boundary conditions. First, organizational inclusion maturity is critical. Organizations lacking inclusive leadership, measurement systems, or cultural readiness for addressing bias may find our framework too demanding. Without preexisting efforts to engage with inclusion meaningfully, proposed mitigation strategies risk devolving into symbolic compliance.

Second, technological readiness limits applicability. Organizations with underdeveloped digital HR infrastructure will struggle to implement or audit AI systems effectively, while those that have rushed into AI adoption without inclusion safeguards face different risks—namely, perpetuating bias through opaque, high-agency systems. For these organizations, our framework offers a roadmap for corrective action but requires substantial shifts in both process and mindset.

Third, the degree of AI agency already present in an organization determines the complexity of implementation. Organizations using mostly assisting AI (e.g., chatbots or dashboards) face manageable risks and may require minimal intervention. However, as they move toward augmenting and automating AI, inclusion risks increase in both subtlety and severity. Our model helps identify not only when to act, but how to act differently depending on the AI's role in protocol development and decision-making.

Finally, data quality and feedback mechanisms represent non-negotiable prerequisites for responsible implementation. Effective mitigation depends on access to representative, debiased training data, as well as systems for monitoring unintended outcomes. Organizations lacking these capabilities will struggle to apply the model meaningfully, especially in high-stakes areas like hiring or promotion.

In summary, our framework provides both practical guidance and diagnostic clarity for organizations adopting AI in HRM, but its effectiveness depends on recognizing contextual limitations. By emphasizing not just whether AI supports inclusion but how, when, and under what conditions, our model enables organizations to adopt AI technologies in a more responsible, inclusive, and strategically aligned manner.

6. Conclusion

The multi-dimensional framework developed in this study advances understanding of AI-enabled workplace inclusion by examining the complex interplay between technological systems and HRM practices across individual, organizational, and interaction levels. Our findings demonstrate that inclusion manifests differently at each level – *in* work, *at* work, and *of* work – requiring distinct but interconnected mitigation strategies. This reconceptualization extends beyond existing research by revealing how AI adoption fundamentally reshapes inclusion processes through the lens of conjoined agency.

Looking ahead, our model provides a foundation for future research examining how different types of AI technology might be optimally deployed across these three dimensions. Particularly promising areas include investigating how organizations align AI implementation with specific inclusion goals and identifying effective combinations of mitigation strategies for different AI applications and organizational contexts.

Our findings are extensible to the broader discussion about AI and workplace inclusion. The model thus becomes a challenge to purely technological approaches to the implementation of AI, by requiring attention to both the technical design and the social dynamics of the model in order to achieve genuine inclusion. The key practical implications for organizations trying to navigate the complexities of AI adoption in their practices are thus understood from this holistic perspective, and the critical role of human agency in shaping inclusive workplaces is also highlighted.

CRediT authorship contribution statement

Alessandra Lazazzara: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Stefano Za:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Andri Georgiadou:** Writing – review & editing, Writing – original draft, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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