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HUMAN RESOURCES MANAGEMENT AS A FACTOR OF AI ADOPTION IN PUBLIC SECTOR INSTITUTIONS: SYSTEMATIC LITERATURE REVIEW

ABSTRACT: The purpose of this paper is to examine the role of Human Resources Management (HRM) processes/constructs in the adoption of artificial intelligence (AI) in public sector institutions and to provide recommendations for the relevant stakeholders. The study utilized a systematic literature review following the PRISMA approach in the Scopus database, analyzing 90 publications. The study found that human resources (HR) development (including skills/knowledge development and talent management), change management, leadership, and organizational culture are the most frequently discussed HRM factors associated with AI adoption in public sector institutions. Internal stakeholders, particularly managers, employees, HR departments, and IT departments, are more prominently represented in the reviewed literature, while external stakeholders, including policy makers/regulatory bodies, AI solution providers and consultants, academic institutions, and professional associations, appear less frequently and mainly in relation to HR development. Based on the coded evidence, the study develops a qualitative taxonomy and a review-derived evidence map linking key HRM processes/constructs with stakeholder roles in AI adoption. The evidence map represents a conceptual synthesis rather than an empirically validated diagnostic tool, and it highlights gaps in reported stakeholder involvement and priorities for future research.

KEYWORDS: *artificial intelligence*, *human resources management*, *public sector*, *systematic literature review*.

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1. INTRODUCTION

Artificial intelligence (AI) is increasingly recognized as a transformative force that can improve efficiency, transparency and sustainability in all sectors (Babšek et al., 2025; Dwivedi et al., 2021). In the public sector, AI supports the automation of routine tasks, data-driven decision-making and improved interaction with stakeholders. These capabilities help address persistent challenges such as bureaucratic inefficiencies, limited budgets and the pressures of an aging workforce (Sharma et al., 2020). Public sector institutions are already using AI to optimize tax administration, strengthen public safety, improve health diagnostics and streamline hiring, among other things (Androniceanu, 2024; Tomaževič et al., 2024; Wirtz & Müller, 2019). Despite these benefits, the adoption of AI also raises ethical and social concerns, including risks to accountability, human rights and public trust (Babšek et al., 2025; Mainardi, 2025). Successful integration into the public sector requires more than just technical capacity. According to Dunleavy and Evans (2019), implementation of technology is often undermined by organizational and cultural barriers. Therefore, institutions need to rethink their structures and processes and foster a culture that is open to innovation and collaboration (Tomaževič et al., 2024) to effectively adopt AI. Systematic human resources management (HRM) processes/constructs are relevant to this transformation. They can help align AI initiatives with institutional goals, support employee engagement, and contribute to responsible AI adoption. HRM factors such as organizational culture, communication, leadership, competencies, trust, and stakeholder interaction have been associated with AI adoption and implementation outcomes (Spatola & MacDorman, 2021). Hence, the aim of this paper is to examine the role of HRM processes/constructs in the adoption of AI in public sector institutions, while providing recommendations for internal and external stakeholders. The main objective is to address the existing research gap by examining HRM processes/constructs associated with AI adoption in public sector institutions through the lens of stakeholder theory. To address this objective, the study examines the following research questions:

RQ1. Which HRM processes/constructs are identified in the reviewed literature as factors associated with AI adoption in public sector institutions?

RQ2. How are internal and external stakeholders represented in relation to HRM processes/constructs before and during AI adoption in public sector institutions?

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To address these research questions, a systematic literature review following the PRISMA approach was conducted in the Scopus database, analyzing 90 publications. Based on the coded evidence, the study developed a review-derived evidence map of reported stakeholder–HRM relationships and identified areas receiving comparatively limited attention in the literature. The paper is structured as follows: the next section sets out the theoretical background, followed by a section on methodology. The third section presents the results of the study, which are then discussed in the fourth section. Finally, the paper concludes by summarizing its key contributions.

2. THEORETICAL BACKGROUND

The literature indicates that HRM processes/constructs and the involvement of internal stakeholders such as managers, HR departments (HR managers and HR specialists), and IT managers are important in the adoption of AI in the public sector. These stakeholders can contribute to retraining employees and developing digital competencies, data analytics capabilities, and human-AI collaboration skills (Fenwick et al., 2024). External stakeholders such as policy makers/regulatory bodies, AI solution providers, consultants, academic institutions and professional associations also play an important role in AI adoption (Guenduez & Mettler, 2023; Tomaževič et al., 2024). According to Chowdhury et al. (2023), they contribute to regulatory frameworks, technical expertise, innovation, research and standards, and help public sector institutions comply with policies and access key resources and networks.

Despite the growing body of research on AI, little attention has been paid to how internal and external stakeholders are engaged specifically in HRM processes/constructs to support the adoption of AI in the public sector. Current studies focus on the use of AI in HRM processes (e.g., in HR data analytics, in selection procedures within hiring processes, as analyzed by Androniceanu, 2025; Döring et al., 2024; Indarapu et al., 2023; Nankervis et al., 2021; Tong et al., 2021) or the influence of HRM on the adoption of AI in the private sector (e.g., Hearn et al., 2023; Kim et al., 2025; Nguyen et al., 2022; Rojas-Berrio et al., 2022). However, there are few studies that examine the role of different internal and external stakeholders within HRM processes/constructs as important factors of the adoption of AI in public sector institutions. This gap is significant given the regulatory constraints, stakeholder

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complexity and normative obligations that characterize the public sector. Internal stakeholders are primarily associated with operational implementation and readiness for change, while external stakeholders contribute to the legal, political, and educational context. Clarifying these roles and their interplay is important for understanding how internal and external stakeholders are represented within HRM processes/constructs related to AI adoption.

In this review, HRM processes refer to formal organizational practices and activities through which employees and work are planned, developed, coordinated, and managed. Consistent with the coding framework presented in Table 3 and Figure 2, these include HR/workforce/employee planning, recruitment and hiring, HR development, communication, collaboration and collaborative management, the HR performance system, HR/workforce analytics and human capital analytics, workplace, remote work, and change management. In substantive terms, the coded categories “workplace” and “remote work” encompass workplace-design practices and remote-work arrangements, respectively. HRM constructs refer to psychological, cultural, and relational organizational conditions represented in the coding framework by leadership, psychological safety, organizational culture, and organizational climate. Conceptually related terms identified in the reviewed literature were grouped under the broader content-based categories shown in Table 3 and Figure 2. Throughout the study, the term HRM processes/constructs is used as an umbrella expression when referring collectively to both categories. Organizational culture refers to shared organizational values, norms, and assumptions, whereas organizational climate refers to employees’ shared perceptions of organizational practices and working conditions.

To capture this dynamic, this article draws on stakeholder theory, originally developed by Freeman (1984), which views organizations as embedded in relationships with actors who can affect or are affected by the achievement of organizational objectives. Rather than focusing exclusively on internal organizational actors, stakeholder theory provides a framework for understanding how different groups contribute resources, knowledge, authority, legitimacy, and expectations that shape organizational decisions and outcomes (Freeman, 1984; Parmar et al., 2010). This perspective is particularly relevant to public sector institutions, where organizational decisions involve multiple internal and external actors and must respond not only to organizational goals but also to public values, regulatory

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requirements, and broader societal expectations (Bryson, 2004; Sarturi et al., 2025). Stakeholders may also differ in their power, legitimacy, and urgency, which can affect the extent to which their interests and contributions are reflected in organizational processes (Mitchell et al., 1997).

Stakeholder theory was selected for this study because AI adoption in public sector institutions is not solely a technological or internal organizational process. It requires the coordinated involvement of managers, employees, HR and IT departments, as well as policy makers/ regulatory bodies, AI solution providers and consultants, academic institutions, and professional associations. These stakeholders contribute distinct but interdependent resources, including strategic direction, employee capabilities, technical expertise, regulatory guidance, and external knowledge. In this context, HRM processes/constructs can be understood as mechanisms through which stakeholder contributions are coordinated, interests are aligned, and potential imbalances are addressed (Matthews et al., 2025). For these reasons, stakeholder theory is used in this review as an interpretive and organizing lens for examining who is involved in HRM-related AI adoption, how different stakeholder groups contribute to this process, and how their reported relationships with HRM processes/constructs are represented. It is not treated as an empirically tested causal theory, and the prominence of particular stakeholders in the reviewed literature should not be interpreted as direct evidence of their actual influence or salience in practice.

3. METHODOLOGY

To address the research questions, a systematic literature review (SLR) was conducted according to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol, which provides a structured framework to ensure rigor, transparency, and reproducibility (Page et al., 2021). The review followed the four PRISMA phases: identification, screening, eligibility assessment and inclusion. The literature search was conducted in Scopus in July 2024. Scopus was selected due to its comprehensive coverage of peer-reviewed publications in the social sciences and related disciplines, as highlighted by Falagas et al. (2008). The expanded query combined terms related to AI, HRM and the public sector (see Table 1). Boolean operators and truncation operators were applied to maximize coverage, and several pilot runs were conducted to refine the query.

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Table 1: Scopus search query

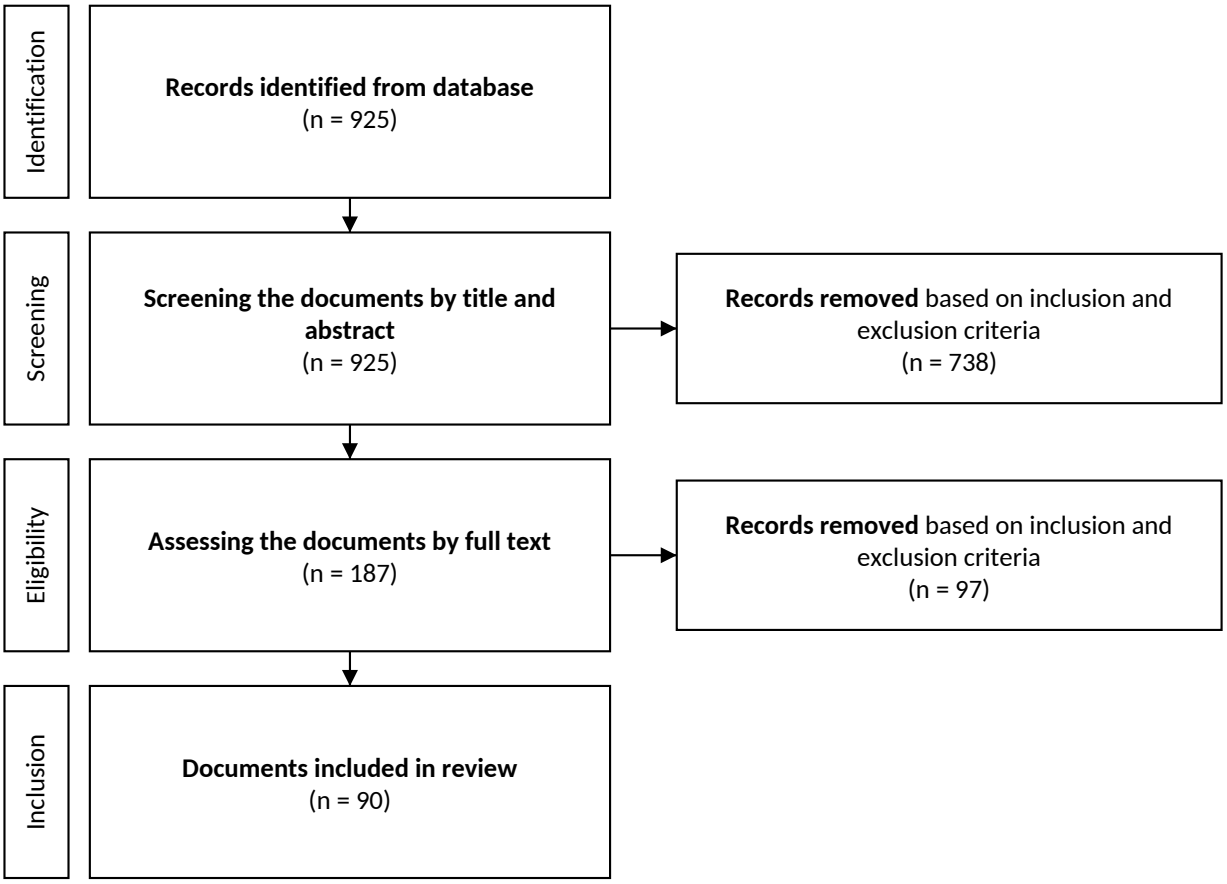
TITLE-ABS-KEY ("artificial intelligence" OR "ai" OR "machine learning" OR "natural language processing" OR "neural network*" OR "deep learning" OR "big data" OR "chatbot") AND TITLE-ABS-KEY ("human resource*" OR "hr*" OR "employee" OR "leader*" OR "skills" OR "organisational culture" OR "organizational culture" OR "motivat*" OR "job" OR "recruit*" OR "change management" OR "reward*" OR "educat*") AND TITLE-ABS-KEY ("government" OR "public sector" OR "public administration" OR "public policy" OR "e-government" OR "public governance" OR "public service*" OR "digital government" OR "public organisation" OR "public organization" OR "public institution") AND (LIMIT-TO (SUBJAREA,"SOCI") OR LIMIT-TO (SUBJAREA,"BUSI") OR LIMIT-TO (SUBJAREA,"PSYC") OR LIMIT-TO (SUBJAREA,"ARTS")) AND (LIMIT-TO (DOCTYPE,"ar")) AND (LIMIT-TO (LANGUAGE,"English"))

Source: *Authors' elaboration.*

As shown in Figure 1, the initial search yielded 925 articles. Screening of titles and abstracts led to the removal of 738 articles that did not meet the inclusion criteria. Studies were included if they met the following criteria: (i) they examined a public-sector organization, public-sector employees or managers, or a public-service institutional setting relevant to the public sector; (ii) they addressed the adoption or implementation of AI or its subtechnology covered by the search strategy; (iii) they contained theoretical or empirical evidence concerning at least one HRM process or construct, workforce capability, or stakeholder role relevant to adoption; and (iv) they met the document-type and language restrictions specified in the search strategy.

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Figure 1: PRISMA flow diagram of study selection



Source: *Authors' elaboration.*

During the full-text eligibility assessment, public-service institutional settings included government-owned professional education institutions when the study directly addressed AI-related competency development and the preparation of the future public-service workforce. Studies were excluded if they focused exclusively on private-sector organizations without direct public-sector relevance; addressed technology use without a direct HRM- or workforce-related implication; examined AI governance, ethics, or regulation without an HRM-related implication; or did not provide findings relevant to AI adoption in a public-sector or public-service institutional context. Where public-sector relevance was not evident from the title or abstract, eligibility was determined during full-text assessment on the basis of the institutional setting and the relevance of the findings to public-sector HRM and AI adoption.

Subsequently, 187 full-text articles were assessed in full text, and 97 were excluded in the eligibility stage. Ultimately, 90 articles were selected, which are listed in Table A1 in Appendix A. These articles formed the evidence base for this review. The full texts were

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coded and analyzed using NVivo 14. Consistent with the conceptual distinction established in the Theoretical background, the coding framework distinguished between HRM processes and HRM constructs. Conceptually related terms identified in the reviewed literature were grouped under broader content-based categories, which are reported in Table 3 and visualized in Figure 2. Publications appearing after the search date are used only as supplementary theoretical or contextual sources and are not included among the 90 publications in the coded review.

Internal stakeholders were defined as managers, IT department (IT managers and IT specialists), HR Department (HR managers and specialists) and employees, while external stakeholders were defined as policy makers/regulatory bodies, AI solution providers and consultants, academic institutions and professional associations. Specific codes were assigned to each process or construct (e.g., plan for workforce planning, train for training, reward for reward practices) to ensure systematic analysis and comparability. Coding focused on identifying patterns in how stakeholders are represented in relation to HRM processes/constructs in the adoption of AI in public institutions.

To ensure reliability, the coding scheme was applied and refined independently by two coders. Authors' meetings were held at regular intervals to reconcile differences, adjust definitions and update stakeholder categories. This iterative process allowed the framework to evolve dynamically while ensuring transparency, consistency and alignment with theoretical and empirical findings.

The review-derived evidence map was subsequently developed as a synthesis of coded evidence. Shape size in the evidence map was determined by the number of coded references associated with each HRM process/construct. Stakeholder links to individual HRM processes/constructs were based on relationships identified in the reviewed sources, and their relative prominence reflects how frequently they appear in the reviewed literature. HRM areas for which no stakeholder links were identified in the coded literature were retained as unlinked elements to indicate potential research gaps. The resulting evidence map should therefore be understood as a conceptual synthesis of the reviewed literature rather than an empirically validated representation of causal relationships. The relative prominence of stakeholders and HRM processes/constructs reflects their representation in

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the reviewed literature and should not be interpreted as a measure of causal influence or practical importance.

To make the composition of the evidence base transparent, each included study was assigned one primary public-sector context based on its main empirical or analytical setting. The six categories were general public administration; local government; education and higher education; health and emergency services; public finance and taxation; and other/cross-sector services. Studies addressing specialized public services, multiple sectors, or policy- or system-level settings without a single dominant sector were classified as other/cross-sector services. The classification is descriptive and is not used for sector-specific comparative analysis. The distribution of the 90 reviewed studies across these contexts is presented in Table 2.

Table 2: Distribution of reviewed studies across primary public-sector contexts

Public-sector context	No. of studies	Examples of institutions/settings
General public administration	27	Ministries, government agencies, public administrations
Local government	6	Municipalities, cities, local government authorities
Education and higher education	25	Public schools, universities, higher-education institutions
Health and emergency services	3	Public health, nursing and emergency-service settings
Public finance and taxation	4	Tax authorities, public-sector accounting and audit institutions
Other/cross-sector services	25	Specialized public services, national policy/system-level and cross-sector settings
Total	90	

Note: *Each study was assigned one primary public-sector context. Other/cross-sector services include specialized public services and policy-, system-level, or cross-sector studies without a single dominant sector.*

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4. RESULTS

The reviewed corpus was unevenly distributed across public-sector contexts. The largest groups were general public administration, with 27 studies; education and higher education, with 25 studies; and other/cross-sector services, also with 25 studies. Local government was represented by six studies, public finance and taxation by four, and health and emergency services by three. These figures describe the composition of the reviewed evidence base; no sector-specific comparative analysis was conducted.

The results of the systematic review, summarized in Table 3, show the HRM processes/constructs most frequently discussed as factors associated with AI adoption in the public sector. Among internal stakeholders, managers and employees are discussed most frequently, followed by HR and IT departments. The most frequently discussed HRM factors are the HRM processes of HR development and change management and the HRM constructs of leadership and organizational culture.

In contrast, external stakeholders such as policy makers/regulatory bodies, AI solution providers and consultants, academic institutions and professional associations are mentioned less frequently and mainly in relation to HR development, collaboration and communication. Some areas such as HR planning, HR analytics, workplace-design practices, remote-work arrangements, and psychological safety receive comparatively limited attention in the reviewed literature.

HR development, which includes skills development, training, mentoring and talent management, emerges as the most frequently discussed factor. Internally, the training of employees and managers is seen as essential (Ahn & Chen, 2022; Kaplan & Haenlein, 2020). Externally, universities and professional associations develop curricula and competency frameworks, while policy makers contribute through national strategies (Aldemir & Uçma Uysal, 2024; Attard-Frost et al., 2024). Nevertheless, the skills shortage and limited talent retention remain a challenge, exacerbated by unattractive remuneration structures (Andrews, 2019; Kempeneer & Heylen, 2023).

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Table 3: HRM processes and constructs associated with AI adoption by stakeholder group — Internal stakeholders

HRM process/construct as a factor of AI adoption	Code	Managers	IT department (IT managers and IT specialists)	HR department (HR managers and HR specialists)	Employees
HR/Workforce/Employee planning	plan	55, 84		55	84
Recruiting, Hiring	recruit, hiring, hire	6, 11, 14, 45, 47, 50, 66, 67, 68, 74	23, 47, 50, 66, 67, 68	6, 8, 11, 14, 23, 45, 47, 50, 66, 67, 68	68
HR development: Talent management, Talent analytics, Skills, Training, Professional development, Tutoring, Knowledge transfer	talent, skill, train, knowledge, mentor, tutor	2, 3, 5, 8, 11, 12, 14, 16, 20, 23, 24, 26, 30, 34, 43, 44, 45, 47, 48, 49, 52, 54, 57, 58, 59, 66, 67, 69, 70, 71, 73, 79, 80, 81, 83, 84, 87, 89, 90	2, 4, 12, 23, 24, 30, 34, 43, 44, 47, 50, 56, 57, 58, 66, 77	1, 2, 3, 4, 5, 8, 11, 14, 16, 23, 26, 30, 34, 43, 44, 45, 47, 49, 50, 52, 56, 58, 59, 66, 67, 69, 70, 71, 72, 79, 80, 81, 84, 87, 89, 90	1, 2, 3, 4, 12, 14, 20, 23, 24, 26, 30, 34, 38, 43, 44, 45, 47, 49, 56, 57, 58, 66, 67, 70, 71, 72, 73, 77, 79, 80, 81, 86, 87
Communication	communicat	2, 3, 16, 30, 35, 45, 54, 58, 70, 82, 87		3, 16, 87	2, 30, 35, 45, 54, 70, 82, 87
(Human) Collaboration, Collaborative management	collaborat	1, 16, 18, 35, 49, 50, 54, 71, 81, 87	4, 23, 87	16, 71	1, 4, 10, 16, 23, 35, 45, 49, 54, 72, 81
HR performance system: Motivation, Rewarding/Rewards, Salaries	motivat, reward, salar	6, 23, 30, 38, 45, 47		6, 23, 30, 47, 50	30, 38
HR/Workforce analytics, Human capital analytics	analytics				
Workplace	workplace				
Remote work	remote				
Change management	change	2, 17, 18, 19, 23, 24, 26, 30, 39, 47, 52, 54, 58, 66, 69, 70, 71, 75, 87, 89	26, 47, 58, 66, 69	17, 18, 47, 58, 66, 87	2, 9, 18, 19, 23, 43, 47, 53, 54, 57, 58, 66, 70, 71, 73, 75, 89
Leadership, Leadership style, Informal leader	leader	2, 4, 14, 17, 23, 24, 28, 30, 39, 50, 52, 54, 58, 66, 68, 70, 87	17, 28, 50	2, 23, 24, 58, 66, 68, 87	24, 30, 50, 54, 58, 66, 70
Psychological safety	safety				
Organizational culture	culture	1, 2, 20, 24, 30, 37, 44, 47, 48, 54, 58, 61, 68, 71, 81, 84, 87		2, 24, 30, 44, 47, 68	1, 2, 20, 24, 30, 37, 47, 48, 54, 58, 61, 71, 81, 87
Organizational climate	climate				

Note: *Numbers represent the sources listed in Table A1 in Appendix A.*

Source: *Authors' elaboration.*

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Table 3: HRM processes and constructs associated with AI adoption by stakeholder group — External stakeholders (continued)

HRM process/construct as a factor of AI adoption	Code	Policy makers/regulatory bodies	AI solutions providers and consultants	Academic institutions	Professional associations
HR/Workforce/Employee planning	plan	84			
Recruiting, Hiring	recruit, hiring, hire	10		67	
HR development: Talent management, Talent analytics, Skills, Training, Professional development, Tutoring, Knowledge transfer	talent, skill, train, knowledge, mentor, tutor	3, 10, 11, 16, 20, 26, 34, 43, 56, 57, 66, 73, 79, 80, 83	4, 23, 26, 45, 47, 71, 73, 77, 86	16, 26, 43, 48, 56, 57, 59, 67, 69, 78, 88	3, 57, 73
Communication	communicat		23, 45, 47	45	45
(Human) Collaboration, Collaborative management	collaborat	10, 43, 50	22, 23, 43, 50, 72	22, 43, 45, 50	45
HR performance system: Motivation, Rewarding/Rewards, Salaries	motivat, reward, salar	45			
HR/Workforce analytics, Human capital analytics	analytics				
Workplace	workplace				
Remote work	remote				
Change management	change	43, 70, 73			
Leadership, Leadership style, Informal leader	leader	4			
Psychological safety	safety				
Organizational culture	culture				
Organizational climate	climate				

Note: *Numbers represent the sources listed in Table A1 in Appendix A.*

Source: *Authors' elaboration.*

Change management is also frequently discussed in the reviewed literature. Many public institutions lack structured change plans, which leads to fragmented implementation, as Sienkiewicz-Małyjurek (2023) points out. Employee resistance, which is often rooted in fear of losing their job, hinders adoption (Al Wael et al., 2023; Fetais et al., 2022).

Managers play a key role in communicating the purpose of AI and aligning it with institutional goals (Coulthart & Riccucci, 2022). Externally, according to Pautz (2023), regulators shape change processes through legal frameworks and national strategies. Leadership is another frequently discussed factor and is presented in the reviewed literature as both an enabler and an obstacle.

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Leadership readiness and capabilities are important for supporting AI-related organizational change (Maponya & Naidoo, 2023). However, many managers lack digital skills, remain tied to hierarchical structures, and resist change (Broomfield & Reutter, 2021; Kuoppakangas et al., 2019). These deficits often increase dependence on IT departments and external consultants, as Maponya and Naidoo (2023) emphasize.

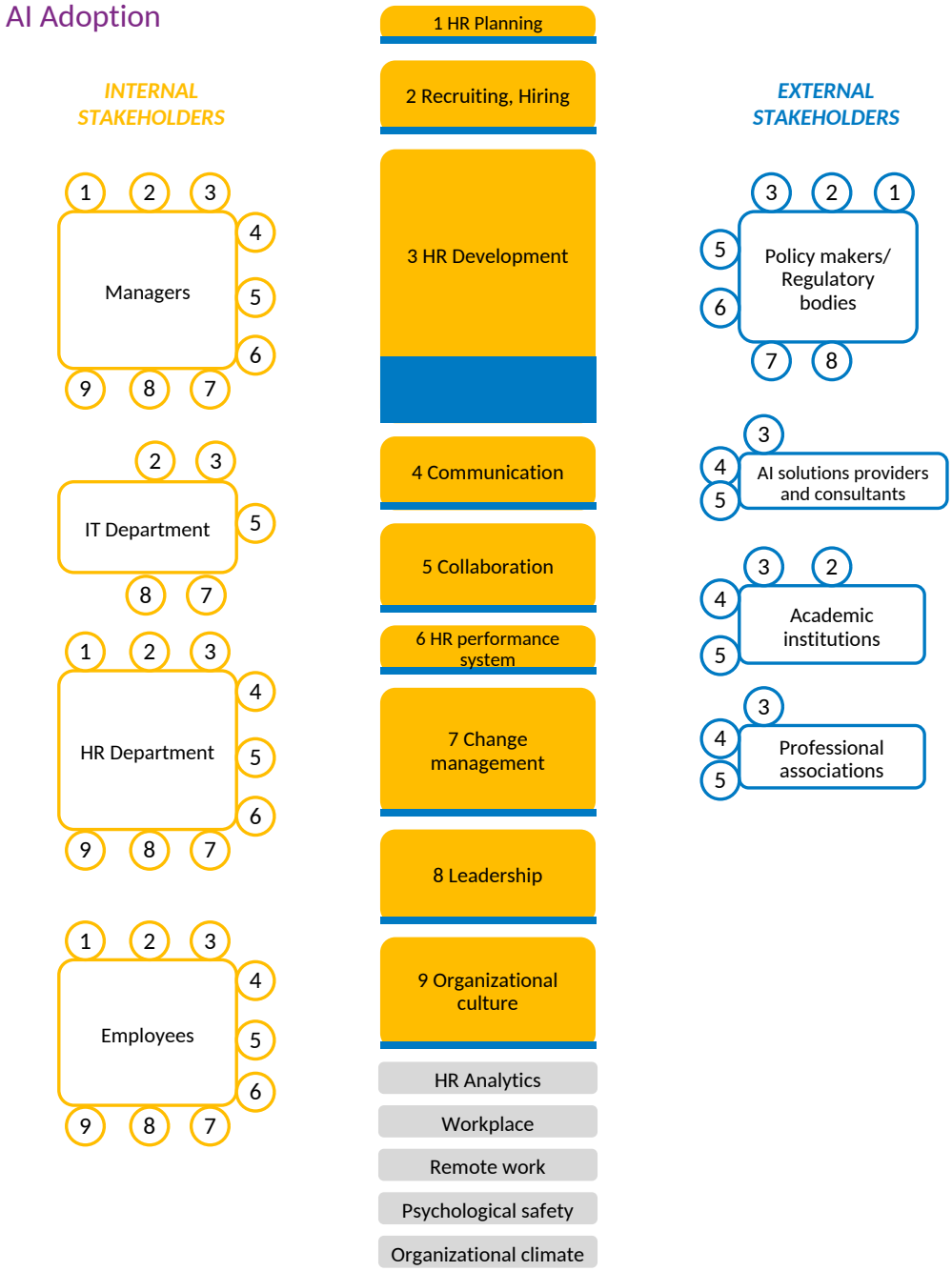
Organizational culture is also frequently discussed in relation to AI adoption. Innovation-oriented and flexible cultures facilitate AI integration, while hierarchical, bureaucratic environments slow it down (Behl et al., 2021; Fetais et al., 2022). In this context, according to Kaplan and Haenlein (2020), trust in AI is a key component: skepticism towards algorithmic decisions can be reduced through transparency and ethical guidelines.

The representation of stakeholder roles varies across the reviewed literature. Internally, managers are prominently represented in relation to strategic leadership and change, while employees require training and reassurance to allay concerns about job security (Al Wael et al., 2023). IT departments provide technical expertise but often work in isolation (Anwar et al., 2022), and HR departments struggle to meet talent needs (Iuga & Socol, 2024). Externally, academic institutions and professional associations contribute frameworks and training (McQuiston & Manoharan, 2021), while policy makers and regulatory bodies encourage adoption through policies, legislation and initiatives (Gamage, 2016).

AI providers and consultants provide technical support when in-house expertise is lacking, as Chen et al. (2024) emphasize. However, fragmented coordination between these stakeholders often limits coherent strategies (Sienkiewicz-Małyjurek, 2023). Despite the prominence of HR development, change management, leadership, and organizational culture in the reviewed literature, several other HRM areas receive comparatively limited attention. HR planning and analytics receive comparatively limited attention in the reviewed literature. The reviewed literature also gives limited attention to external stakeholder involvement in predictive models and data-driven HR strategies. Workplace-design practices and remote-work arrangements are also rarely represented in the reviewed literature. Psychological safety is also rarely examined explicitly in the reviewed literature in relation to AI adoption.

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Figure 2: Review-derived evidence map of reported stakeholder–HRM relationships in public-sector AI adoption



Note: *The size of each shape reflects the number of coded references associated with the respective HRM process/construct in the reviewed literature and does not represent effect size, causal influence, or practical importance. Yellow indicates links with internal stakeholders; blue indicates links with external stakeholders; gray indicates HRM processes/constructs for which no stakeholder links were identified in the reviewed literature and therefore potential research gaps; this does not imply that these relationships are absent in practice. Numbers in circles indicate links between stakeholders and specific HRM processes/constructs.*

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Based on these findings, a review-derived evidence map was developed to illustrate the reported relationships between internal and external stakeholders and HRM processes/constructs in AI adoption (see Figure 2). The evidence map illustrates an asymmetry in the reviewed literature: internal stakeholders are linked to a larger number of HRM processes/constructs, while external stakeholders are represented more selectively. The unassigned "gray" elements (HR analytics, workplace, remote work, psychological safety and organizational climate) indicate areas for which stakeholder links were not identified in the reviewed literature and therefore represent potential research gaps. The originality of the evidence map lies in the combination of stakeholder theory (Freeman, 1984; Parmar et al., 2010) with a comprehensive HRM framework. The evidence map presents a structured conceptual synthesis of stakeholder involvement and under-researched areas identified in the reviewed literature. Rather than serving as a validated diagnostic or prescriptive tool, it provides a foundation for future empirical testing and the development of subsequent assessment approaches.

5. DISCUSSION

This study presents a review-derived stakeholder–HRM evidence map that synthesizes the relationships reported in the reviewed literature. The evidence map draws on stakeholder theory (Freeman, 1984; Parmar et al., 2010) and highlights reported relationships between different stakeholders and HRM processes/constructs, as well as gaps in the reviewed literature. While the adoption of AI requires profound behavioral and psychological adaptation (Dwivedi et al., 2021; Edmondson, 2018), the existing literature gives greater attention to operational HR functions such as training than to interpersonal and cultural constructs related to trust and acceptance (Haesevoets et al., 2025; Mainardi, 2025). Stakeholder salience theory (Mitchell et al., 1997) helps to explain these imbalances. From a stakeholder salience perspective, policy makers and regulatory bodies can be associated with authority, while employees and professional associations may contribute urgency or legitimacy (Bryson, 2004). Public values further influence these relationships (Sarturi et al., 2025). This perspective helps interpret differences in stakeholder visibility across the reviewed literature, although such prominence should not be taken as direct evidence of actual stakeholder power or influence in practice.

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Although HR development is widely discussed in the reviewed literature, it is often presented as short-term and reactive. Workforce planning and HR analytics receive comparatively limited attention in the reviewed literature. This finding is consistent with broader AI-readiness literature emphasizing the need to anticipate organizational and workforce requirements for AI adoption (Jöhnk et al., 2021). External institutions provide curricula and frameworks, but their influence is advisory rather than strategic. The reviewed literature often presents change management as procedural, with limited attention to employees' concerns and identity-related fears. Managers are expected to lead communication but often lack relational skills, while policy makers are largely limited to regulatory guidance, reflecting broader public-sector management literature that calls for context-sensitive practices aligned with organizational challenges (Santos & Laureano, 2023). Organizational culture and psychological safety, which are essential for meaningful change, are rarely integrated into AI adoption processes (Mainardi, 2025). Leadership acts both as a facilitator and an obstacle. Leaders' readiness and digital capabilities are important for supporting AI-related organizational change, yet many public sector leaders remain risk-averse and digitally unprepared (Kuoppakangas et al., 2019; Maponya & Naidoo, 2023). As a result, reliance on IT departments and consultants is growing. External actors could play a stronger role as co-creators of organizational change instead of limiting themselves to technical support, as Alawamleh (2025) and Tangi et al. (2025) suggest. Organizational culture, conceptualized in this study as an HRM construct, remains important but underdeveloped in the literature. Innovative, collaborative cultures accelerate adoption, while bureaucratic traditions slow it down (Kaplan & Haenlein, 2020). The reviewed literature also gives limited attention to psychological safety. From a broader organizational perspective, psychological safety is important for experimentation and learning (Edmondson, 2018). Several HRM areas receive comparatively limited attention in the reviewed literature. HR analytics receive limited attention in relation to anticipating workforce needs. The reviewed literature also gives comparatively limited attention to the HR performance system. Workplace-design practices and remote-work arrangements are rarely addressed in the reviewed literature. Psychological safety is recognized in theory but not operationalized in practice (Haesevoets et al., 2025). These patterns suggest that human-centered considerations remain comparatively underrepresented in the reviewed literature.

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This study has its limitations. Because it relies on Scopus, the study excludes gray literature and practice-based reports. Although the reviewed literature covers several public sector contexts, the analysis does not provide sector-specific syntheses, so differences in HRM environments across these contexts should be taken into account when interpreting the findings. Furthermore, the conceptual evidence map is derived from a qualitative synthesis of the reviewed literature and has not yet been independently or empirically validated. Its proposed relationships and practical applicability should therefore be examined in future empirical studies conducted in diverse public-sector contexts. Accordingly, the evidence map should not be interpreted as implying that stakeholder configurations or HRM priorities are uniform across public sector contexts. Future research should test the evidence map at different levels of the public sector, focusing on coordination between internal and external stakeholders. Methods such as longitudinal studies, surveys and comparative analysis could capture the dynamics of trust, leadership and collaboration. The development and validation of assessment approaches for stakeholder engagement and HRM processes/constructs would support this agenda.

6. CONCLUSIONS

The review identifies four HRM factors as the most prominently represented in the reviewed literature: the HRM processes of HR development and change management and the HRM constructs of leadership and organizational culture (RQ1). Internal stakeholders, particularly managers, employees, HR departments, and IT departments, are more prominently represented in relation to these HRM processes/constructs, while external stakeholders are represented less frequently (RQ2). Several HRM areas remain under-researched in the reviewed literature, including HR planning, HR analytics, the HR performance system, psychological safety, and organizational climate. These patterns indicate gaps in the reviewed literature and should not be interpreted as evidence that these HRM areas are absent from public-sector practice. The review-derived stakeholder–HRM evidence map developed in this study provides a structured synthesis of the relationships identified in the reviewed literature and a basis for future empirical testing.

For practical implementation, public-sector institutions should strengthen coordination among management, HRM, IT, employees, and relevant external stakeholders;

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assess affected roles, competency gaps, training needs, work redesign, and employee concerns before AI deployment; and invest in continuous AI-related competency development. Employees should be involved in implementation, feedback, and evaluation processes, while institutions monitor human and organizational outcomes such as competence, workload, trust, psychological safety, service quality, and unintended consequences. Cooperation with policymakers, AI solution providers, academic institutions, and professional associations can offer additional expertise, training, standards, and regulatory guidance. These implementation pathways should be adapted to specific institutional and sectoral contexts.

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APPENDIX A

Table A1: Sources included in the review, type of research, and primary public-sector context

No.	Author(s), year	Type	Sector
1	Ahn & Chen, 2022	C	GPA
2	Al Wael et al., 2023	C	PFT
3	Aldemir & Uçma Uysal, 2024	A	PFT
4	Ali et al., 2024	C	EHE
5	Amankwah-Amoah, 2015	A	GPA
6	Andrews, 2019	A	GPA
7	Anwar et al., 2022	A	GPA
8	Ariansyah et al., 2024	C+D	LG
9	Asquer & Krachkovskaya, 2022	B	EHE
10	Attard-Frost et al., 2024	A	OCS
11	Baig et al., 2021	C	EHE
12	Baig et al., 2023	C	EHE
13	Banabilah et al., 2022	A	OCS
14	Baškarada & Koronios, 2017	D	GPA
15	Behl et al., 2021	C	HES
16	Bentley et al., 2024	D	HES
17	Broomfield & Reutter, 2021	C+D	GPA
18	Brunetti et al., 2020	C	OCS
19	Bukartaite & Hooper, 2023	D	OCS
20	Cantens, 2024	A	GPA
21	Cath et al., 2018	A	OCS
22	Chen et al., 2023	A+C	GPA
23	Chen et al., 2024	B	GPA
24	Coulthart & Riccucci, 2022	B	OCS
25	Curiel-Ramirez et al., 2022	B	EHE
26	Damar et al., 2024	A	GPA
27	Dankloff et al., 2024	D	GPA
28	Desouza & Jacob, 2017	A+D	GPA
29	Feldstein, 2024	A	OCS
30	Fetais et al., 2022	A	GPA
31	Filgueiras, 2024	A	EHE
32	Fleming, 2019	A	OCS

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No.	Author(s), year	Type	Sector
33	Fu & Ji, 2024	A	EHE
34	Gamage, 2016	A	GPA
35	Glennie et al., 2023	C+D	GPA
36	Goralski & Tan, 2020	B	OCS
37	Heeks et al., 2021	D	OCS
38	Hirzallah & Alshurideh, 2023	C	GPA
39	Hong et al., 2022	B	LG
40	Huang, 2023	C	EHE
41	Huy & Phuc, 2023	C	OCS
42	Ionescu, 2019	C	OCS
43	Iuga & Socol, 2024	C	OCS
44	Ivanov et al., 2024	C	EHE
45	Jaillant & Rees, 2023	D	OCS
46	Jha, 2023	A	OCS
47	Kalema & Mokgadi, 2017	C	PFT
48	Kaplan & Haenlein, 2020	A	OCS
49	Keane et al., 2016	A	EHE
50	Kempeneer & Heylen, 2023	A	GPA
51	Kidwell & Cainas, 2024	B	EHE
52	Kim, 2020	C	GPA
53	Kim et al., 2017	C	OCS
54	Kim et al., 2022	A	GPA
55	Knight et al., 2023	D	EHE
56	Knox, 2020	A	EHE
57	Kumar et al., 2021	D	OCS
58	Kuoppakangas et al., 2019	B	LG
59	Labrague et al., 2023	C	HES
60	Lavertu, 2016	A	GPA
61	Lee, 2023	B	OCS
62	Lijie et al., 2024	C	EHE
63	Lloyd & Payne, 2019	C	OCS
64	Luo & Yang, 2023	B	EHE
65	Lynch, 2017	A	EHE
66	Maponya & Naidoo, 2023	D	GPA

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No.	Author(s), year	Type	Sector
67	McQuiston & Manoharan, 2021	D	EHE
68	Melati & Janissek-Muniz, 2022	A	GPA
69	Mergel, 2016	A	EHE
70	Mogas et al., 2022	C	EHE
71	Opesemowo & Adekomaya, 2024	D	EHE
72	Papyshev, 2024	D	EHE
73	Pautz, 2023	D	GPA
74	Rigley et al., 2024	A	OCS
75	Robayo-Pinzon et al., 2024	D	EHE
76	Robinson, 2020	A	OCS
77	Rolan et al., 2019	B	OCS
78	Saheb & Saheb, 2023	D	OCS
79	Sahid et al., 2021	C	GPA
80	Sani et al., 2021	C	GPA
81	Saragih et al., 2023	A+D	PFT
82	Shah et al., 2017	C	GPA
83	Shin, 2016	C+D	OCS
84	Sienkiewicz-Małyjurek, 2023	A+C	LG
85	Sihag & Vibha, 2024	A	EHE
86	Southworth et al., 2023	B	EHE
87	Valle-Cruz & García-Contreras, 2023	A	GPA
88	Vodenko & Lyausheva, 2020	C	EHE
89	Yigitcanlar et al., 2023	C+D	LG
90	Zhang et al., 2022	D	LG

Note: *Type of the research: A – literature review, B – case study, C – quantitative analysis, D – qualitative analysis. Public-sector context: GPA – General public administration; LG – Local government; EHE – Education and higher education; HES – Health and emergency services; PFT – Public finance and taxation; OCS – Other/cross-sector services. Each study was assigned one primary public-sector context.*

Source: *Authors' elaboration.*

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