Sinergi International Journal of Management and Business

Check for updates

OPEN ACCESS

RECEIVED 16 December 2025
ACCEPTED 12 June 2026
PUBLISHED 30 November 2026

CITATION
Prasetia AR, Rofaida R, Senen SH (2026). Artificial Intelligence and HR Analytics in Strategic Human Resource Management: A Systematic Review of Workforce Agility. Sinergi International Journal of Management and Business. 4 (4), 159-169. doi: 10.61194/ijmb.v4i4.947

TYPE Original Research
PUBLISHED 30 November 2026
DOI 10.61194/ijmb.v4i4.947
VOL 4 Issue 4 November 2026

COPYRIGHT
© 2026 Prasetia, Rofaida and Senen. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

Artificial Intelligence and HR Analytics in Strategic Human Resource Management: A Systematic Review of Workforce Agility

Arus Reka Prasetia[1], Rofi Rofaida[2], Syamsul Hadi Senen[3]
[123]Universitas Pendidikan Indonesia, West Java, Indonesia
Correspondence: arreka.prasetia@upi.edu[1]

Abstract

This article presents a systematic literature review (SLR) that maps and synthesizes scholarly evidence on the role of artificial intelligence (AI) and human resource analytics (HR analytics) in strategic human resource management (SHRM) to strengthen workforce agility in a global context. The review followed the PRISMA 2020 principles through a structured search of the Scopus database covering publications from 2015 to 2025. The selection process included title and abstract screening, eligibility assessment, and study quality appraisal, resulting in 18 articles that met the inclusion criteria from 108 identified documents. Data were systematically extracted from abstracts and metadata and then analyzed using thematic synthesis to address RQ1–RQ4, including the mapping of technologies, SHRM practices, mechanisms, and agility-related outcomes. The findings indicate that AI and HR analytics tend to contribute to workforce agility through data-driven HR decision making, the strengthening of analytical capability, faster organizational responses, and competency development that supports adaptability. However, their effects depend on human readiness, data and AI governance, and human-centered work design. This review underscores that AI and HR analytics should be positioned as strategic capabilities within SHRM architecture and identifies directions for future research, particularly the need for more consistent workforce agility measurement, longitudinal and multi-level designs, and assessments of fairness and accountability in AI-enabled HR decision making.

KEYWORDS

artificial intelligence; HR analytics; strategic human resource management; workforce agility; people analytics.

Introduction

Over the past decade, advances in digital technologies have reshaped how organizations formulate strategy, manage business processes, and sustain competitive advantage. Digital transformation is no longer understood as the mere adoption of new technologies. Instead, it refers to an organization-wide change process enabled by digital technologies that can disrupt markets and require strategic responses in structures, capabilities, and governance (Vial, 2019). Within this context, artificial intelligence (AI) and data-driven analytical capabilities have become pivotal enablers because they can enhance decision quality, accelerate organizational learning, and strengthen adaptive capacity in highly dynamic environments (Mikalef & Gupta, 2021).

These implications become more pronounced as AI increasingly functions as a “decision technology” that complements human judgement through assessment, recommendation, and automation of organizational decisions. Prior research suggests that the future of work is moving toward human–AI symbiosis, in which technology not only replaces certain tasks but also reshapes job configurations, coordination patterns, and the ways managers and professionals make decisions (Jarrahi, 2018). In human resource management (HRM), this shift is particularly salient because HR practices directly involve individual-level data, capability dynamics, and organizations’ need to sustain workforce performance. Technology, including AI, has influenced the evolution of HR functions ranging from recruitment and training to performance appraisal and

workforce planning (Stone et al., 2015).

Strategic Human Resource Management (SHRM) positions HR practices as instruments to align workforce behaviors and capabilities with organizational strategic objectives. Accordingly, SHRM is not limited to operational HR policies. It emphasizes how HR systems are designed as coherent "bundles" that produce strategic outcomes through social, motivational, and capability-based mechanisms (Jiang & Messersmith, 2018). Evidence also indicates that a systems perspective, rather than isolated HR practices, offers a more consistent explanation of organizational performance because HR practices are interdependent and interact within a configuration (Boon et al., 2019). From a dynamic capabilities perspective, alignment among human resources, processes, and strategy is essential for organizations to sense change, seize opportunities, and reconfigure resources under environmental turbulence (Teece et al., 2016).

In parallel, HR analytics has emerged as an evidence-based approach intended to bridge HR practices and strategic organizational agendas. HR analytics extends beyond descriptive reporting and seeks to generate explanations and predictions that inform strategic decisions about people, including productivity, retention, and capability requirements (Marler & Boudreau, 2017). Nonetheless, research has repeatedly noted that HR analytics often fails to reach its strategic potential due to limited analytical competence, data quality constraints, and weak integration between analytics and managerial decision-making (Angrave et al., 2016). In this respect, analytics should be conceptualized as an organizational capability that encompasses data quality, analytical competence, and the capacity to act strategically on analytical insights (Minbaeva, 2018). Within the broader domain of digital HRM, meta-analytic evidence also suggests that the adoption of e-HRM and digital HR systems is shaped by context and implementation design, and it yields varying consequences for efficiency and perceived HR service quality (Zhou et al., 2022).

The entry of AI into HR practices expands the scope of HR analytics while simultaneously increasing governance complexity. AI enables automation and augmentation of decisions, for example through algorithm-based candidate screening, AI-supported performance management, and algorithmic management of work arrangements. However, the literature also highlights social and ethical concerns, including potential bias, model opacity, unfairness risk, and shifts in power relations between organizations and workers (Kellogg et al., 2019; Mehrabi et al., 2022). AI ethics frameworks and governance principles emphasize transparency, accountability, and fairness as prerequisites for AI deployment in social domains, including employment and HRM (Floridi et al., 2018; Jobin et al., 2019). At the managerial level, AI integration also raises questions about how organizations balance algorithmic efficiency with human judgment, legitimacy, and employee acceptance, so that AI-based decisions create strategic value without triggering reputational and compliance risks (Tambe et al., 2019).

Within a strategy-oriented SHRM perspective, workforce agility has become an increasingly relevant outcome. Workforce agility refers to employees' capacity to respond to change through behavioral flexibility, rapid learning, role adaptation, and effective contribution in dynamic work contexts (Muduli, 2017). The need for workforce agility is growing as organizations face market volatility, technology-driven disruption, and AI-induced changes in job configurations. Systematic research in information systems also emphasizes that information technology can strengthen organizational agility by supporting sensing, coordination, and rapid response, although mechanisms and empirical evidence remain heterogeneous across contexts (Tallon et al., 2019). Consequently, workforce agility represents a logical strategic outcome at the intersection of AI, HR analytics, and SHRM because agility requires integrated orchestration of human capabilities, data, and managerial processes.

Although the literature on AI in organizations, HR analytics, and digital HRM continues to expand, the evidence base remains fragmented in several respects. First, many studies examine AI or HR analytics in isolation, which limits comprehensive conceptual integration within an SHRM framework. Second, outcomes often emphasize process efficiency, productivity, or performance, while workforce agility as a strategic outcome related to adaptation and human capability dynamics has been less systematically synthesized. Third, studies employ diverse concepts and indicators, which complicates the accumulation of consistent knowledge across organizational contexts and industries. Under such conditions, a systematic literature review (SLR) is warranted because it enables transparent evidence mapping, assessment of consistency across findings, and the formulation of research agendas based on identified gaps (Snyder, 2019). Moreover, advances in systematic review reporting guidance, such as PRISMA 2020, strengthen standards for transparent identification, selection, and synthesis, thereby enhancing academic accountability (Page, McKenzie, et al., 2021).

Motivated by these needs, this article conducts an SLR to synthesize evidence on how AI and HR analytics operate within SHRM with a particular focus on workforce agility. The review is guided by four research questions that examine how AI and HR analytics are conceptualized and implemented within SHRM to build workforce agility, which theories and mechanisms explain this relationship, which contexts and study characteristics dominate the evidence base including indicators and levels of analysis, and which gaps can inform future research agendas. Theoretically, this review aims to clarify the positioning of AI and HR analytics as strategic capabilities within SHRM architecture while bridging HRM and information systems scholarship that often develops in parallel. Practically, this review offers a map of managerial implications for data-driven HR system design, AI governance, and capability development strategies that support agility without compromising ethics and organizational legitimacy.

At the level of knowledge development, systematic review approaches have also been applied to other SHRM and HRM domains, including systematic work on green HRM (Susanto et al., 2022) and a systematic review of SHRM in social enterprises (Wijaya & Senen, 2024). In addition, SLR has been used to examine the integration of AI in broader strategic issues such as platform business models and digital ecosystems (Prasetia, 2025). Nevertheless, synthesis that explicitly integrates AI, HR analytics, and SHRM with workforce agility as the focal outcome remains underdeveloped, particularly in terms of building a robust thematic map, articulating explanatory mechanisms, and offering a structured global research agenda.

The remainder of this article is organized as follows. The next section presents the review method and the literature selection procedure. The subsequent section reports the results of the thematic synthesis aligned with the research questions. The discussion section then links the findings to relevant theory and managerial implications. Finally, the conclusion summarizes the contributions and proposes directions for future research.

Methods

The Methods section outlines the procedures used to conduct this systematic literature review, with the aim of ensuring transparency, rigor, and replicability. It explains the review design and reporting framework, the formulation of research questions, the information sources and search strategy, and the criteria and stages applied to identify and

select relevant studies. This section also describes how study quality was appraised, how data were extracted in a structured manner, and how the evidence was synthesized through a thematic narrative approach to address RQ1 through RQ4.

Study Design and Reporting Framework

This study employed a systematic literature review (SLR) to synthesize scholarly evidence on the role of artificial intelligence (AI) and HR analytics in strategic human resource management (SHRM) and their implications for workforce agility. The SLR design was selected because it enables a transparent and replicable procedure for searching, selecting, appraising, and synthesizing the literature, which supports evidence mapping, gap identification, and the development of a research agenda (Okoli, 2015; Snyder, 2019; Xiao & Watson, 2017). The reporting of the review process and the documentation of the study selection flow followed PRISMA 2020 principles, particularly to ensure clarity in the identification, screening, eligibility assessment, and inclusion stages (Page, McKenzie, et al., 2021; Page, Moher, et al., 2021).

Research Questions

This SLR was guided by four research questions derived from the article title and scope. First, RQ1 examines how AI and HR analytics in SHRM practices contribute to workforce agility, including the most dominant conceptual pathways described in prior studies. Second, RQ2 maps the forms of technology, analytical approaches, and strategic HR practices that are most frequently reported in the literature when organizations seek to develop an agile workforce. Third, RQ3 identifies outcomes and mechanisms associated with AI and HR analytics in SHRM across individual, team, and organizational levels, including potential mediators or moderators reported in the studies. Fourth, RQ4 formulates knowledge gaps, contextual boundaries, and future research directions, with particular attention to underexplored yet relevant themes in the context of contemporary digital transformation. This research question framework aligns with SLR guidance that emphasizes structuring data extraction and synthesis around explicit review objectives (Okoli, 2015; Xiao & Watson, 2017).

Data Sources and Search Strategy

The primary data source was Scopus, as it is widely used in management and business research to retrieve curated and indexed scholarly publications and it supports consistent metadata-based tracking. The search was conducted within the title, abstract, and keyword fields using Boolean operators to combine concepts of SHRM, AI, HR analytics, and agility. This approach is consistent with SLR guidelines that stress the importance of explicitly formulating search terms, testing the sensitivity of keywords, and balancing precision with coverage (Okoli, 2015; Snyder, 2019; Xiao & Watson, 2017).

Conceptually, the query structure was designed to capture common terminological variants. For example, SHRM may be expressed as “HR strategy” or “strategic HR”; HR analytics may appear as “people analytics,” “workforce analytics,” or “HR data analytics”; and AI may be presented through terms such as “machine learning” or “algorithmic management,” among others. The agility construct was also operationalized through related keywords, including “workforce agility,” “employee agility,” “organizational agility,” “adaptability,” and “resilience,” so that studies using different but conceptually connected terminology could be captured.

The publication time window was set to 2015–2025 to meet the need for evidence novelty and to reflect developments in contemporary technologies. Classic methodological literature was retained when needed to justify synthesis procedures or thematic analytic decisions (Braun & Clarke, 2008; Page, McKenzie, et al., 2021).

Record Management and De-duplication

All retrieved results were exported from Scopus in CSV format to support systematic metadata tracking, documentation of selection decisions, and consistency in data extraction. Records were checked for potential duplicates based on combinations of title, author names, and publication year. Although the use of a single database typically reduces duplication risks, this procedure was still implemented to protect dataset integrity and maintain alignment with the PRISMA logic (Okoli, 2015; Page, McKenzie, et al., 2021).

Inclusion and Exclusion Criteria

Inclusion criteria were established to ensure that selected studies were conceptually relevant and sufficiently informative to answer the research questions. Studies were included if they addressed SHRM or HR practices that were explicitly positioned at a strategic level and connected these practices with AI and or HR analytics as enablers of decision-making, HR system design, or data-driven workforce management. In addition, studies needed to discuss agility at the workforce level or closely related constructs such as adaptability and resilience, provided that these constructs could be linked to workforce capability or strategic HR systems.

Exclusion criteria were applied to preserve focus and prevent topic drift. Studies were excluded if they did not demonstrate a clear connection to SHRM or HR strategy, for example studies on digital transformation, ESG, or organizational strategy that did not treat HR as a central mechanism. Studies were also excluded if AI or analytics were not related to HR decision-making, HR practices, or HR systems, or if the primary outcomes were unrelated to workforce agility. Records that did not provide minimum information in the abstract and metadata to assess relevance and to support initial extraction were deprioritized because they may compromise the accuracy of evidence-based synthesis (Okoli, 2015; Xiao & Watson, 2017).

Study Selection Procedure

Study selection was conducted in a staged manner aligned with the PRISMA 2020 logic, beginning with title and abstract screening and continuing with eligibility assessment at the subsequent stage (Page, McKenzie, et al., 2021; Page, Moher, et al., 2021). At the title and abstract stage, each record was evaluated based on its fit with SHRM, the presence of AI and or HR analytics, and the stated relationship to workforce agility. At the eligibility stage, the research team attempted to obtain full texts when feasible. When full-text access was limited, eligibility decisions relied more strictly on the abstract and Scopus metadata, for example by verifying whether agility-related constructs were explicitly addressed, whether the strategic HR context was defined, and whether the study provided sufficient information for consistent extraction.

Each inclusion or exclusion decision was documented together with a specific reason to strengthen auditability and transparency. The PRISMA flow and the number of records at each stage are reported in the Results section using a PRISMA diagram, so that the Methods section remains focused on procedures rather than reporting counts (Page, McKenzie, et al., 2021).

Quality Appraisal

Quality appraisal was conducted to evaluate the robustness of evidence and to support interpretation, particularly because included studies varied in design. The appraisal approach was informed by the Mixed Methods Appraisal Tool (MMAT) 2018, which supports consistent assessment across qualitative, quantitative, and mixed-method studies (Hong et al., 2018).

However, because a portion of the dataset relied on abstract and metadata information, the appraisal was implemented as a reporting-based appraisal. Accordingly, the appraisal emphasized the clarity of study design, the traceability of procedures, the adequacy of contextual and data descriptions, and the coherence of conclusions as reflected in the available summaries.

Quality appraisal was not used solely as an exclusion mechanism. Instead, it was used to support weighting during interpretation and to identify areas requiring caution when drawing patterns or proposing a research agenda (Snyder, 2019; Xiao & Watson, 2017).

Data Extraction

Data extraction was conducted using a structured extraction sheet that integrated bibliographic elements and substantive elements aligned with the research questions. Extracted information included author(s), year, title, document type, country or sector context, HR domain addressed, research method, and a summary of key findings, reported limitations, and relevance to each research question. This approach followed SLR guidance that recommends deriving extraction variables directly from review objectives to reduce selective reporting and synthesis bias (Okoli, 2015; Xiao & Watson, 2017).

Due to uneven access to full texts, extraction primarily relied on abstracts and metadata. To maintain consistency, each entry was prepared through careful paraphrasing, a clear separation between claims explicitly stated in the abstract and the reviewers' interpretation, and explicit marking of information that was not available. This practice supports evidence accountability and interpretive discipline in the synthesis (Snyder, 2019).

Data Synthesis Strategy

Data synthesis was conducted as a thematic narrative synthesis to develop an integrative understanding of the relationship among AI, HR analytics, SHRM, and workforce agility, while also mapping variations across contexts. A thematic approach was selected because the literature in this domain is typically heterogeneous in study design, industry context, and conceptualization of agility. The synthesis process was guided by thematic analysis principles that emphasize iterative reading, coding, clustering codes into themes, reviewing themes, and producing a coherent thematic narrative (Braun & Clarke, 2008; Nowell et al., 2017).

In the initial phase, extracted findings were coded in relation to the research questions, for example codes related to HR analytics capability, HR decision automation, algorithmic management, reskilling and upskilling, resilience, and adaptability. These codes were then consolidated into cross-study themes that supported systematic answers to RQ1 through RQ4. To strengthen the credibility of the synthesis, themes were not derived from single studies. Instead, they were developed through identifying recurring patterns, examining meaningful differences, and tracing contextual conditions that might explain variations in findings (Nowell et al., 2017).

Ethical Considerations, Transparency, and Methodological Limitations

This SLR relied on secondary data from scholarly publications and did not involve direct human participants, so formal ethical approval for human subject research was not required. Nevertheless, transparency was maintained through documented selection decisions, explicit reasons for exclusion, and the use of the PRISMA framework to support process traceability (Page, McKenzie, et al., 2021).

A key methodological limitation is the reliance on abstracts and metadata for part of the dataset when full texts could not be accessed consistently. As a result, detailed methodological information, sample characteristics, or statistical analyses may not be fully identifiable for all studies. Therefore, interpretation was conducted cautiously and the quality appraisal emphasized the adequacy of available reporting (Hong et al., 2018; Snyder, 2019).

In addition, to contextualize review practices in management and HRM, this SLR also considered examples of systematic reviews authored by Indonesian scholars, including an SLR in the SHRM domain (Wijaya & Senen, 2024) and an SLR on AI and digital ecosystems as a comparative reference for reporting and synthesis structure (Prasetia, 2025; Rofaida, 2016).

Result and Discussion

This section reports the outcomes of the study-selection process, a summary of the characteristics of the included studies, a narrative summary of the quality appraisal results, an overview of how the included studies contribute to RQ1 through RQ4, and the thematic synthesis derived from the final 18 studies. The presentation of results is intentionally structured to avoid repeating procedural explanations that have already been addressed in the Methods section. Accordingly, the emphasis here is on the outputs of the SLR process and the substantive findings from the synthesis.

Study Selection Results Based on PRISMA

The study selection flow followed PRISMA 2020 and is summarized in Figure 1 (PRISMA Flow Diagram) (Page, McKenzie, et al., 2021). As shown in Figure 1, the Scopus search retrieved 108 records, all of which proceeded to title and abstract screening. At this stage, 84 records were excluded because they were not relevant to the integration of AI and or HR analytics within the context of SHRM and did not align with agility or related strategic outcomes. Subsequently, 24 articles were assessed for eligibility, and 6 articles were excluded at the eligibility stage because three did not focus on workforce agility or adaptability as an outcome, two did not demonstrate adequate integration of SHRM with AI or analytics, and one had insufficient methodological or reporting quality to support synthesis. As a result, 18 studies met the inclusion criteria and were included in the qualitative synthesis.

Characteristics of the Included Studies

From a temporal perspective, the included studies are strongly concentrated in the most recent period, namely 2024 and 2025. This pattern indicates that scholarly discussions on AI and HR analytics in SHRM, particularly those linked to agility and resilience, are expanding rapidly and remain relatively emergent, with substantial empirical and conceptual contributions appearing primarily in the last two years.

In terms of context, many studies are situated in Asia, particularly China and India, followed by Saudi Arabia, Australia, Malaysia, Italy, Spain, the United Kingdom, and the United States. Several studies adopt cross-industry settings or do not explicitly state the geographical location in their abstracts, although author affiliations and survey designs can be traced through Scopus metadata, as in (Al-Qassem et al., 2025). In relation to study design, the included literature covers quantitative survey-based studies (for example, (Al-Ayed, 2024; Dhilipan et al., 2025; Vadithe et al., 2025; Yamin et al., 2024), qualitative studies (for example, (Del Barone et al., 2025; Roy et al., 2025), conceptual or framework-oriented papers (for example, (Bastida et al., 2025; Chowdhury et al., 2024), and review articles (for example, (Ng et al., 2025; Tenakwah & Watson, 2024).

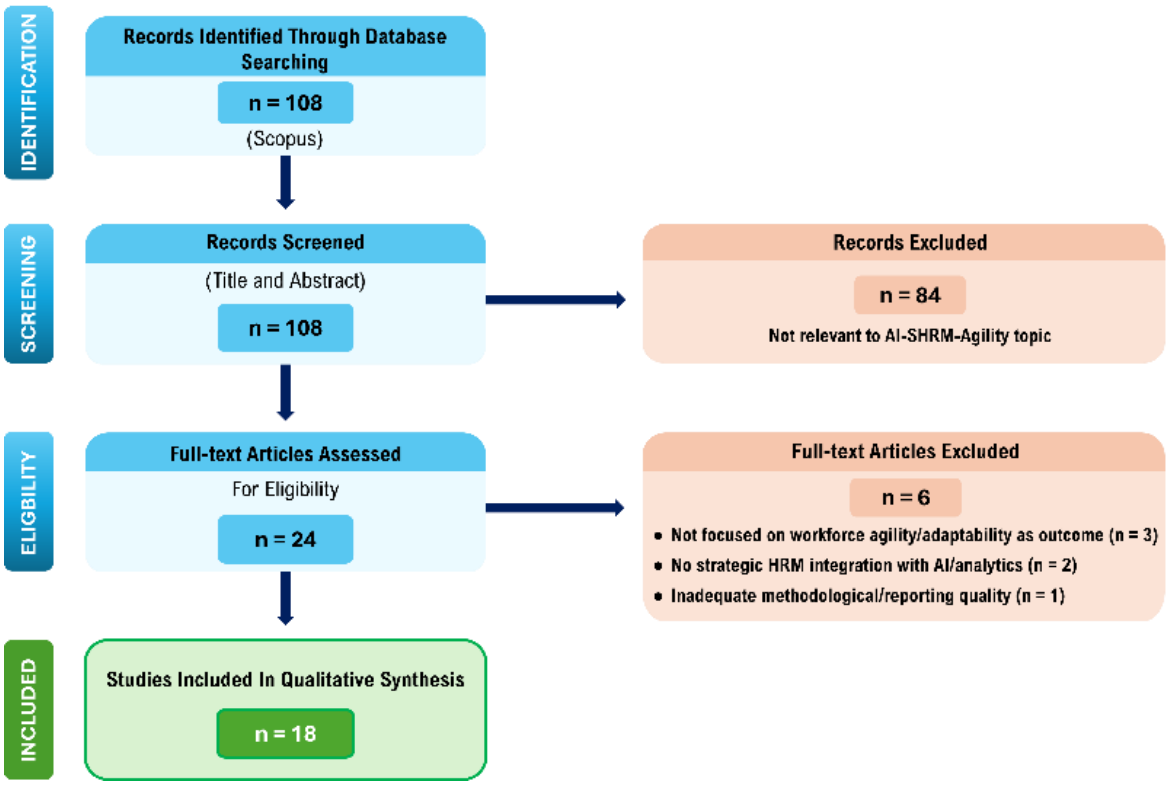

Figure 1. PRISMA 2020 Flow Diagram

Dominant HR domains include recruitment and talent acquisition, training and development, performance management, workforce planning, and the strengthening of HR analytics capability through HRIS and HR big data (Safa'atillah et al., 2025; Vadithe et al., 2025; H. Zhang, 2024). Table 1 summarizes the characteristics of the included studies to facilitate evidence tracing during synthesis.

Narrative Summary of Study Quality Appraisal Results

The quality appraisal results show substantial variation, with scores ranging from 1 to 8 on a 0–10 scale and an average of approximately 5.17. In categorical terms, there are two high-quality studies, eight studies of moderate quality, and eight studies of low quality. The two highest-rated studies are (Yamin et al., 2024) and (Al-Ayed, 2024) because their abstracts and metadata provide relatively complete information on design, context, sample size, analytical techniques, and measurable outcomes. The moderate-quality group includes (Ng et al., 2025), (Tenakwah & Watson, 2024), (Roy et al., 2025), (Al-Qassem et al., 2025), (Del Barone et al., 2025), (Vadithe et al., 2025), (Indravathy & Rahim, 2024), and (H. Zhang, 2024), which generally specify objectives, approaches, and central findings but remain limited in certain procedural details. The low-quality group includes (Dhilipan et al., 2025), (Liu et al., 2025), (Safa'atillah et al., 2025), (Bastida et al., 2025), (Cady et al., 2024), (Chowdhury et al., 2024), (Wu, 2024), and (R. Zhang et al., 2024), primarily due to limited reporting completeness in abstracts for elements such as analytical detail, data specification, or the clarity of empirical design. This variation in quality informed a cautious stance during thematic interpretation, particularly when a claim was supported mainly by studies with limited reporting.

Narrative Summary of Mapping Study Contributions to RQ1–RQ4

The mapping indicates that the depth of relevance differs across research questions, although the dominant patterns are clear. For RQ1, which concerns how AI and HR analytics contribute to workforce agility and related constructs, 11 studies show direct relevance, 3 studies show indirect relevance, and 4 studies do not present explicit evidence in the abstract or metadata. The studies with direct relevance to RQ1 include (Dhilipan et al., 2025), (Liu et al., 2025), (Safa'atillah et al., 2025), (Bastida et al., 2025), (Ng et al., 2025), (Roy et al., 2025), (Del Barone et al., 2025), (Vadithe et al., 2025), (Cady et al., 2024), (Indravathy & Rahim, 2024), and (Yamin et al., 2024). Studies with indirect relevance to RQ1 include (Al-Qassem et al., 2025), (R. Zhang et al., 2024), and (Al-Ayed, 2024). Studies without explicit RQ1 evidence in their abstracts include (Tenakwah & Watson, 2024), (Chowdhury et al., 2024), (H. Zhang, 2024), and (Wu, 2024).

For RQ2, which maps dominant technologies and SHRM practices, most studies are directly relevant, comprising 14 studies, while 4 studies are indirectly relevant. Direct RQ2 contributions include, among others, (Bastida et al., 2025), (Tenakwah & Watson, 2024), (Vadithe et al., 2025), (H. Zhang, 2024), (Wu, 2024), and (Chowdhury et al., 2024), which emphasizes generative AI and the need to update SHRM frameworks. Indirect RQ2 contributions include (Liu et al., 2025), (Ng et al., 2025), (Roy et al., 2025), and (Al-Ayed, 2024), mainly because their abstracts emphasize outcomes or mechanisms rather than a systematic mapping of technologies.

For RQ3, which examines outcomes and mechanisms, 12 studies are directly relevant, 4 studies are indirectly relevant, and 2 studies do not provide explicit evidence in the abstract. Direct RQ3 studies include (Vadithe et al., 2025), which positions HR analytics as a mediator toward agility, (Liu et al., 2025), which outlines mediation pathways to team resilience, and (Yamin et al., 2024), which links SHRM and AI to supply chain agility and resilience. The two studies without explicit RQ3 evidence in the abstract are (Bastida et al., 2025) and (Cady et al., 2024) because they are primarily conceptual and do not report measurable empirical outcomes in the available metadata.

Table 1. Summary of Included Study Characteristics (n = 18)

No.	Author(s) (Year)	Geographic Context	Study Focus	HR Domain Focus and Highlighted Outcomes
1.	Dhilipan et al. (2025)	India	AI anxiety	Performance, well-being, career prospects; adaptive strategies in response to AI disruption
2.	Liu et al. (2025)	China	Algorithmic management	Team resilience; cognitive and behavioral mechanisms via reduced objectification and informal leadership
3.	Safa'atillah et al. (2025)	Indonesia	AI-based learning technology	HR competencies for Industry 4.0; digital literacy, adaptive leadership, agility, data-driven decision-making
4.	Bastida et al. (2025)	Spain	AI for HRM (automation)	Recruitment, performance evaluation, development; algorithmic bias, technostress, readiness, resilience
5.	Ng et al. (2025)	Australia	Megatrends including AI	Implications for HRM in the future of work and the need to adapt HR practices
6.	Tenakwah & Watson (2024)	Australia	AI and automation	Strategic workforce planning, upskilling, AI literacy, HR as the bridge between humans and machines
7.	Roy et al. (2025)	India	AI adaptation taxonomy	Role of SHRM in business model innovation, value appropriation, and AI adaptation
8.	Al-Qassem et al. (2025)	Cross-country	AI, automation, cloud platform	Transforming HR practices for speed and efficiency; recruitment, training, performance; outcomes include process acceleration and HR efficiency
9.	Del Barone et al. (2025)	Italy	AI-enabled HRM	Public-sector resilience; mechanisms via core HR processes, managerial competencies, culture, structure, and crisis-response tools
10.	Vadithe et al. (2025)	India	HRIS, HR big data, HR analytics	HR analytics as a mediator toward organizational agility and operational performance
11.	Cady et al. (2024)	United States	AI and work design	Strengthening human skills for adaptability, innovation, and AI-era workforce readiness
12.	Chowdhury et al. (2024)	United Kingdom	Generative AI	SHRM framework for adopting generative AI; efficiency, innovation, learning culture, responsible practices
13.	Indravathy & Rahim (2024)	Malaysia	AI for ambidexterity	Mapping AI roles including organizational agility, managerial skills, and multiple organizational areas
14.	Yamin et al. (2024)	Saudi Arabia	AI plus SHRM	Supply chain agility and supply chain resilience; roles of leadership, skills, human capital development, flexibility
15.	H. Zhang (2024)	China	AI for HR processes	Recruitment efficiency, productivity, job satisfaction, turnover, trust, employee engagement
16.	Wu (2024)	China	XGBoost	Turnover prediction and HR reform; improved HR management performance and reduced separation rate
17.	R. Zhang et al. (2024)	China	IT and AI for talent decisions	Talent decision-making strategies based on criteria including ethical concerns and trend adaptability
18.	Al-Ayed (2024)	Saudi Arabia	AI in HR; tech. competence	HR system strength; mediation by technology competence; emphasis on agility and adaptability in HR strategy

Source: Authors' extraction based on Scopus metadata and abstracts (processed from the SLR dataset).

For RQ4, which addresses evidence gaps and future research directions, 11 studies are directly relevant, 5 are indirectly relevant, and 2 do not offer explicit evidence in the abstract. This pattern suggests that many studies mention governance, cultural readiness, ethics, and future research needs, yet the depth of gap articulation varies considerably and often appears as general implications or recommendations.

Thematic Synthesis Based on RQ1–RQ4

Building on the evidence mapping in above section, the thematic synthesis integrates the included studies across RQ1–RQ4 and consolidates the findings into a coherent cross-RQ explanation of how AI and HR analytics operate within SHRM to support workforce agility. Overall, the literature converges on a socio-technical capability view in which agility-relevant benefits do not arise from technology adoption alone, but from the extent to which AI and analytics are embedded in a coherent SHRM system and complemented by human readiness and governance. It is also evident that "workforce agility" is frequently represented through adjacent constructs such as organizational agility, team resilience, organizational resilience, or supply chain agility and resilience, which jointly capture adaptive capacity at multiple levels (Del Barone et al., 2025; Liu et al., 2025; Vadithe et al., 2025; Yamin et al., 2024). This indicates that agility is commonly treated as an emergent outcome of integrated people, process, and decision-system design rather than a single directly measured endpoint.

Across studies, a dominant pathway to agility is analytics-enabled decision capability. Evidence shows that HRIS and HR big data enhance HR analytics capability, which then supports more timely and reliable HR decision making and contributes to organizational agility and operational performance (Vadithe et al., 2025). Related work illustrates the increasing use of predictive and data-driven approaches in workforce risk management and talent decisions, including turnover prediction and HR optimization (Wu, 2024) and structured talent decision frameworks that explicitly consider technology and evaluative criteria (R. Zhang et al., 2024).

Table 2. Cross-RQ Thematic Synthesis (Summary of Themes and Supporting Evidence)

Dominant Theme	Core Finding	Illustrative Supporting Studies
Data capability and HR analytics as agility enablers	HRIS, HR big data, and HR analytics accelerate HR decisions and improve agility and performance	Vadithe et al. (2025); Al-Qassem et al. (2025); H. Zhang (2024)
AI-enabled HRM strengthens resilience via process improvement and managerial competencies	AI integration into HR processes is effective when accompanied by managerial competency development and organizational readiness	Del Barone et al. (2025); Bastida et al. (2025)
Algorithmic management shapes resilience through social mechanisms	Algorithmic systems shape managerial perceptions and trigger informal leadership that strengthens team resilience	Liu et al. (2025)
SHRM enablers as conditions for successful AI-driven agility and resilience	Leadership, culture, skills, and human capital development interact with AI to determine agility and resilience	Yamin et al. (2024); Safa'atillah et al. (2025); Tenakwah & Watson (2025)
Human factors as mediators, including anxiety and human skills	AI impacts on adaptability are shaped by psychological factors and investments in human skills that are difficult to automate	Dhilipan et al. (2025); Cady et al. (2024)
Governance, ethics, and technology competence as cross-cutting issues	Ethical concerns, bias, technostress, and technology competence shape AI implementation quality and HR system strength	Bastida et al. (2025); Al-Ayed (2024); R. Zhang et al. (2024)

Source: Authors' thematic synthesis based on the included studies.

At the process level, AI-enabled HR practices are associated with improvements in recruitment efficiency, productivity, and reduced turnover, which indirectly strengthen the stability and responsiveness of the workforce base during change (H. Zhang, 2024). Taken together, these findings suggest that agility-relevant outcomes emerge when analytics is translated into strategic workforce actions rather than used primarily for descriptive reporting.

A second, closely related pathway concerns AI-enabled HRM and work design as mechanisms shaping adaptive capacity. Several studies frame AI adoption in HR as a shift from automation to augmentation, implying that agility depends on redesigning HR processes and managerial work while developing new coordination and capability-building routines (Bastida et al., 2025; Chowdhury et al., 2024). Algorithmic management highlights the socio-behavioral mechanisms through which AI can influence resilience at the team level, particularly by shaping managerial perceptions and enabling informal leadership dynamics that support team resilience (Liu et al., 2025). In the public sector, AI-enabled HRM is linked to organizational resilience through improvements in core HR processes, strengthened managerial competencies, and reduced structural and cultural barriers that otherwise constrain adaptive responses (Del Barone et al., 2025). Practice-oriented contributions further emphasize strategic workforce planning, upskilling, and HR's bridging role in human–machine collaboration as prerequisites for sustained adaptability in AI-intensive contexts (Tenakwah & Watson, 2024). Overall, the evidence indicates that AI strengthens agility when it is integrated into SHRM as a redesigned system of work and HR practices, not as an isolated tool.

A third synthesis outcome concerns enabling conditions, governance, and research gaps. Empirical evidence indicates that leadership, skills, culture, and human capital development amplify the contribution of AI-enabled SHRM to agility and resilience outcomes, implying that SHRM enablers function as necessary complements to technology (Yamin et al., 2024). At the individual level, workforce responses such as AI anxiety can undermine performance and well-being, suggesting that continuous learning and supportive change management are critical if AI is to reinforce adaptability rather than trigger resistance (Dhilipan et al., 2025). Technology competence also appears as a key condition that links AI adoption to stronger HR systems and more consistent HR functioning in digital transformation settings (Al-Ayed, 2024). Meanwhile, governance concerns related to ethics, bias, and technostress recur across studies, indicating that fairness, transparency, and accountability are not peripheral issues but core design requirements for AI-enabled HR practices (Bastida et al., 2025; R. Zhang et al., 2024). These patterns point to persistent research gaps: the need for more explicit and consistent measurement of workforce agility, stronger causal inference through longitudinal and multi-level designs, and operationalizable governance approaches, including systematic evaluation of fairness and accountability in AI-enabled HR decisions and the emerging implications of generative AI for SHRM architecture and workforce dynamics (Chowdhury et al., 2024). Table 2 summarizes the cross-RQ thematic structure and illustrates the key supporting studies.

This section interprets the findings of the systematic review on the integration of artificial intelligence (AI) and human resource analytics (HR analytics) in strategic human resource management (SHRM) and its implications for workforce agility. The discussion clarifies the meaning of the results, connects them with the broader SHRM and digital transformation literature, articulates practical implications for organizations, and identifies limitations and future research opportunities grounded in the evidence from the included studies.

Interpretation of Key Findings

The results of this review indicate that AI and HR analytics are commonly positioned as strategic capabilities that strengthen SHRM in a turbulent environment, particularly by improving decision quality, accelerating organizational responsiveness, and enhancing workforce readiness and adaptability (Bastida et al., 2025; Vadithe et al., 2025; Yamin et al., 2024). This pattern is consistent with the view that digital transformation requires organizations to sense change rapidly, convert information into strategic action, and continuously reconfigure resources and work practices (Teece et al., 2016; Vial, 2019). In SHRM, AI and HR analytics should therefore not be reduced to process automation tools. Instead, they function as enablers of adaptive work and HR systems that remain aligned with strategy under uncertainty (Chowdhury et al., 2024; Ng et al., 2025).

Substantively, the relationship between AI and HR analytics and workforce agility appears strongest when these technologies are integrated with competence development, organizational learning, and supportive leadership. Evidence on AI anxiety suggests that psychological readiness and workforce capability development are essential conditions for

AI to reinforce agility rather than generate resistance and uncertainty (Dhilipan et al., 2025). This direction aligns with the idea that the organizational value of AI is shifting from a pure automation logic to an augmentation logic, where technology expands human capacity to work more adaptively and create higher value (Bastida et al., 2025; Raisch & Krakowski, 2021). Conversely, when the human dimension is underemphasized, AI may weaken the meaningfulness of work, increase anxiety, or create social distance in employment relationships (Cady et al., 2024; Liu et al., 2025).

The evidence also suggests that HR analytics serves as a bridge between HR data infrastructure and strategic outcomes, because analytics can help organizations map capability requirements, anticipate workforce change, and redesign talent allocation in line with strategic priorities (Vadithe et al., 2025; R. Zhang et al., 2024). However, HR analytics is not simply a technical activity. It is an organizational capability that depends on data quality, analytical competence, stakeholder legitimacy, and the ability to translate analytical insights into credible and valuable decisions (Angrave et al., 2016; Marler & Boudreau, 2017; Minbaeva, 2018). Accordingly, workforce agility is more likely to emerge when AI and HR analytics are embedded in a coherent and strong SHRM system rather than implemented as standalone technology initiatives.

Comparison with Previous Studies

The findings enrich ongoing debates on people analytics and HR digitalization by highlighting that the linkage among AI, HR analytics, and workforce agility is multi-level, involving individuals, teams, and organizations. Prior people analytics research has emphasized the promise of analytics for improving HR decisions and performance, while also warning that implementation often fails when HR functions do not build sufficient analytical capability and governance (Angrave et al., 2016; Tursunbayeva et al., 2018). The present review supports this argument, as several included studies identify managerial capability and organizational competence as critical conditions for AI to strengthen resilience and agility, including in the public sector where governance constraints differ from those in private organizations (Del Barone et al., 2025).

From an SHRM perspective, the review indicates that AI and HR analytics are strategically productive when understood as part of an integrated HR system that sends consistent signals to employees. SHRM research underscores the importance of alignment, coherence, and consistency across HR practices to shape employee behavior and capabilities in line with strategy (Boon et al., 2019; Jiang & Messersmith, 2018). In this context, AI and HR analytics may strengthen HR system strength by improving talent placement accuracy, identifying skills gaps more precisely, and increasing the effectiveness of learning interventions, but these benefits are more likely when organizations possess adequate technology competence and orchestration capability (Al-Ayed, 2024; Vadithe et al., 2025). This insight is consistent with broader digital transformation scholarship, which emphasizes that value creation requires alignment between technological capabilities and changes in processes, structures, and culture, not mere tool adoption (Vial, 2019).

The review also highlights broader strategic consequences of AI and analytics, including business model innovation and strategic renewal. Evidence on AI adaptation in business model innovation suggests that SHRM is necessary to ensure AI-driven change is supported by appropriate job design, capability development, and governance arrangements (Roy et al., 2025). This narrative aligns with (Prasetia, 2025), who emphasizes the role of aligning AI capability with strategy and orchestrating digital ecosystems to sustain competitive advantage. In Indonesia, the importance of talent as a source of competitive advantage is also reflected in (Rofaida, 2016) on talent management and competitive advantage and in (Irawan et al., 2019), who report links between HR practices and competitive advantage through operational excellence. Overall, these findings extend the discussion by positioning workforce agility as a strategic outcome that connects investment in AI and HR analytics with adaptive performance and organizational sustainability.

Practical and Managerial Implications

A key managerial implication is that organizations should design the integration of AI and HR analytics as a human-centered SHRM transformation program rather than as isolated technology projects. Organizations need to prioritize digital and analytical competence building for HR professionals and line managers so that analytics can be converted into decisions that are relevant, fair, and accountable (Marler & Boudreau, 2017; Minbaeva, 2018). Evidence on workforce readiness also implies that technology investment should be paired with learning strategies, reskilling, and upskilling so that AI genuinely enhances workforce adaptability and agility (Dhilipan et al., 2025; Safa'atillah et al., 2025; Tenakwah & Watson, 2024). In addition, HR analytics should be oriented toward strategic decisions on talent mobility, workforce planning, and adaptive employee experience design, as these domains directly shape agility (Ng et al., 2025; R. Zhang et al., 2024).

Organizations must also manage the shift from automation to augmentation by adopting work design principles that protect employee dignity and the quality of workplace social relations. Evidence on algorithmic management indicates that algorithm-based work management can influence team resilience through psychosocial mechanisms such as objectification and informal leadership, which implies the need for managerial interventions to ensure technology does not erode the human quality of work (Cady et al., 2024; Liu et al., 2025). This direction is consistent with the automation–augmentation paradox, where organizations gain efficiency from automation while still relying on human creativity and judgment to navigate uncertainty (Raisch & Krakowski, 2021).

From a governance perspective, using AI for HR and talent decisions requires strong attention to transparency, accountability, and bias risk. The findings underscore the role of technology competence in strengthening HR systems, which implies that organizations should establish data governance, ensure data quality, audit models, and retain human oversight for AI-supported decisions (Al-Ayed, 2024; Vadithe et al., 2025). This recommendation aligns with AI ethics frameworks that emphasize principles such as fairness, accountability, and protection of individual rights, and the need to translate these principles into operational procedures (Floridi et al., 2018; Jobin et al., 2019). Given that research also highlights the risk of bias and unfairness in machine learning, organizations should institutionalize bias evaluation as a routine governance practice, particularly when AI is used for recruitment, selection, and performance evaluation (Mehrabi et al., 2022; H. Zhang, 2024).

Limitations and Cautions

Several limitations should be considered when interpreting these findings. First, the evidence base in the included studies is concentrated in the most recent years, so the results reflect an early and rapidly evolving phase of research on AI, HR analytics, and workforce agility. This is important because AI concepts, terminology, and HR practices can change quickly, particularly with the emergence of generative AI as a new paradigm (Chowdhury et al., 2024; Ng et al., 2025). Second, heterogeneity in methods and contexts limits generalizability, especially for highly regulated domains such as public administration and supply chains (Del Barone et al., 2025; Yamin et al., 2024).

Third, several included articles are conceptual or context-specific, meaning that strong empirical evidence on causal relationships among AI, HR analytics, and workforce agility remains limited. This challenge echoes prior HR analytics scholarship emphasizing the importance of validity, credibility, and value demonstration so that analytics does not remain at the level of metric reporting (Angrave et al., 2016; Minbaeva, 2018). Fourth, some articles discuss HR transformation and technology broadly, which implies that workforce agility may be treated implicitly rather than operationalized as a rigorously measured construct. Therefore, interpretations related to agility should be made with careful attention to how each study defines and operationalizes relevant constructs (Al-Qassem et al., 2025; Wu, 2024).

Recommendations for Future Research

Future research should strengthen conceptual clarity, methodological rigor, and governance considerations. Conceptually, scholars should develop more consistent operational definitions of workforce agility and test its mechanisms more rigorously, including the roles of psychological empowerment, learning, and technology-enabled work design. Prior work suggests that organizational practices and psychological empowerment relate to workforce agility, providing a basis for examining how AI and HR analytics influence agility through psychosocial pathways and capability development (Muduli, 2017; Petermann & Zacher, 2022). From an SHRM perspective, further research should test how HR system strength and HR practice configurations act as enabling conditions for AI and HR analytics to produce sustainable agility (Boon et al., 2019; Jiang & Messersmith, 2018).

Methodologically, more longitudinal and multi-level studies are needed to assess whether AI and HR analytics integration produces sustained adaptive behavior or merely short-term efficiency gains. Research should also expand across industries and countries to examine institutional and regulatory differences that shape AI-enabled SHRM design (Indravathy & Rahim, 2024; Ng et al., 2025). In addition, ethics and algorithmic fairness should become central research priorities, given that AI-driven HR decisions directly affect employment opportunities, employee experience, and organizational legitimacy. Therefore, future research should incorporate AI ethics principles as design and governance variables rather than treating them as purely normative concerns, for example through bias audits, decision transparency, and strengthened accountability mechanisms (Floridi et al., 2018; Jobin et al., 2019; Mehrabi et al., 2022). Ultimately, more integrative research on AI, HR analytics, and SHRM will help clarify when and how technology supports workforce agility as a strategic capability that enhances resilience, innovation, and competitive advantage (Duchek, 2020; Roy et al., 2025; Teece et al., 2016).

Conclusion

Based on the systematic synthesis conducted in this review, the study concludes that integrating artificial intelligence (AI) and human resource analytics (HR analytics) within a strategic human resource management (SHRM) framework has strong potential to strengthen workforce agility, particularly when these technologies are positioned as strategic capabilities that support evidence-based decision making, faster organizational responses, and the development of an adaptive workforce. The primary value of AI and analytics in SHRM does not lie merely in process automation, but rather in enabling organizations to build more adaptive HR systems through the orchestration of data, competencies, and work design that are aligned with strategic intent.

From a practical perspective, these findings suggest that organizations should design AI and HR analytics implementation as an integrated SHRM transformation program, with explicit attention to data quality, analytical competence, and managerial capability to translate insights into strategic decisions. Organizations should also ensure that enhanced workforce agility is supported by competency development strategies, continuous learning, and a human-centered work experience, so that technology functions as an enabler of adaptability rather than a trigger of resistance or psychosocial strain. In addition, AI governance should be established from the outset so that the use of AI in HR decisions remains accountable, transparent, and fair, while also safeguarding organizational legitimacy in the eyes of employees and other stakeholders.

Nevertheless, the conclusions of this review should be interpreted with caution because the evidence base on AI, HR analytics, and workforce agility is still evolving rapidly and shows substantial variation in context, definitions, and construct operationalization. Limited access to some full-text articles also constrained the depth of analysis regarding mechanisms and organizational implementation details. Future research should therefore strengthen the consistency of workforce agility measurement, expand the use of longitudinal and multi-level designs to capture sustained adaptation processes, and broaden evidence across industries and countries. Research agendas should also test governance as an operationalizable variable, including bias evaluation, transparency, and accountability in AI-enabled HR decision making, while examining the implications of increasingly advanced technologies such as generative AI for SHRM architecture and workforce dynamics.

Author contributions

Arus Reka Prasetia: Conceptualization, development of the review protocol and research questions, search strategy design, study screening and eligibility assessment, quality appraisal, data extraction, thematic synthesis, visualization, and writing of the original draft. Rofi Rofaida: Methodological guidance, supervision, validation of the review approach and interpretation, and critical review and editing of the manuscript. Syamsul Hadi Senen: Supervision, validation of findings and conclusions, and critical review and editing to strengthen the theoretical framing and managerial implications. All authors have read and approved the final version of the manuscript and agree to be accountable for its content.

Acknowledgements

The authors would like to acknowledge Universitas Pendidikan Indonesia for providing academic facilities and library resources that supported the literature search and manuscript preparation. The authors also appreciate the support of library staff in facilitating access to scholarly databases and related research services. Any remaining errors or omissions are the sole responsibility of the authors.

References

Al-Ayed, S. (2024). Role of Artificial Intelligence for Strengthening Human Resource System Via Mediation of Technology Competence. *Problems and Perspectives in Management*, *22*(2), 518–526. https://doi.org/10.21511/ppm.22(2).2024.40

Al-Qassem, A. H., Ryad Momani, H., Alkhazali, Z., Alshawabkeh, R., Al-Abbadi, L. H., Al Sheyab, S. N., Jizza Anawarseh, T. E., Alzoubi, M., & Bani Ahmad, A. (2025). The Impact of Technological Advancements on Human Resource Management Practices: Adapting to the Digital Era. *Data and Metadata*, *4*, 1–16. https://doi.org/10.56294/dm2025731

Angrave, D., Charlwood, A., Kirkpatrick, I., Lawrence, M., & Stuart, M. (2016). HR and analytics: why HR is set to fail the big data challenge. *Human Resource Management Journal*, *26*(1), 1–11. https://doi.org/10.1111/1748-8583.12090

Bastida, M., Vaquero García, A., Vazquez Taín, M. Á., & Del Río Araujo, M. (2025). From automation to augmentation: Human resource's journey with artificial intelligence. *Journal of Industrial Information Integration*, *46*(May), 100872. https://doi.org/10.1016/j.jii.2025.100872

Boon, C., Den Hartog, D. N., & Lepak, D. P. (2019). A Systematic Review of Human Resource Management Systems and Their Measurement. *Journal of Management*, *45*(6), 2498–2537. https://doi.org/10.1177/0149206318818718

Braun, V., & Clarke, V. (2008). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Cady, Steven H, Willing, Jari G, & Cady, Deakon A. (2024). The AI Imperative: On Becoming Quintessentially Human. *The Journal of Applied Behavioral Science*, *60*(4), 721–731. https://doi.org/10.1177/00218863241284310

Chowdhury, S., Budhwar, P., & Wood, G. (2024). Generative Artificial Intelligence in Business: Towards a Strategic Human Resource Management Framework. *British Journal of Management*, *35*(4), 1680–1691. https://doi.org/10.1111/1467-8551.12824

Del Barone, L., de Gennaro, D., & Buonocore, F. (2025). AI-driven HRM and managerial competencies: strengthening organizational resilience in Public Administration. *Management Decision*. https://doi.org/10.1108/MD-06-2024-1252

Dhilipan, C., Kannan, A. S., & B, E. (2025). Addressing AI anxiety: workforce development strategies for an AI-driven era. *International Journal of System Assurance Engineering and Management*, *16*(12), 4131–4141. https://doi.org/10.1007/s13198-025-02916-z

Duchek, S. (2020). Organizational resilience: a capability-based conceptualization. *Business Research*, *13*(1), 215–246. https://doi.org/10.1007/s40685-019-0085-7

Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., Luetge, C., Madelin, R., Pagallo, U., Rossi, F., Schafer, B., Valcke, P., & Vayena, E. (2018). AI4People—An Ethical Framework for a Good AI Society: Opportunities, Risks, Principles, and Recommendations. *Minds and Machines*, *28*(4), 689–707. https://doi.org/10.1007/s11023-018-9482-5

Hong, Quan Nha, Fàbregues, Sergi, Bartlett, Gillian, Boardman, Felicity, Cargo, Margaret, Dagenais, Pierre, Gagnon, Marie-Pierre, Griffiths, Frances, Nicolau, Belinda, O'Cathain, Alicia, Rousseau, Marie-Claude, Vedel, Isabelle, & Pluye, Pierre. (2018). The Mixed Methods Appraisal Tool (MMAT) version 2018 for information professionals and researchers. *Education for Information*, *34*(4), 285–291. https://doi.org/10.3233/EFI-180221

Indravathy, K., & Rahim, N. A. (2024). Emerging Ambidextrous Opportunities: How Malaysian GLCS Can Leverage Artificial Intelligence. *Journal of Theoretical and Applied Information Technology*, *102*(16), 6038–6061.

Irawan, A., Senen, S., & Kurniawan, A. (2019). Influence of Human Resource Management Practices on Competitive Advantage through Operational Excellence in SME Food and beverage in Banjar City West Java. *The First International Conference On Islamic Development Studies 2019*, 1–9. https://doi.org/10.4108/eai.10-9-2019.2289337

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, *61*(4), 577–586. https://doi.org/10.1016/j.bushor.2018.03.007

Jiang, K., & Messersmith, J. (2018). On the shoulders of giants: a meta-review of strategic human resource management. *The International Journal of Human Resource Management*, *29*(1), 6–33. https://doi.org/10.1080/09585192.2017.1384930

Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence*, *1*(9), 389–399. https://doi.org/10.1038/s42256-019-0088-2

Kellogg, K. C., Valentine, M. A., & Christin, A. (2019). Algorithms at Work: The New Contested Terrain of Control. *Academy of Management Annals*, *14*(1), 366–410. https://doi.org/10.5465/annals.2018.0174

Liu, P., Yuan, L., & Wang, J. (2025). Unpacking Algorithmic Management: Pathways to Team Resilience Through Reduced Objectification and Informal Leadership. *Asia Pacific Journal of Human Resources*, *63*(4), e70031. https://doi.org/10.1111/1744-7941.70031

Marler, J. H., & Boudreau, J. W. (2017). An evidence-based review of HR Analytics. *The International Journal of Human Resource Management*, *28*(1), 3–26. https://doi.org/10.1080/09585192.2016.1244699

Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., & Galstyan, A. (2022). A Survey on Bias and Fairness in Machine Learning. *ACM Computing Surveys*, *54*(6), 1–35. https://doi.org/10.1145/3457607

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information and Management*, *58*(3), 103434. https://doi.org/10.1016/j.im.2021.103434

Minbaeva, D. B. (2018). Building credible human capital analytics for organizational competitive advantage. *Human Resource Management*, *57*(3), 701–713. https://doi.org/10.1002/hrm.21848

Muduli, A. (2017). Workforce agility: Examining the role of organizational practices and psychological empowerment. *Global Business and Organizational Excellence*, *36*(5), 46–56. https://doi.org/10.1002/joe.21800

Ng, E. S., Stanton, P., Umeh, C., Bamber, G. J., Stone, D., Lukaszewski, K., Aw, S., Lyons, S., Schweitzer, L., Ren, S., Özbilgin, M. F., & Varma, A. (2025). Megatrends affecting the world of work: Implications for human resource management. *Personnel Review*, *54*(5), 1113–1149. https://doi.org/10.1108/PR-02-2025-0100

Nowell, L. S., Norris, J. M., White, D. E., & Moules, N. J. (2017). Thematic Analysis: Striving to Meet the Trustworthiness Criteria. *International Journal of Qualitative Methods*, *16*(1), 1–13. https://doi.org/10.1177/1609406917733847

Okoli, C. (2015). A Guide to Conducting a Standalone Systematic Literature Review. *Communications of the Association for Information Systems*, *37*(1), 879–910. https://doi.org/10.17705/1cais.03743

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, *372*. https://doi.org/10.1136/bmj.n71

Page, M. J., Moher, D., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., Mcdonald, S., … Mckenzie, J. E. (2021). PRISMA 2020 explanation and elaboration: Updated guidance and exemplars for reporting systematic reviews. *The BMJ*, *372*. https://doi.org/10.1136/bmj.n160

Petermann, M. K. H., & Zacher, H. (2022). Workforce Agility: Development and Validation of a Multidimensional Measure. *Frontiers in Psychology*, *13*(March). https://doi.org/10.3389/fpsyg.2022.841862

Prasetia, A. R. (2025). AI-Powered Platform Business Models: A Systematic Literature Review of Digital Ecosystems for Sustainable Competitive Advantage. *The 4th International Conference on Education, Economics, Business, Entrepreneurship, and Finance (ICEBEF)*, 1–5.

Raisch, S., & Krakowski, S. (2021). Artificial Intelligence and Management: The Automation–Augmentation Paradox. *Academy of Management Review*, *46*(1), 192–210. https://doi.org/10.5465/amr.2018.0072

Rofaida, R. (2016). Competitive Advantage Through Talent Management. *Proceedings of the 2016 Global Conference on Business, Management and Entrepreneurship*, *15*, 615–617. https://doi.org/10.2991/gcbme-16.2016.115

Roy, S. K., Dey, B. L., Brown, D. M., Abid, A., Apostolidis, C., Christofi, M., & Tarba, S. (2025). Business Model Innovation through AI Adaptation: The Role of Strategic Human Resources Management. *British Journal of Management*, *36*(2), 546–559. https://doi.org/10.1111/1467-8551.12894

Safa'atillah, N., Rr. Ella Evrita, H., Estiana, R., Kusumawati, B., & Judijanto, L. (2025). HR Competency Development Strategy to Increase Company Competitiveness in The Midst of Industrial Revolution 4.0. *International Journal of Accounting and Economics Studies*, *12*(5), 1021–1028. https://doi.org/10.14419/m7ybkd07

Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research*, *104*(March), 333–339. https://doi.org/10.1016/j.jbusres.2019.07.039

Stone, D. L., Deadrick, D. L., Lukaszewski, K. M., & Johnson, R. (2015). The influence of technology on the future of human resource management. *Human Resource Management Review*, *25*(2), 216–231. https://doi.org/10.1016/j.hrmr.2015.01.002

Susanto, E., Rofaida, R., & Senen, S. H. (2022). Green Human Resources Management in Hospitality Industries: a Systematic Literature Review. *European Journal of Human Resource Management Studies*, *5*(4), 19–34. https://doi.org/10.46827/ejhrms.v5i4.1212

Tallon, P. P., Queiroz, M., Coltman, T., & Sharma, R. (2019). Information technology and the search for organizational agility: A systematic review with future research possibilities. *The Journal of Strategic Information Systems*, *28*(2), 218–237. https://doi.org/10.1016/j.jsis.2018.12.002

Tambe, Prasanna, Cappelli, Peter, & Yakubovich, Valery. (2019). Artificial Intelligence in Human Resources Management: Challenges and a Path Forward. *California Management Review*, *61*(4), 15–42. https://doi.org/10.1177/0008125619867910

Teece, David, Peteraf, Margaret, & Leih, Sohvi. (2016). Dynamic Capabilities and Organizational Agility: Risk, Uncertainty, and Strategy in the Innovation Economy. *California Management Review*, *58*(4), 13–35. https://doi.org/10.1525/cmr.2016.58.4.13

Tenakwah, E. S., & Watson, C. (2024). Embracing the AI/automation age: preparing your workforce for humans and machines working together. *Strategy & Leadership*, *53*(1), 32–48. https://doi.org/10.1108/SL-05-2024-0040

Tursunbayeva, A., Di Lauro, S., & Pagliari, C. (2018). People analytics—A scoping review of conceptual boundaries and value propositions. *International Journal of Information Management*, *43*(July), 224–247. https://doi.org/10.1016/j.ijinfomgt.2018.08.002

Vadithe, R. N., Sreenu, N., Kesari, B., Chiranjeevi, V., Mudavath, C. B. N., & Rajput, R. C. (2025). The role of HR analytics in driving organizational agility and operational performance: evidence from the construction sector. *Engineering, Construction and Architectural Management*. https://doi.org/10.1108/ECAM-01-2025-0076

Vial, G. (2019). Understanding digital transformation: A review and a research agenda. *The Journal of Strategic Information Systems*, *28*(2), 118–144.

https://doi.org/10.1016/j.jsis.2019.01.003
Wijaya, F., & Senen, S. H. (2024). Strategic Human Resource Management in Social Enterprises: A Systematic Review of Practices and Challenges. *Journal of Social Entrepreneurship Theory and Practice*, *3*(2), 74–89. https://doi.org/10.31098/jsetp.v3i2.2821
Wu, M. (2024). Human Resource Management Optimization Strategies for Diverse Work Environments Based on Artificial Intelligence. *Applied Mathematics and Nonlinear Sciences*, *9*(1), 1–16. https://doi.org/10.2478/amns-2024-2556
Xiao, Yu, & Watson, Maria. (2017). Guidance on Conducting a Systematic Literature Review. *Journal of Planning Education and Research*, *39*(1), 93–112. https://doi.org/10.1177/0739456X17723971
Yamin, M. A., Almuteri, S. D., Bogari, K. J., & Ashi, A. K. (2024). The Influence of Strategic Human Resource Management and Artificial Intelligence in Determining Supply Chain Agility and Supply Chain Resilience. *Sustainability (Switzerland)*, *16*(7), 1–15. https://doi.org/10.3390/su16072688
Zhang, H. (2024). Exploring the Impact of AI on Human Resource Management: A Case Study of Organizational Adaptation and Employee Dynamics. *IEEE Transactions on Engineering Management*, *71*, 14991–15004. https://doi.org/10.1109/TEM.2024.3457520
Zhang, R., Li, X., & Liu, G. (2024). Maximizing Human Capital: Talent Decision-Making Using Information Technology. *International Journal of Advanced Computer Science and Applications*, *15*(6), 646–657. https://doi.org/10.14569/IJACSA.2024.0150665
Zhou, Y., Cheng, Y., Zou, Y., & Liu, G. (2022). e-HRM: A meta-analysis of the antecedents, consequences, and cross-national moderators. *Human Resource Management Review*, *32*(4), 100862. https://doi.org/10.1016/j.hrmr.2021.100862