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Artificial Intelligence, Sustainable Human Resource Management, and Organisational Sustainability: A Multi-Level Integrative Framework

Masyhuri[1], Iqbal Lhutfi[2*], Siswanto[3] and Amlan Haque[4]

[1]Department of Management, Faculty of Economics and Business, Institut Teknologi dan Bisnis Widya Gama Lumajang, Lumajang, 67352, Indonesia
[2]Department of Accounting Education, Universitas Pendidikan Indonesia, Bandung, 40154, Indonesia
[3]Department of Islamic Banking, Faculty of Economics and Business, Universitas Islam Negeri Maulana Malik Ibrahim Malang, Malang, 65144, Indonesia
[4]School of Business and Law, CQ University, Rockhampton, 4701, Australia

ABSTRACT

Purpose – This study proposes a multilevel integrative framework explaining how AI capabilities are transformed into sustainability outcomes through HRM architectures and employee mechanisms under institutional and governance contingencies.
Design/methodology/approach – A systematic literature review (SLR) was conducted following PRISMA guidelines. This study identified 326 records, of which 36 studies met the inclusion criteria and were included in the final review.
Finding/Results –The findings indicate that AI enhances sustainable HRM by strengthening employee abilities, motivation, and opportunities, while simultaneously enabling organisational dynamic capabilities such as sensing, seizing, and transforming. From a socio-technical perspective, effective AI implementation depends on the alignment between technological systems and human factors.
Originality/Value – This study provides theoretical and practical implications by demonstrating that the integration of the AMO framework, dynamic capabilities, and socio-technical systems strengthens the understanding of how AI-driven HRM contributes to sustainability has implication for managers, policy makers and regulators.

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*Corresponding Author at:
Department of Accounting Education, Faculty of Economics and Business Education, Universitas Pendidikan Indonesia, Jl. Dr. Setiabudi No. 229, Isola, Sukasari, Bandung, 40154, Indonesia.
E-mail address: iqbal@upi.ac.id (Iqbal Luthfi)

1. Introduction

The rapid advancement of artificial intelligence (AI) has fundamentally reshaped organisational processes, particularly within human resource management (HRM), where data-driven decision-making, automation, and predictive analytics increasingly influence workforce management (Marler & Boudreau, 2017; Tambe et al., 2019; Davenport & Ronanki, 2018; Huang & Rust, 2021). Beyond operational efficiency, emerging research suggests that AI-enabled HRM may contribute to broader sustainability objectives, including environmental performance, social well-being, and governance quality (Stahl et al., 2020; Eccles et al., 2014; Friede et al., 2015). As organisations face growing pressure to align with environmental, social, and governance (ESG) principles and the Sustainable Development Goals (SDGs), the integration of AI into HRM has been increasingly positioned as a strategic mechanism for embedding sustainability within organisational systems (Jabbour & de Sousa Jabbour, 2016; United Nations, 2015; Kramar, 2014).

Despite this growing interest, the literature at the intersection of AI, sustainability, and HRM remains conceptually fragmented. Existing studies are dispersed across multiple research streams, including AI-enabled HRM, sustainable HRM, green HRM, and AI-driven sustainability, each offering partial insights into the relationship between technological capability, human resource systems, and sustainability outcomes (Renwick et al., 2013; Minbaeva, 2021; Aust et al., 2020; Tursunbayeva et al., 2018). While some studies focus on the role of AI in enhancing HR efficiency and decision-making, others emphasise sustainability-oriented HR practices or ESG performance, often without systematically integrating these perspectives. This fragmentation limits the development of a coherent understanding of how AI-enabled HRM contributes to sustainable organisational outcomes.

In addition to fragmentation, the literature lacks theoretical integration. Many studies adopt isolated theoretical lenses, such as the resource-based view, institutional theory, or socio-technical perspectives, without examining how these frameworks interact to explain the mechanisms through which AI-enabled HRM influences sustainability (Delery & Roumpi, 2017; Barney, 1991; Teece et al., 1997). Furthermore, the causal pathways linking AI capability, HRM systems, and sustainability outcomes remain insufficiently specified. Existing research often assumes that AI adoption leads to improved sustainability performance, yet provides limited explanation of the mediating role of HRM architectures or the moderating influence of governance and institutional contexts (Boudreau & Cascio, 2017; Leicht-Deobald et al., 2019). As a result, the conditions under which AI-enabled HRM generates sustainable value or poses unintended risks, such as bias, inequality, and governance challenges, are not yet fully understood (Floridi et al., 2018; Jobin et al., 2019; Mittelstadt et al., 2016).

These limitations highlight the need for an integrative synthesis that consolidates fragmented findings and advances a multidimensional understanding of AI-enabled sustainable HRM. Systematic literature reviews (SLRs) provide a rigorous approach to synthesising dispersed knowledge, identifying dominant themes, and developing conceptual frameworks to guide future research (Parmentola et al., 2022; Tranfield et al., 2003; Snyder, 2019). However, existing review studies in this domain tend to focus on specific subtopics, such as AI adoption in HRM or sustainability performance metrics, without offering a comprehensive integration of technological, organisational, and sustainability perspectives.

Accordingly, this study conducts a systematic literature review to synthesise and integrate research on the intersection of AI, sustainability, and HRM. Guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework (Moher et al., 2009), this study analyses peer-reviewed articles to map the field's evolution, identify dominant conceptualisations and thematic patterns, and develop an integrative framework that explains how AI-enabled HRM contributes to sustainable organisational outcomes.

This study makes four main contributions. First, this study integrates fragmented AI, HRM, and sustainability literature into a coherent multilevel framework. Second, this study explains the causal mechanisms through which AI capabilities influence sustainability outcomes. Third, this study introduces governance and institutional contingencies as critical boundary conditions. Finally, this study differentiates AI typologies and HRM architectures, reducing conceptual ambiguity.

Our study goes beyond prior reviews by moving from descriptive integration toward explanatory theorisation. Specifically, we develop a multilevel framework demonstrating how AI capabilities are translated into sustainability outcomes through HRM systems and employee-level mechanisms, while recognising governance and institutional contexts as critical boundary conditions. This framework provides a novel conceptual linkage that has not been systematically articulated in previous reviews on AI in HRM, sustainable HRM, green HRM, or AI ethics

The relationship between Artificial Intelligence (AI), Human Resource Management (HRM), and sustainability can be better understood through a multilevel theoretical perspective integrating Dynamic Capabilities Theory, Socio-Technical Systems Theory, Ability–Motivation–Opportunity (AMO) Theory, and Institutional and Governance Perspectives.

At the organizational level, Dynamic Capabilities Theory explains how firms develop, integrate, and reconfigure resources to respond to rapidly changing environments and achieve sustainable competitive advantage (Teece et al., 1997; Teece, 2007). AI capabilities, including predictive analytics, machine learning, and intelligent decision-support systems, represent strategic organizational resources that enable firms to enhance innovation, adaptability, and long-term sustainability (Mikalef et al., 2019). Consequently, organizations possessing strong AI capabilities are more likely to achieve sustainable performance through improved sensing, seizing, and transforming capabilities (Teece, 2007).

At the system level, Socio-Technical Systems Theory suggests that organizational effectiveness depends on the alignment between technological systems and social systems (Trist & Bamforth, 1951; Pasmore et al., 1982). AI implementation alone does not guarantee superior outcomes; rather, sustainable value emerges when AI technologies are effectively integrated with HRM systems and human capabilities (Jarrahi, 2018). In this context, HRM acts as a system-level mediator that translates AI capabilities into organizational outcomes through recruitment, talent management, employee development, workforce planning, and performance management practices (Minbaeva, 2021; Vrontis et al., 2023).

At the individual level, Ability–Motivation–Opportunity (AMO) Theory provides an important micro-foundational explanation of employee behavior (Appelbaum et al., 2000). According to AMO theory, employee performance is influenced by their abilities, motivation, and opportunities to contribute (Jiang et al., 2012). AI-enabled HR practices can enhance employee abilities through personalized learning and reskilling programs, strengthen motivation through data-driven performance management systems, and expand opportunities for participation and collaboration (Thangaraju et al., 2025). These mechanisms subsequently influence employee well-being, creativity, engagement, and sustainable work behaviors.

Finally, Institutional Theory and Governance Perspectives explain the contextual factors shaping AI adoption and its sustainability implications. Institutional Theory argues that organizational practices are influenced by coercive, normative, and mimetic pressures arising from the external environment (DiMaggio & Powell, 1983; Scott, 2014). As AI technologies become increasingly institutionalized, organizations face growing pressures to adopt responsible AI practices that address ethical concerns, transparency, accountability, and data privacy (Jobin et al., 2019; Floridi et al., 2018). Governance perspectives further emphasize that effective AI implementation requires appropriate regulatory frameworks and ethical governance mechanisms to ensure fairness, legitimacy, and sustainable organizational outcomes (Cath et al., 2018).

Taken together, these theoretical perspectives suggest a multilevel framework in which AI capabilities constitute strategic organizational resources, HRM functions as a system-level transformation mechanism, AMO processes represent employee-level behavioral mechanisms, and institutional and governance factors serve as boundary conditions influencing the effectiveness of AI-enabled HRM systems in achieving sustainability outcomes. This integrated perspective provides a comprehensive explanation of how organizations can leverage AI technologies and HRM practices to promote sustainable organizational transformation.

The intersection of artificial intelligence (AI), human resource management (HRM), and sustainability represents an emerging yet conceptually fragmented field of inquiry. Understanding this nexus requires a multidimensional perspective that integrates technological capabilities, organisational systems, and sustainability outcomes within broader institutional and governance contexts. Existing research provides valuable insights across these dimensions; however, these perspectives are often examined in isolation, limiting a comprehensive understanding of how AI-enabled HRM contributes to sustainable organisational development (Aust et al., 2020; Tursunbayeva et al., 2018).

From a technological perspective, AI is increasingly conceptualised as an organisational capability that enables firms to process large volumes of data, automate decision-making, and enhance predictive accuracy. Drawing on the resource-based view (RBV) and dynamic capability theory, AI can be understood as a strategic asset that enhances organisational competitiveness when effectively integrated with complementary resources and capabilities (Tambe et al., 2019; Mikalef et al., 2021; Barney, 1991; Teece et al., 1997; Eisenhardt & Martin, 2000). In the HRM context, AI applications such as HR analytics, machine learning, and decision-support systems enable organisations to optimise recruitment, performance management, and workforce planning processes (Marler & Boudreau, 2017; Angrave et al., 2016; Tursunbayeva et al., 2018). However, the effectiveness of AI as a capability depends not only on technological sophistication but also on how it is embedded within organisational structures and human resource systems.

HRM plays a critical role as a mediating system that translates AI capabilities into organisational outcomes. Contemporary HRM research increasingly emphasises the importance of system-based approaches, including high-performance work systems, sustainable HRM, and green HRM, in shaping organisational performance and sustainability outcomes (Delery & Roumpi, 2017; Renwick et al., 2013; Kramar, 2014; Aust et al., 2020; Guerci et al., 2016). Sustainable HRM, in particular, focuses on aligning HR practices with long-term organisational goals, including employee well-being, environmental responsibility, and social equity. Within this framework, AI-enabled HRM can enhance the effectiveness of HR systems by providing data-driven insights, improving decision quality, and enabling more responsive and adaptive workforce management (Minbaeva, 2018; Leicht-Deobald et al., 2019). Nevertheless, the literature suggests that technological adoption alone is insufficient; the impact of AI on sustainability outcomes depends on the design of HRM architectures and the extent to which sustainability principles are embedded in HR practices (Jabbour & de Sousa Jabbour, 2016).

Sustainability within the AI–HRM nexus is inherently multidimensional, encompassing environmental, social, and governance (ESG) dimensions as well as broader frameworks such as the triple bottom line (TBL) and the Sustainable Development Goals (SDGs) (Elkington, 1997; United Nations, 2015; Eccles et al., 2014; Friede et al., 2015). Prior research indicates that HRM plays a pivotal role in operationalising sustainability strategies by influencing employee behaviour, organisational culture, and governance practices (Stahl et al., 2020). AI-enabled HRM may contribute to sustainability by enhancing transparency, reducing resource inefficiencies, and supporting socially responsible decision-making (Parmentola et al., 2022). However, the literature also highlights tensions between efficiency and ethics, as AI-driven systems may introduce risks related to bias, privacy, and workforce displacement (Floridi et al., 2018; Mittelstadt et al., 2016; Jobin et al., 2019). These tensions underscore the need to consider sustainability not merely as an outcome but as a governance challenge shaped by technological and organisational choices.

Institutional and governance contexts further influence how AI-enabled HRM contributes to sustainability. Institutional theory suggests that organisational practices are shaped by regulatory frameworks, normative pressures, and cultural expectations (DiMaggio & Powell, 1983). In the context of AI adoption, regulatory requirements related to data protection, ethical standards, and corporate governance play a crucial role in shaping how organisations deploy AI technologies within HRM systems (Cath et al., 2018). Moreover, governance mechanisms, including accountability structures, transparency practices, and ethical guidelines, are essential for ensuring that AI-enabled HRM aligns with sustainability objectives (Boudreau & Cascio, 2017; Leicht-Deobald et al., 2019). In the absence of robust governance, AI adoption may exacerbate existing inequalities and undermine trust within organisations.

Despite these diverse perspectives, the literature remains fragmented across disciplinary boundaries. Technological studies often focus on AI capabilities and data analytics; HRM research emphasises organisational systems and employee outcomes; and sustainability research examines ESG performance and institutional dynamics. The interaction between these dimensions has rarely been analysed in an integrated manner (Snyder, 2019). As a result, there is limited understanding of how AI capabilities, HRM systems, and sustainability outcomes interact within complex organisational and institutional environments.

Taken together, these insights highlight the need for an integrative framework that captures the multidimensional nature of AI-enabled sustainable HRM. Such a framework should account for (1) AI as a technological and organisational capability, (2) HRM as a mediating system that shapes the translation of technology into organisational outcomes, (3) sustainability as a multidimensional objective encompassing environmental, social, and governance dimensions, and (4) institutional and governance contexts as boundary conditions that influence these relationships. Developing this integrative perspective is essential for advancing theoretical understanding and for guiding future research on the role of AI in supporting sustainable organisational development.

The present review distinguishes among different forms of artificial intelligence rather than treating AI as a homogeneous construct. AI capability is conceptualised as an organisational-level resource, whereas HR analytics, machine learning, and generative AI represent specific technological applications with distinct implications for HRM practices and sustainability outcomes. Similarly, sustainable HRM, green HRM, digital HRM, and HR analytics are treated as conceptually related but analytically distinct constructs. Sustainability is further conceptualised as a multidimensional outcome encompassing environmental, social, and governance dimensions.

2. Methodology

This study adopts a systematic literature review to synthesise and integrate existing research on the intersection of AI, HRM, and sustainability. The SLR approach enables a structured, transparent, and replicable process for identifying, evaluating, and synthesising prior studies, thereby reducing selection bias and enhancing the reliability of findings (Durach et al., 2017; Tranfield et al., 2003; Kitchenham, 2004; Snyder, 2019). Compared with traditional narrative reviews, SLRs provide a more rigorous methodological framework for consolidating fragmented knowledge and developing theoretical insights. The review process follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, which is widely adopted in interdisciplinary research to ensure methodological transparency and reproducibility (Moher et al., 2009; Page et al., 2021). The PRISMA framework consists of four sequential stages: identification, screening, eligibility assessment, and inclusion. By applying this structured approach, the study ensures a systematic and auditable article selection process.

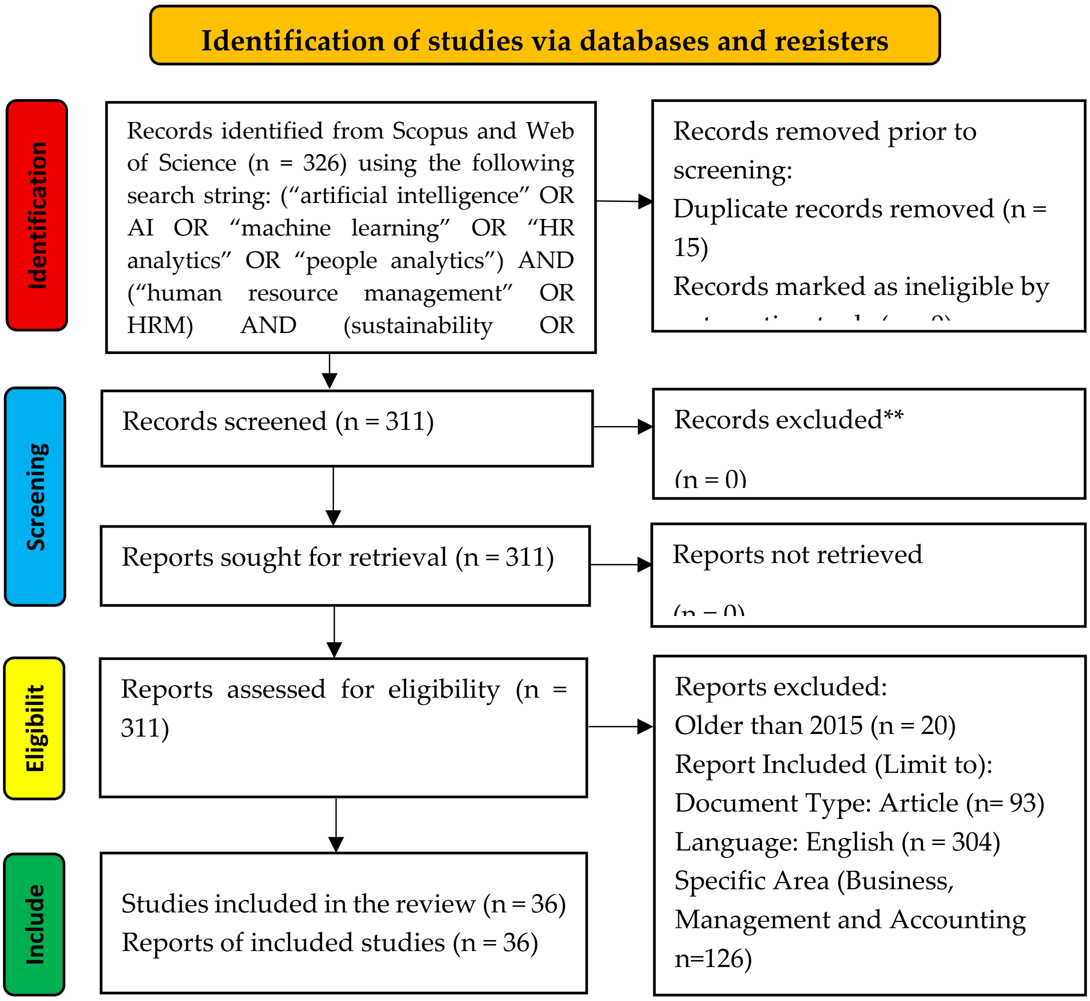
The literature search was conducted using two major international academic databases: Scopus and Web of Science (WoS). These databases were selected due to their comprehensive coverage of peer-reviewed journals across disciplines relevant to this study, including management, information systems, sustainability, and organisational studies (Parmentola et al., 2022; Mongeon & Paul-Hus, 2016). The search was performed using combinations of keywords related to AI, HRM, and sustainability. The primary search string included: “artificial intelligence” OR “AI” OR “machine learning” OR “HR analytics” OR “people analytics” AND “human resource management” OR “HRM” AND “sustainability” OR “sustainable HRM” OR “green HRM” OR “ESG” OR “organisational sustainability”.

The search was limited to publications from 2015 to 2025 to capture contemporary developments in AI technologies and their applications in HRM and sustainability contexts (Tambe et al., 2019; Mikalef et al., 2021). To ensure the relevance and quality of the selected studies, predefined inclusion and exclusion criteria were applied. The inclusion criteria comprised peer-reviewed journal articles, publications written in English, studies explicitly addressing the intersection of artificial intelligence (AI), human resource management (HRM), and sustainability, articles within the disciplines of business, management, accounting, or information systems, and studies with full-text availability. Meanwhile, the exclusion criteria encompassed conference papers, book chapters, and working papers, non-English publications, studies focusing on AI or sustainability without relevance to HRM, and studies lacking a substantive discussion of sustainability outcomes. The application of these criteria ensured that the final dataset consisted of studies directly relevant to the AI–HRM–sustainability nexus (Tranfield et al., 2003; Snyder, 2019).

The article selection process followed the PRISMA procedure. During the identification stage, an initial set of records was retrieved from Scopus and Web of Science using predefined search strings. Duplicate records were removed prior to screening. In the screening stage, titles and abstracts were reviewed to assess relevance. Articles that did not explicitly address the intersection of AI, HRM, and sustainability were excluded. Subsequently, full-text articles were evaluated in the eligibility stage to ensure alignment with the inclusion criteria. The final selection yielded 36 peer-reviewed articles for the analysis. The literature search was conducted on 15 January 2025 using Scopus and Web of Science databases. Searches were restricted to peer-reviewed journal articles published between 2015 and 2025 and written in English. Duplicate records were removed using reference management software and manual verification procedures. Two independent reviewers conducted title, abstract, and full-text screening. Inter-reviewer reliability was assessed using Cohen's Kappa coefficient, indicating substantial agreement. Disagreements were resolved through discussion until consensus was achieved. The following figure illustrates the PRISMA-based article selection process.

To ensure methodological rigor, transparency, and replicability, this study established explicit inclusion and exclusion criteria based on the intersection of three core domains: Artificial Intelligence (AI), Human Resource Management (HRM), and Sustainability. The initial search was conducted in the Scopus and Web of Science databases using predefined keywords related to AI, HRM, and sustainability, resulting in 326 records. Prior to screening, 15 duplicate records were removed, while no records were excluded through automation tools or for other reasons. The remaining records were subsequently screened based on publication characteristics and thematic relevance. Eligibility assessment was performed by limiting the sample to peer-reviewed journal articles published in English between 2015 and 2025 and indexed within the Business, Management, and Accounting subject areas. During this stage, studies published before 2015 (n = 20), documents other than journal articles (n = 93), publications not written in English (n = 304), and studies outside the scope of Business, Management, and Accounting (n = 126) were excluded. Furthermore, studies that focused solely on AI and HRM without sustainability implications, AI and sustainability without an HRM perspective, or addressed only two of the three domains without establishing explicit conceptual or empirical integration were excluded from the review. To enhance consistency during screening, each article was systematically evaluated against the three predefined domains of AI, HRM, and Sustainability. Only studies demonstrating explicit integration among these three domains were retained, resulting in a final corpus of 36 studies included in the systematic review.

Figure 1. PRISMA Flow Diagram of Article Selection Process



Source: Moher et al. (2009)

Figure 1 above shows the systematic process of article identification, screening, eligibility assessment, and final inclusion, ensuring transparency and reproducibility in the literature selection procedure (Moher et al., 2009; Page et al., 2021). Following the final selection of articles, a structured data extraction process was conducted to systematically capture key information from each study. A data extraction template was developed to record the following elements: authors and publication year, research objectives, theoretical frameworks, research methods, data sources and sample characteristics, key variables and measurement approaches, main findings and conclusions, and identified limitations and future research directions. The extracted data were organised in a spreadsheet to facilitate systematic comparison and synthesis across studies (Kitchenham, 2004; Tranfield et al., 2003).

To synthesise the literature, this study employs thematic analysis, which enables the identification of recurring patterns and conceptual relationships across studies (Braun & Clarke, 2006). The coding process was conducted in two stages. First, open coding was used to identify key concepts and recurring themes within the reviewed articles. Second, axial coding was applied to group related concepts into broader thematic categories, enabling the development of higher-level conceptual structures. This process identified major thematic domains that structure the literature on AI-enabled HRM and sustainability (Nowell et al., 2017).

To ensure the robustness and credibility of the systematic review, a quality appraisal was conducted for all included studies. Given the methodological diversity of the selected articles, a generic quality assessment framework was adopted to evaluate studies consistently across different research designs. The assessment focused on five criteria: (1) clarity of research objectives, (2) appropriateness of research design, (3) transparency of data collection and analysis procedures, (4) theoretical and practical contribution, and (5) relevance to the integration of AI, HRM, and Sustainability.

Each criterion was scored on a three-point scale (0 = not addressed, 1 = partially addressed, and 2 = fully addressed), resulting in a maximum score of 10 points for each study. Based on the total score, studies were classified into three quality categories: high quality (8–10 points), moderate quality (5–7 points), and low quality (0–4 points). Only studies classified as high and moderate quality were retained in the final review.

The quality appraisal indicated that the majority of the included studies demonstrated moderate to high methodological quality. Most studies clearly articulated their research objectives and provided substantial theoretical contributions, although variations were observed in methodological transparency and empirical rigor across different research designs.

To enhance the reliability and validity of the review, several procedural safeguards were implemented. The screening and coding processes were conducted independently, and discrepancies were resolved through discussion to ensure consistency in article selection and thematic classification. This approach reduces subjective bias and strengthens the robustness of the findings. Furthermore, the use of the PRISMA framework ensures transparency and replicability, while the application of systematic coding procedures enhances the credibility of the thematic synthesis (Moher et al., 2009; Page et al., 2021; Snyder, 2019).

3. Result and Discussion

The systematic literature review reveals a substantial and accelerating growth of scholarly attention at the intersection of artificial intelligence (AI), human resource management (HRM), and sustainability. This trend reflects the growing strategic importance of digital transformation and the integration of sustainability within organisational contexts (Davenport & Ronanki, 2018; Vrontis et al., 2023). The earliest studies in the dataset emerged around 2015, coinciding with the growing adoption of AI technologies in business processes and the expanding discourse on sustainable HRM (Jabbour & de Sousa Jabbour, 2016; Kramar, 2014).

Between 2015 and 2019, the number of publications remained relatively limited, indicating that research in this domain was still in its formative stage. During this period, studies primarily focused on conceptual discussions of sustainable HRM and early explorations of HR analytics, with limited integration of AI-specific technologies. This pattern aligns with broader observations that the application of AI in HRM was initially constrained by technological maturity and data availability (Marler & Boudreau, 2017; Angrave et al., 2016). From 2020 onwards, the literature demonstrates a marked increase in publication activity. This growth can be attributed to several interrelated developments. First, rapid advancements in AI technologies, including machine learning and data analytics, have expanded the scope of HRM applications (Huang & Rust, 2021; Raisch & Krakowski, 2021). Second, global sustainability agendas, particularly the increasing emphasis on ESG performance and SDGs, have intensified organisational interest in integrating sustainability into HR practices (Stahl et al., 2020; United Nations, 2015; Friede et al., 2015). Third, the COVID-19 pandemic accelerated digital transformation across organisations, further driving the adoption of AI-enabled HR systems and stimulating scholarly inquiry into their implications for workforce management and sustainability (Vrontis et al., 2023). The peak of publication activity is observed in the most recent years of the dataset (2023–2025), indicating that this research field is currently in a phase of rapid expansion. This surge reflects a shift from exploratory and conceptual studies towards more empirically grounded research examining the mechanisms through which AI-enabled HRM influences sustainability outcomes. Notably, recent studies increasingly employ quantitative methods, including structural equation modelling and machine learning, to test relationships among AI capabilities, HRM practices, and sustainability performance (Mikalef et al., 2021). The temporal evolution of the literature suggests a transition from conceptual emergence to empirical consolidation. Early research primarily established the relevance of sustainability in HRM, whereas more recent studies have begun to examine AI's role in driving sustainable organisational transformation. However, despite this growth, the literature remains characterised by conceptual dispersion, with varying definitions and operationalisations of AI, HRM systems, and sustainability outcomes (Snyder, 2019). To illustrate the distribution of publications over time, the following figure presents the annual publication trends in AI, HRM, and sustainability research.

Figure 2. Publication Trends in AI–HRM–Sustainability Research (n = 36)

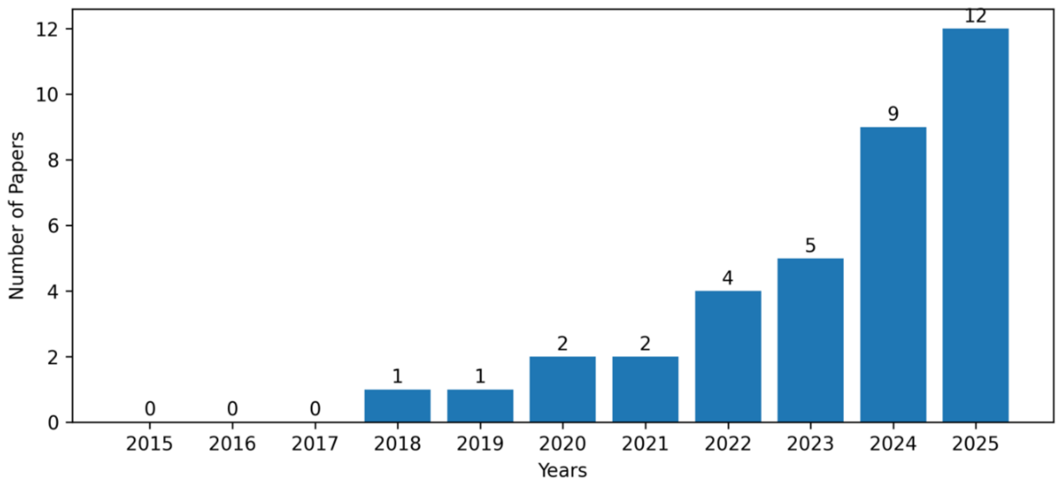


Figure 2 above shows a clear upward trajectory in publication activity, particularly after 2020, highlighting the emergence of AI-enabled sustainable HRM as a rapidly developing research domain. The observed research trends indicate that while scholarly interest in AI-enabled HRM for sustainability is growing rapidly, the field is still evolving and lacks conceptual consolidation. This reinforces the need for integrative frameworks that can synthesise fragmented insights and provide a coherent understanding of how AI capabilities, HRM systems, and sustainability objectives interact within organisational contexts. The reviewed literature demonstrates a diverse yet uneven application of theoretical perspectives in examining the relationship between artificial intelligence (AI), human resource management (HRM), and sustainability. Overall, the field is characterised by theoretical pluralism without integration, where multiple frameworks are applied in isolation rather than as complementary lenses (Snyder, 2019).

The most prominent theoretical foundation is the resource-based view (RBV) and its extension, dynamic capability theory, which conceptualise AI as a strategic organisational resource that can enhance competitive advantage when combined with complementary capabilities (Tambe et al., 2019; Mikalef et al., 2021; Barney, 1991; Teece et al., 1997; Eisenhardt & Martin, 2000). Within this perspective, AI-enabled HRM is often framed as a capability that strengthens organisational performance, including sustainability outcomes (Mikalef et al., 2021). However, RBV-based studies tend to emphasise performance implications while providing limited insight into governance and ethical dimensions.

A second dominant perspective is HRM system theory, particularly in the form of high-performance work systems (HPWS), sustainable HRM, and green HRM. These approaches highlight the role of HR practices as integrated systems that shape employee behaviour and organisational outcomes (Delery & Roumpi, 2017; Renwick et al., 2013; Kramar, 2014; Aust et al., 2020). In this context, HRM functions as a mediating mechanism that translates AI capabilities into sustainability outcomes. Nevertheless, many studies treat HRM as a generic construct rather than specifying distinct HR architectures, limiting theoretical precision (Guerci et al., 2016).

Institutional theory represents another important lens, particularly in studies examining sustainability and governance. This perspective emphasises how regulatory pressures, social norms, and organisational legitimacy influence the adoption of AI and sustainability practices (DiMaggio & Powell, 1983). Institutional perspectives are especially relevant in emerging economies, where variations in governance structures and regulatory frameworks shape the implementation of AI-enabled HRM (Cath et al., 2018). In addition, socio-technical perspectives have been increasingly applied to understand the interaction between humans and AI systems within organisational contexts. These approaches highlight the importance of aligning technological systems with human capabilities, organisational culture, and ethical considerations (Boudreau & Cascio, 2017; Raisch & Krakowski, 2021; Jarrahi, 2018; Wilson & Daugherty, 2018). Such perspectives are particularly relevant to addressing issues in human–AI collaboration, employee trust, and responsible AI adoption. Despite this diversity, the literature lacks integrative theoretical frameworks that combine these perspectives to explain the multidimensional nature of AI-enabled sustainable HRM. Most studies rely on single-theory approaches, resulting in fragmented explanations of how technological, organisational, and institutional factors interact. This limitation underscores the need for a more holistic theoretical framework that integrates capability, system, and institutional perspectives.

To synthesise the diverse conceptualisations within the literature, this study develops a structured mapping across three core dimensions: AI typology, HRM system typology, and sustainability framing. This mapping highlights the conceptual heterogeneity of the field and provides a foundation for integrative analysis. First, AI is conceptualised in multiple ways. The dominant approach treats AI as a general organisational capability, reflecting broad adoption of AI technologies without specifying their functional characteristics. A second stream focuses on HR analytics and people analytics, emphasising data-driven decision-making in HR processes (Marler & Boudreau, 2017). Additional conceptualisations include machine learning and data mining approaches, STARA (smart technology, AI, robotics, and algorithms), decision-support systems, and emerging generative AI applications. These variations indicate that AI is not a uniform construct but rather a portfolio of technologies with distinct implications for HRM and sustainability (Huang & Rust, 2021). Second, HRM is conceptualised through several system-level frameworks. These include green HRM (GHRM), which focuses on environmental sustainability; sustainable HRM, which integrates long-term organisational and employee well-being objectives; HR analytics, which emphasises data-driven HR decision-making; and digital HRM, which reflects broader digital transformation processes. However, a significant proportion of studies treat HRM generically, without specifying system configurations, limiting the explanatory power of the literature (Aust et al., 2020). Third, sustainability is framed using multiple approaches. The most common is general sustainability, where outcomes are broadly defined without specific indicators. More refined approaches include environmental/green performance, triple-bottom-line (TBL) sustainability, and ESG-oriented outcomes. A smaller number of studies explicitly align with SDGs, indicating an emerging but still limited integration with global sustainability frameworks (Stahl et al., 2020; United Nations, 2015; Elkington, 1997). To summarise these conceptual dimensions, the following table presents the classification of AI, HRM, and sustainability constructs.

Table 1. Conceptual Classification of AI, HRM, and Sustainability in the Literature

Dimension	Sub-Category	Conceptualisation	Representative Focus in Literature
Artificial Intelligence (AI)	General AI Capability	AI as organisational resource/capability	Enhancing decision-making, automation, and predictive analytics

	HR Analytics / People Analytics	Data-driven HR decision systems	Workforce analytics, performance prediction, talent optimisation
	Machine Learning & Data Mining	Algorithm-based learning systems	Pattern recognition, predictive modelling in HR
	STARA (Smart Technology, AI, Robotics, Algorithms)	Integrated intelligent technologies	Automation of HR processes and job transformation
	Decision-Support Systems	AI-assisted managerial decision tools	Recruitment, performance appraisal, and workforce planning
	Generative AI	AI systems producing content/knowledge	HR communication, knowledge generation, and emerging risks
Human Resource Management (HRM)	Green HRM (GHRM)	Environmentally oriented HR practices	Green recruitment, training, and performance evaluation
	Sustainable HRM	Long-term HRM aligned with sustainability goals	Employee well-being, social responsibility, and long-term value
	HR Analytics Systems	Data-driven HRM architecture	Evidence-based HR decision-making
	Digital HRM	Technology-enabled HR systems	Digital transformation of HR functions
	Generic HRM	Non-specified HR practices	Broad HRM influence on organisational outcomes
Sustainability	General Sustainability	Broad, non-specific sustainability outcomes	Overall organisational sustainability
	Environmental Performance	Ecological and environmental outcomes	Energy efficiency, emission reduction
	Triple Bottom Line (TBL)	Economic, social, and environmental integration	Holistic sustainability performance

ESG (Environmental, Social, Governance)	Governance-oriented sustainability	ESG reporting, compliance, accountability
SDGs Alignment	Alignment with global development goals	Contribution to UN Sustainable Development Goals

Source: Author analysis by Scopus and Web of Science Database.

Table 1 above shows the conceptual classification of artificial intelligence, human resource management, and sustainability across the reviewed literature. The mapping reveals a high degree of heterogeneity in how key constructs are defined and operationalised. AI is conceptualised not as a single technology but as a portfolio of capabilities, ranging from general organisational resources to specific applications such as HR analytics and generative AI. Similarly, HRM is represented through multiple system-level configurations, including green HRM, sustainable HRM, and digital HRM, although many studies still adopt generic conceptualisations. Sustainability is also framed in diverse ways, from broad definitions to more structured approaches such as ESG and the triple bottom line. This conceptual diversity contributes to the fragmentation of the field and underscores the need for integrative frameworks that align technological, organisational, and sustainability dimensions.

Building upon the conceptual mapping, the thematic analysis identifies five interconnected thematic domains that structure the literature on AI-enabled HRM and sustainability. These domains represent not isolated clusters, but interrelated mechanisms through which AI capabilities are translated into sustainability outcomes. The first domain focuses on AI-enabled green HRM and environmental performance, conceptualising AI as a capability that enhances environmentally oriented HR practices. Studies in this domain demonstrate that AI adoption can strengthen green HRM practices, which in turn improve environmental performance outcomes. However, the effectiveness of this relationship depends on employee engagement and organisational commitment to sustainability, indicating that technology alone is insufficient (Renwick et al., 2013; Guerci et al., 2016). The second domain concerns AI-driven capabilities and triple-bottom-line sustainability, positioning AI as a strategic resource that contributes to economic, social, and environmental outcomes. This domain highlights the mediating role of intangible organisational resources, such as green intellectual capital, in translating AI capabilities into sustainability performance (Mikalef et al., 2021; Friede et al., 2015). It reflects a more holistic understanding of sustainability beyond environmental indicators.

The third domain emphasises HR analytics as a sustainability capability, where AI is operationalised through analytics-driven HR systems. Studies in this domain show that HR analytics enhances organisational sustainability by improving decision quality, workforce stability, and performance outcomes. At the same time, this domain highlights emerging risks related to data governance, privacy, and algorithmic bias, underscoring the need for responsible AI practices (Marler & Boudreau, 2017; Leicht-Deobald et al., 2019). The fourth domain focuses on digital HRM and human–AI collaboration, where sustainability outcomes are linked to digital transformation and organisational resilience. This domain highlights the importance of human–AI interaction, employee adaptability, and digital capabilities in achieving sustainable outcomes. It reflects a shift from technology-centric perspectives towards socio-technical integration (Boudreau & Cascio, 2017; Raisch & Krakowski, 2021).

The fifth domain captures emerging risk-oriented themes, including shadow AI, generative AI, and governance challenges. This domain emphasises that AI adoption may lead to unintended consequences, including knowledge leakage, ethical risks, and workforce disruption. These findings reinforce the importance of governance mechanisms in ensuring that AI-enabled HRM contributes to sustainability rather than undermining it (Floridi et al., 2018; Jobin et al., 2019; Mittelstadt et al., 2016). To illustrate the relationships among these thematic domains, the following figure presents the literature's thematic structure.

Figure 3. Thematic Structure of AI–HRM–Sustainability Research

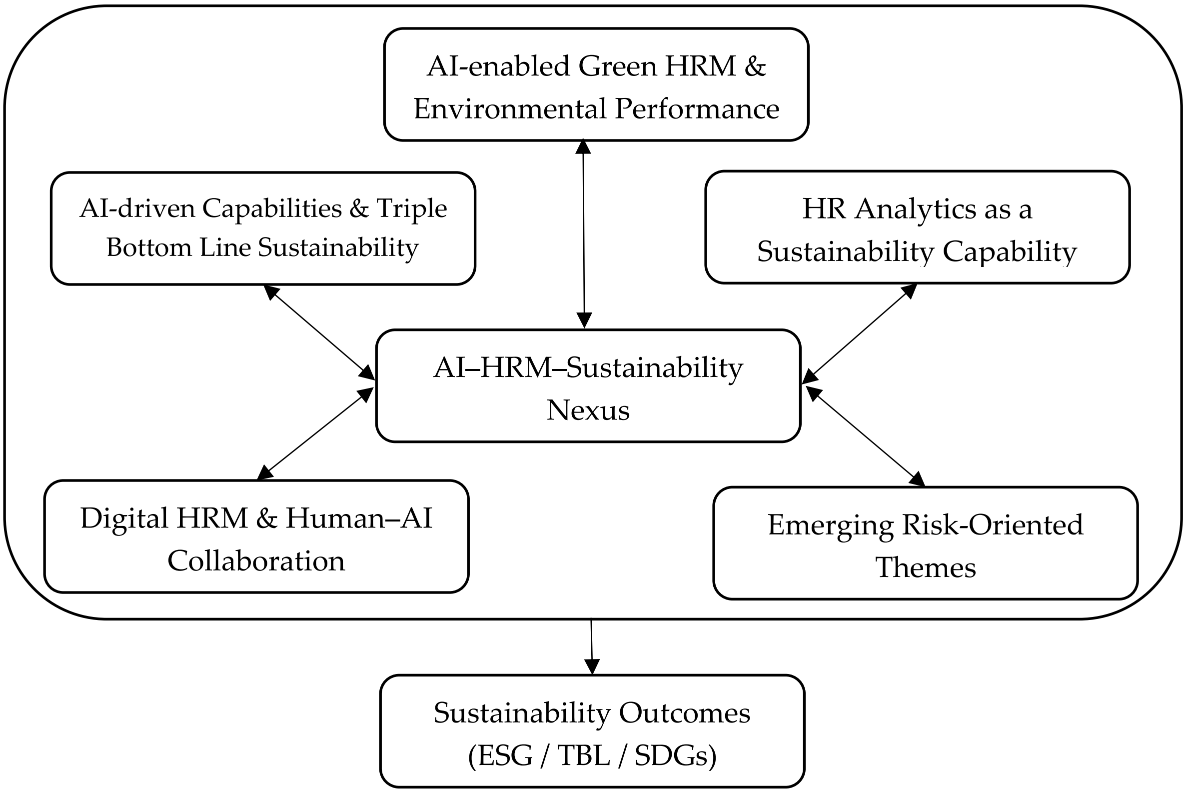


Figure 2 shows the interconnected structure of the five thematic domains, highlighting that AI-enabled HRM and sustainability research function as an integrated, interdependent system rather than isolated streams. The figure illustrates how AI capabilities are translated through HRM systems into sustainability outcomes, while being shaped by governance and institutional contexts.

Building upon the thematic synthesis, this study develops an integrative framework to explain how artificial intelligence (AI)-enabled human resource management (HRM) contributes to sustainability outcomes. The framework addresses the fragmentation identified in prior literature by integrating technological, organisational, and institutional dimensions into a unified analytical model. At its core, the framework conceptualises AI as an organisational capability, consistent with the resource-based view and dynamic capability theory, where technological resources create value when combined with complementary organisational processes (Tambe et al., 2019; Mikalef et al., 2021; Barney, 1991; Teece et al., 1997). However, AI capability alone is insufficient to generate sustainable outcomes. Instead, its impact is mediated through HRM systems, which function as the primary mechanism translating technological potential into organisational practices and employee-level outcomes.

The thematic findings reveal substantial heterogeneity across contexts and methodologies. Governance and ethical issues are predominantly discussed in conceptual studies, whereas AI-enabled green HRM themes are largely supported by quantitative evidence from manufacturing industries. Human–AI collaboration themes are more common in service and knowledge-intensive sectors. This contextual variation suggests that the AI–HRM–sustainability nexus remains highly contingent upon industrial and institutional environments. Human–AI collaboration emerged primarily within service industries, whereas environmental sustainability themes were concentrated in manufacturing settings.

Table 2. Summary of Reviewed Studies in AI–HRM–Sustainability Research (n = 36)

No	Author(s) (Years)	Main Context/Sector	AI Concept	HRM Concept	Sustainability Outcome	Key Finding
1	Freihat et al. (2025)	Industrial sector (Jordan)	Eco/Green Innovation	Green Supply Chain Management	Sustainable Development	Green innovation capabilities support sustainability transformation in emerging economies.
2	Ali et al. (2025)	Multi-sector	AI-driven Capabilities	Green HRM	Organizational Sustainability	Digital literacy and GHRM mediate the relationship between AI capability and sustainability.
3	Thangaraju et al. (2025)	Indian IT Industry	AI-driven HRM	Sustainable HRM	Employee Creative Performance	AI-enabled sustainable HRM enhances employee creativity through idiosyncratic deals.
4	Azhar et al. (2025)	Multi-sector	AI Adoption	Green HRM	Green Performance	AI adoption positively influences green organizational performance.
5	Hossain et al. (2025)	Hospitality	STARA	Green HRM	Green Performance	STARA improves green performance through GHRM and

						employee commitment.
6	Hussain et al. (2025)	Manufacturing	AI Technologies	Strategic HRM	ESG Performance	Digital orientation and AI capabilities support sustainability performance.
7	Vrontis et al. (2023)	International HRM	AI and Robotics	HR Transformation	Sustainable Workforce	AI significantly transforms international HR practices.
8	Raisch & Krakowski (2021)	Organizations	Artificial Intelligence	Human–AI Collaboration	Organizational Sustainability	Sustainable outcomes depend on balancing automation and augmentation.
9	Minbaeva (2021)	Multi-sector	Digital HR Technologies	Workforce Transformation	Sustainable HR Systems	Digital disruption reshapes HR systems and sustainability agendas.
10	Mikalef et al. (2019)	Organizations	Big Data Analytics	Innovation Capability	Sustainable Competitive Advantage	Dynamic capabilities mediate AI-driven sustainability outcomes.
11	Tambe et al. (2019)	HRM	Artificial Intelligence	Talent Management	Sustainable Transformation	AI creates both opportunities and challenges in HR functions.
12	Leicht-Deobald et al. (2019)	Organizations	Algorithmic Decision Systems	Recruitment and Evaluation	Social Sustainability	Algorithmic HR decisions raise fairness and ethical concerns.
13	Jarrahi (2018)	Organizations	Human–AI Symbiosis	Decision-making	Workforce Sustainability	Human–AI collaboration enhances managerial effectiveness.

14	Huang & Rust (2018)	Service Industry	AI Service Systems	Employee Role Transformation	Service Sustainability	AI changes employee roles and service ecosystems.
15	Tursunbayeva et al. (2018)	Multi-sector	People Analytics	Workforce Analytics	Workforce Sustainability	People analytics improves organizational sustainability capability.
16	Boudreau & Cascio (2017)	Organizations	Human Capital Analytics	Strategic HRM	Sustainable Performance	HR analytics enables better strategic decisions.
17	Marler & Boudreau (2017)	Organizations	HR Analytics	Talent Management	Organizational Sustainability	Analytics-driven HR practices improve evidence-based decisions.
18	Aust et al. (2020)	Multi-sector	Digital Technologies	Sustainable HRM	Common Good Sustainability	HRM should contribute to broader societal sustainability.
19	Stahl et al. (2020)	Multi-sector	Emerging Technologies	Sustainable HRM	ESG/CSR	HRM plays a central role in corporate sustainability.
20	Guerci et al. (2016)	Manufacturing	Digital HR Support	Green HRM	Environmental Performance	GHRM mediates stakeholder pressure and sustainability outcomes.
21	Muchowe et al. (2024)	Organizations	HR Analytics	Employee Performance	Sustainable Performance	HR analytics strengthens employee performance and organizational effectiveness.
22	Suganthi et al. (2024)	HRM Context	HR Analytics	Talent Management	Employee Sustainability	Data-driven HR decisions improve talent allocation and employee outcomes.

23	Panda et al. (2024)	Multi-sector	AI Systems	Employee Creativity	Sustainable Innovation	AI-enabled creativity increasingly contributes to innovation capability.
24	Tassabehji et al. (2024)	Software Industry	AI Monitoring Systems	Workplace Behaviour	Social Sustainability	Digital monitoring influences employee behaviour and organizational ethics.
25	Adiasto et al. (2024)	Organizations	Artificial Intelligence	Sustainable Employability	Workforce Sustainability	AI capabilities support long-term employability and workforce resilience.
26	Singh et al. (2024)	Multi-sector	Digital Technologies	Sustainable HRM	Organizational Sustainability	Sustainable HRM has become an emerging research hotspot.
27	Abid et al. (2024)	Organizations	Technological Intelligence	Green HRM	Sustainable Performance	Technological intelligence strengthens sustainability-oriented HR systems.
28	Sareminia et al. (2024)	Organizations	Smart Technologies	Quality of Work Life	Employee Well-being	AI-supported HR practices improve quality of work life and employee well-being.
29	Ogbeibu et al. (2024)	Organizations	Organizational Smart Systems	Knowledge Management	Sustainable Innovation	Smart systems improve innovation capability and organizational sustainability.
30	Ghosh et al. (2024)	Global	Smart Systems	Future of Work	Sustainable Workforce	AI and smart systems significantly influence future workforce

						transformation.
31	Setrojoyo et al. (2024)	Indonesia	Machine Learning	Employee Loyalty	Workforce Sustainability	AI-based prediction models improve workforce retention strategies.
32	Gupta et al. (2024)	Organizations	Predictive Analytics	Sustainable Training	Employee Sustainability	Sustainable training practices positively affect employee outcomes.
33	Younes-Sinaki et al. (2024)	Manufacturing	AI Optimization	Human Factors	Sustainable Manufacturing	AI contributes to sustainable manufacturing design and operations.
34	Larbi-Siaw et al. (2024)	SMEs	Eco-Innovation Technologies	Green Capabilities	Sustainable Business Performance	Eco-innovation capabilities improve sustainable business outcomes.
35	Ogbeibu et al. (2024)	Organizations	AI-enabled Systems	Green Talent Management	Employee Retention	Green talent management reduces turnover intention.
36	Das et al. (2023)	Sports Industry	Artificial Intelligence	Human Capital Management	Organizational Sustainability	AI enhances decision-making and organizational competitiveness.

Table 2 provides a comprehensive overview of the characteristics of the included studies, including their methodological approaches, theoretical foundations, AI-related concepts, HRM dimensions, sustainability outcomes, and principal findings. This detailed mapping enhances the transparency and reproducibility of the review and facilitates cross-study comparisons. The evidence indicates substantial heterogeneity in conceptualizations and methodologies, reinforcing the need for integrative frameworks to explain the AI–HRM–Sustainability nexus.

Table 3. Evidence Mapping of AI-HRM-Sustainability Themes

Theme	Number of Studies	Dominant Method	Main Context	Representative Studies	Main Findings
AI-enabled Green HRM	8	Survey	Manufacturing	Renwick et al.; Guerci et al.	AI strengthens green HR practices and environmental performance
HR Analytics	7	Quantitative	Multi-sector	Marler & Boudreau	AI improves evidence-based HR decisions
Human-AI Collaboration	6	Mixed-method	Services and IT	Raisch & Krakowski	Human adaptability determines AI success
Governance and Ethics	9	Conceptual	Cross-sector	Floridi et al.; Jobin et al.	Governance mechanisms mitigate AI risks
Emerging Risks	6	Conceptual	Various	Mittelstadt et al.	Bias and shadow AI threaten sustainability

Table 3 shows that the evidence mapping further reveals significant contextual and methodological imbalances within the existing literature. Quantitative studies are heavily concentrated on AI-enabled green HRM and HR analytics, whereas governance and ethical issues remain dominated by conceptual discussions with limited empirical validation. Moreover, the literature is largely concentrated in manufacturing, hospitality, and information technology sectors, with relatively little attention given to public organisations, non-profit institutions, and highly regulated industries. Geographically, research remains disproportionately focused on emerging economies, raising concerns regarding the generalisability of current findings across institutional contexts.

These observations suggest that the AI–HRM–sustainability nexus is not a universally applicable phenomenon but rather a context-dependent mechanism shaped by organisational capabilities, governance arrangements, and institutional environments. Consequently, future studies should move beyond descriptive examinations and develop more context-sensitive, longitudinal, and multilevel research designs to better explain the complex mechanisms through which AI-enabled HRM contributes to organisational sustainability.

Table 4. Frequency of Themes

Theme	Frequency	Percentage
Governance	9	25%
Green HRM	8	22%
HR Analytics	7	19%
Human-AI Collaboration	6	17%
Emerging Risks	6	17%

Table 4 shows that the thematic frequency analysis further suggests the emergence of three major research trajectories within the field. The first trajectory focuses on AI as an organisational capability for enhancing HR effectiveness and sustainability performance. The second trajectory emphasises governance, ethics, and institutional legitimacy as critical boundary conditions for responsible AI implementation. The third, more recent trajectory concerns human–AI collaboration and unintended consequences arising from advanced AI technologies, particularly generative AI.

Interestingly, the relatively lower frequency of studies addressing employee-level dynamics and risk-oriented perspectives indicates that the current literature remains predominantly technology-centric and organisationally oriented. Consequently, substantial opportunities remain for future studies to develop multilevel frameworks that incorporate individual, organisational, and institutional mechanisms simultaneously. Such efforts would contribute to a more comprehensive understanding of how AI-enabled HRM can generate sustainable value while mitigating potential adverse consequences.

Taken together, the frequency patterns reinforce the argument that the AI–HRM–sustainability nexus is inherently multidimensional and cannot be adequately explained through direct-effect relationships alone. Rather, sustainability outcomes appear to emerge through the interaction of AI capabilities, HRM architectures, governance mechanisms, and contextual contingencies, thereby justifying the need for the integrative framework proposed in this study.

Table 5. Sectoral and Geographical Distribution

	Distribution	Number of Studies
Sector	Manufacturing	10
	Hospitality	8
	IT	7
	Public Sector	2
	Multi-sector	9
Geographical	Asia	15
	Europe	8
	North America	5
	Middle East	4
	Cross-country	4

Table 5 reveals that studies on the AI–HRM–sustainability nexus are predominantly concentrated in manufacturing, hospitality, and technology-intensive sectors, with most empirical evidence originating from Asian and European contexts. This uneven distribution suggests that current knowledge has been developed within relatively narrow industrial and institutional settings, potentially limiting the generalisability of existing findings. The observed contextual concentration further indicates that the effectiveness of AI-enabled sustainable HRM is highly contingent upon sectoral characteristics, technological maturity, and institutional environments. Consequently, industry and geographical contexts should be considered important boundary conditions in explaining how AI capabilities are translated into organisational sustainability outcomes.

Table 6. Methodological Distribution

Method	Number
Survey	18
Conceptual	8
Qualitative	5
Mixed-method	3
Longitudinal	2

Table 6 indicates that the existing literature is methodologically dominated by quantitative survey studies, followed by conceptual and qualitative research, while mixed-method and longitudinal designs remain relatively limited. This pattern suggests that current knowledge on the AI–HRM–sustainability nexus is largely based on cross-sectional evidence, emphasizing associative relationships rather than causal mechanisms and dynamic processes. The limited use of longitudinal and mixed-method approaches also indicates insufficient understanding of how AI capabilities evolve over time and how contextual factors shape sustainable HRM outcomes. Therefore, future research should adopt more diverse and robust methodological designs to develop deeper, multilevel, and context-sensitive explanations of the mechanisms linking AI, HRM systems, and organisational sustainability.

Table 7. llustrative Coding Structure

Representative Findings	First-order Codes	Second-order Themes	Aggregate Dimension
AI improves environmental training	Green training	AI-enabled Green HRM	Sustainability mechanism
AI improves workforce analytics	HR decision support	HR Analytics	Sustainability mechanism
AI creates ethical concerns	Bias and privacy	Governance issues	Boundary condition

Table 7 illustrates the analytical pathway through which the final thematic domains were generated from the reviewed studies. The coding process followed an iterative and hybrid thematic approach, beginning with the identification of representative findings extracted from the selected articles. These findings were subsequently transformed into first-order codes capturing specific concepts and recurring patterns in the literature. Related codes were then grouped into broader second-order themes that reflected higher-level conceptual similarities. Finally, these themes were synthesised into aggregate dimensions representing the major domains of the AI–HRM–sustainability nexus. This coding structure enhances the transparency and rigor of the review by demonstrating how the final thematic framework emerged systematically from empirical evidence rather than being predetermined conceptually. Moreover, the iterative coding process allows for a more nuanced understanding of the relationships among AI capabilities, HRM practices, governance mechanisms, and sustainability outcomes, thereby strengthening the credibility and replicability of the thematic synthesis.

Figure 4. Thematic Development Process

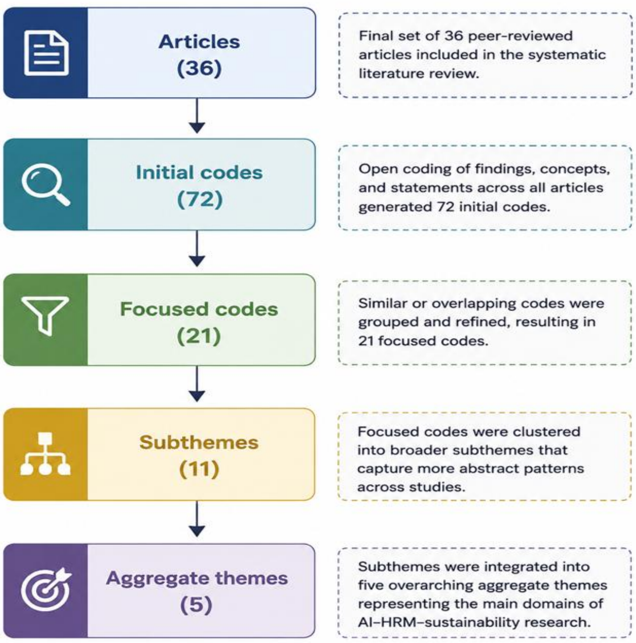
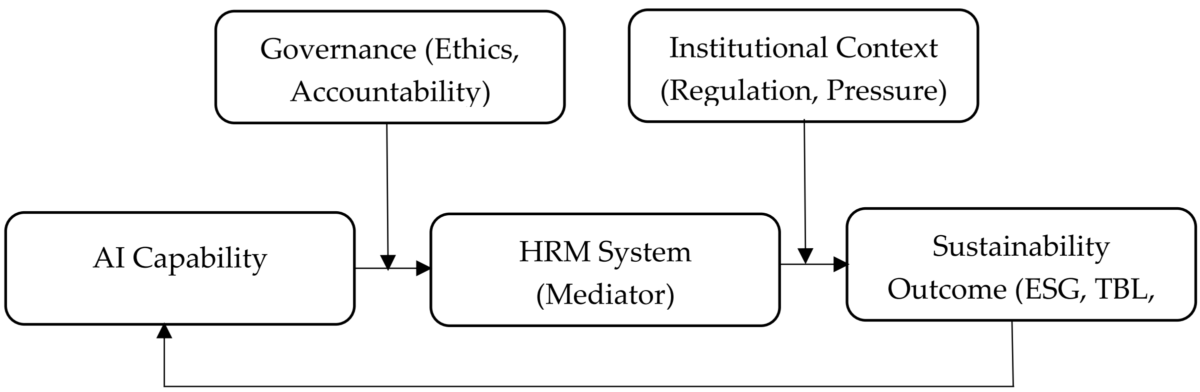


Figure 4 presents the analytical pathway through which the final thematic domains were derived from the reviewed literature. Beginning with 36 eligible studies, the iterative coding process generated 72 initial codes, which were progressively refined into 21 focused codes, 11 subthemes, and ultimately five aggregate themes. This coding structure demonstrates the systematic and evidence-based development of the thematic framework and provides transparency regarding how the principal dimensions of the AI–HRM–sustainability nexus emerged from the literature. The resulting aggregate themes subsequently served as the empirical foundation for developing the integrative framework proposed in this study, linking AI capabilities, HRM mechanisms, governance considerations, and organisational sustainability outcomes. To enhance analytical transparency, this study employed a hybrid thematic coding procedure combining deductive categories derived from prior literature with inductively emerging themes. The coding process proceeded iteratively from first-order concepts to second-order themes and aggregate dimensions, resulting in five overarching thematic domains.

Within this framework, HRM is conceptualised as a multi-layered mediating system, encompassing green HRM, sustainable HRM, HR analytics, and digital HRM. These systems shape how AI is operationalised within organisations, influencing decision-making processes, employee behaviour, and organisational culture (Delery & Roumpi, 2017; Kramar, 2014). This mediating role explains why similar levels of AI adoption may produce different sustainability outcomes across organisations. Sustainability is positioned as a multidimensional outcome, incorporating environmental, social, and governance (ESG) dimensions, as well as broader frameworks such as the triple bottom line. Importantly, the framework recognises that sustainability outcomes are not deterministic but are contingent upon organisational and institutional conditions (Stahl et al., 2020; Elkington, 1997; United Nations, 2015). A critical extension of prior literature is the inclusion of governance and institutional context as moderating conditions. Governance mechanisms, including ethical guidelines, accountability structures, and regulatory compliance, influence whether AI-enabled HRM produces sustainable value or unintended negative consequences, such as bias or inequality (Floridi et al., 2018; Jobin et al., 2019). Similarly, institutional pressures shape organisational adoption and implementation of AI and sustainability practices (DiMaggio & Powell, 1983; Cath et al., 2018). The integrative framework also incorporates feedback loops, recognising that sustainability outcomes may influence future AI adoption and HRM system design. For example, successful sustainability initiatives may reinforce investment in AI capabilities, while negative outcomes may trigger governance adjustments. To visualise these relationships, the following figure presents the integrative framework of AI-enabled HRM and sustainability.

Figure 5. Integrative Framework of AI–HRM–Sustainability Nexus



Source: Author's analysis

Figure 4 presents the integrative framework of the AI–HRM–sustainability nexus, illustrating the causal relationships among AI capability, HRM systems, and sustainability outcomes. The figure highlights the mediating role of HRM systems and the moderating influence of governance and institutional contexts in shaping these relationships. It further demonstrates a feedback loop in which sustainability outcomes inform the development of subsequent AI capabilities and the design of HRM systems.

The integrative analysis of the literature reveals several important directions for future research, reflecting theoretical, methodological, and contextual gaps in the current body of knowledge. First, a critical gap concerns the operationalisation of sustainability outcomes. Many studies rely on broad or proxy measures of sustainability, limiting comparability and the accumulation of theory. Future research should adopt more precise and standardised metrics, particularly those aligned with ESG frameworks and SDGs, to enhance measurement validity and cross-study comparability (Stahl et al., 2020; Eccles et al., 2014; Friede et al., 2015). Second, the literature demonstrates a lack of AI-specific conceptualisation. Most studies treat AI as a general capability, without distinguishing between different technologies such as machine learning, HR analytics, decision-support systems, and generative AI. Future research should differentiate these technologies and examine their distinct mechanisms and implications for HRM and sustainability outcomes (Mikalef et al., 2021; Huang & Rust, 2021). Third, there is a need to advance governance-oriented research models. While ethical and governance issues are increasingly acknowledged, empirical studies examining how governance mechanisms shape AI-enabled HRM outcomes remain limited. Future research should develop and test models that incorporate accountability, transparency, and ethical AI practices as core constructs (Floridi et al., 2018; Jobin et al., 2019; Mittelstadt et al., 2016). Fourth, the literature is characterised by the limited specificity of HRM systems. Many studies treat HRM as a generic construct, without examining how different HR architectures influence the translation of AI capabilities into sustainability outcomes. Future studies should adopt a system-level perspective to identify which configurations of HR practices are most effective in enabling sustainable outcomes (Delery & Roumpi, 2017; Aust et al., 2020).

Fifth, methodological limitations remain significant. The dominance of cross-sectional survey designs restricts causal inference and limits the ability to capture long-term sustainability impacts. Future research should employ longitudinal, multilevel, and mixed-methods approaches and integrate advanced analytical techniques, such as machine learning and system dynamics modelling, to better capture complex relationships (Marler & Boudreau, 2017). Finally, contextual diversity remains limited. Existing studies are concentrated in specific sectors (e.g., hospitality, IT, manufacturing) and geographic regions, particularly emerging economies. Future research should expand to underexplored contexts, including public sector organisations, non-profit institutions, and knowledge-intensive industries, to enhance the generalisability of findings (Vrontis et al., 2023). To summarise these research directions, the following table presents key gaps and corresponding future research opportunities.

Table 8. Future Research Agenda in AI–HRM–Sustainability Research

Research Domain	Identified Gap	Future Research Direction	Potential Research Questions

Sustainability Measurement	Over-reliance on broad or proxy indicators of sustainability	Develop precise, standardised, and multidimensional measures aligned with ESG and SDGs	How can sustainability outcomes be operationalised using ESG and SDG-aligned indicators in AI-enabled HRM contexts?
AI Conceptualisation	AI is treated as a generic capability without differentiation	Distinguish between AI typologies (e.g., machine learning, HR analytics, generative AI) and examine their specific mechanisms	How do different AI technologies produce distinct effects on HRM systems and sustainability outcomes?
Governance and Ethics	Limited empirical models on governance mechanisms in AI-enabled HRM	Integrate governance constructs (ethics, accountability, transparency) into empirical frameworks	How do governance mechanisms moderate the relationship between AI-enabled HRM and sustainability performance?
HRM System Specificity	HRM is often treated as a generic construct	Examine specific HRM architectures (e.g., GHRM, sustainable HRM, digital HRM) as mediating systems	Which configurations of HRM systems most effectively translate AI capability into sustainability outcomes?
Methodological Advancement	Dominance of cross-sectional and single-method designs	Employ longitudinal, multi-level, and mixed-method approaches; integrate advanced analytics	How do AI-enabled HRM systems influence sustainability outcomes over time across organisational levels?
Contextual Diversity	Limited sectoral and geographical variation	Expand research to underexplored contexts (public sector, non-profit, different institutional environments)	How do institutional contexts shape the effectiveness of AI-enabled HRM in achieving sustainability goals?
Human–AI Interaction	Limited focus on employee-level dynamics	Explore the socio-technical interaction between AI systems and employees	How does human–AI collaboration influence employee well-being and sustainability outcomes?

Risk and Unintended Consequences	Emerging risks (bias, shadow AI, ethical issues) are underexplored	Develop risk-oriented frameworks and empirical testing of unintended consequences	What are the unintended consequences of AI adoption in HRM, and how can they be mitigated?

Source: Author analysis by Scopus and Web of Science Database.

Advancing research in this domain requires a shift towards integrative, theory-driven, and methodologically robust approaches. By addressing these gaps, future studies can contribute to a more comprehensive understanding of how AI-enabled HRM can be leveraged to achieve sustainable organisational development.

This study contributes to the literature by differentiating among various forms of AI, HRM architectures, and sustainability outcomes, thereby reducing conceptual ambiguity in the AI–HRM–sustainability literature. Rather than treating these constructs as homogeneous phenomena, the proposed framework highlights their multilevel and context-dependent relationships. Clarifying these conceptual boundaries allows the proposed framework to move beyond descriptive integration and provide a more rigorous explanation of the specific mechanisms through which AI-enabled HRM contributes to organisational sustainability under varying institutional and governance conditions.

4. Conclusion and Suggestion

This study provides a systematic literature review of research at the intersection of AI, sustainability, and HRM, synthesising evidence from peer-reviewed studies published between 2015 and 2025. The findings demonstrate that AI-enabled HRM represents a rapidly evolving research domain, characterised by increasing scholarly attention yet persistent conceptual fragmentation (Snyder, 2019). Existing studies have examined AI capabilities, HRM systems, and sustainability outcomes from multiple perspectives; however, these dimensions are often analysed in isolation, limiting a comprehensive understanding of their interaction.

The thematic synthesis identifies five interconnected domains: AI-enabled green HRM and environmental performance; AI-driven capabilities and triple-bottom-line sustainability; HR analytics as a sustainability capability; digital HRM and human–AI collaboration; and emerging risk-oriented themes. These findings indicate that sustainability outcomes are not a direct consequence of AI adoption, but rather emerge through the mediating role of HRM systems and the influence of governance and institutional contexts. This aligns with prior research emphasising that technological capabilities generate value only when integrated with organisational systems and complementary resources (Mikalef et al., 2021; Barney, 1991; Teece et al., 1997). By developing an integrative framework, this study advances the literature by conceptualising AI as an organisational capability, HRM as a mediating system, and sustainability as a multidimensional outcome shaped by governance conditions. Overall, the findings highlight that AI-enabled HRM is a complex and context-dependent mechanism for achieving sustainable organisational development (Raisch & Krakowski, 2021).

This study contributes to the literature in several important ways. First, it advances theoretical understanding by providing an integrative synthesis of fragmented research across AI, HRM, and sustainability domains. While prior studies have examined these areas independently, this review demonstrates the importance of analysing their interaction within a unified framework (Tranfield et al., 2003). Second, the study highlights the limitations of single-theory approaches and emphasises the need for multi-theoretical integration, combining resource-based, HRM system, institutional, and socio-technical perspectives. This integrative approach responds to calls for more holistic frameworks that capture the complexity of digital transformation and sustainability in organisations (Delery & Roumpi, 2017; Snyder, 2019; Eisenhardt & Martin, 2000). Third, the proposed framework contributes to theory development by identifying mechanisms and boundary conditions, including the mediating role of HRM systems and the moderating influence of governance and institutional contexts. This extends existing research by moving beyond direct-effect models and providing a more nuanced explanation of how AI-enabled HRM influences sustainability outcomes (Leicht-Deobald et al., 2019; Jobin et al., 2019).

The findings of this study offer several implications for practitioners, policymakers, and organisational leaders. First, organisations should recognise that AI adoption alone is insufficient to achieve sustainability objectives. Instead, the effectiveness of AI depends on its integration within HRM systems, including recruitment, training, performance management, and employee engagement practices (Kramar, 2014; Aust et al., 2020). Second, the study highlights the importance of governance mechanisms in ensuring the responsible implementation of AI. Organisations should develop clear policies on data governance, transparency, and the ethical use of AI to mitigate risks such as bias, privacy violations, and workforce inequality (Floridi et al., 2018; Mittelstadt et al., 2016; Jobin et al., 2019). Third, the findings emphasise the need for capability development, particularly in HR analytics and digital competencies, to enable effective human–AI collaboration. Investing in employee skills and organisational learning is essential for translating AI capabilities into sustainable outcomes (Minbaeva, 2018; Angrave et al., 2016). Finally, policymakers should consider the broader institutional environment, including regulatory frameworks and ESG standards, to support the responsible adoption of AI in HRM and promote sustainable organisational practices (Eccles et al., 2014; Friede et al., 2015; United Nations, 2015).

5. Limitations and Future Research

Despite its contributions, this study has several limitations. First, the review focuses exclusively on peer-reviewed journal articles indexed in Scopus and Web of Science and published in English. While this ensures academic quality, it may exclude relevant studies from other sources or languages (Mongeon & Paul-Hus, 2016). Second, the dataset is limited to studies published between 2015 and 2025, which, although appropriate for capturing contemporary AI developments, may overlook earlier foundational research on HRM and sustainability (Barney, 1991; Elkington, 1997). Third, the analysis relies on thematic synthesis, which involves interpretive judgement and may introduce a degree of subjectivity, despite efforts to ensure methodological rigour (Braun & Clarke, 2006; Nowell et al., 2017). Fourth, the reviewed studies are unevenly distributed across sectors and geographic contexts, with a concentration in emerging economies and specific industries such as hospitality and information technology. This limits the generalisability of findings across different organisational settings. Future research should address these limitations by expanding data sources, incorporating longitudinal and multi-level research designs, and exploring underrepresented contexts, such as public-sector organisations and non-profit institutions (Snyder, 2019; Vrontis et al., 2023). In addition, further empirical testing of the proposed integrative framework is needed to validate its applicability and refine its theoretical constructs.

To enhance the practical relevance of the review, future research should move beyond descriptive examinations and develop more context-sensitive, longitudinal, and multilevel investigations of AI-enabled HRM. Similarly, organisations should complement technological investments with robust governance mechanisms, ethical safeguards, employee participation, and responsible HR analytics practices to ensure that AI adoption contributes to long-term organisational sustainability.

Declaration of AI and AI-assisted technologies in the writing process (if author[s] utilize AI)

During the preparation of this work, the author(s) used **ChatGPT** in order to **improve the clarity and grammar**. After using this tool, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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