2 (2026) 100246

Contents lists available at ScienceDirect

Strategic Business Research

journal homepage: www.sciencedirect.com/journal/strategic-business-research

Artificial intelligence and sustainable human resource management: a conceptual framework and future research agenda

Rimpy Singhwal *, Ipshita Bansal

Department of Management Studies, Bhagat Phool Singh Mahila Vishwavidyalaya, Khanpur Kalan, Sonipat, India

ARTICLE INFO

Keywords:
Artificial intelligence
AI-enabled HRM
Sustainable human resource management
Employee experience
Ethical governance
Socio-technical systems
Resource-based view

ABSTRACT

Artificial intelligence (AI) is increasingly reshaping human resource management (HRM), yet existing research remains fragmented in explaining how AI-enabled HRM may contribute to sustainable HRM outcomes. Prior studies have generally examined AI either as a tool for efficiency, automation, and data-driven decision-making or as a source of ethical and employee-related risks. Less attention has been given to the conditions under which AI-enabled HRM creates sustainable value, the organisational mechanisms through which this value emerges, and the risks that may limit such outcomes. To address this gap, this conceptual paper develops an AI-enabled sustainable HRM framework grounded in the Resource-Based View and Socio-Technical Systems theory. The framework explains AI-enabled HRM as an organisational capability whose effects are translated through three interrelated but distinct mechanisms: HR practice transformation, employee experience and engagement, and decision-making quality. It further explains how digital readiness and ethical governance shape these relationships by supporting responsible implementation and reducing risks such as algorithmic bias, surveillance, autonomy loss, technostress, opaque decision-making, and employee distrust. The framework also clarifies that sustainable HRM outcomes should be assessed across economic, social, and environmental dimensions, with environmental sustainability linked to green skills, sustainability-oriented HR practices, and employee eco-oriented behaviour rather than digital efficiency alone. The paper contributes by proposing a conditional and testable conceptual framework that explains when AI-enabled HRM may support sustainable HRM outcomes, when it may undermine them, and how future empirical research can examine these relationships.

Introduction

Background of the study

Artificial intelligence (AI) is increasingly transforming human resource management (HRM) by enabling predictive, data-driven, and automated approaches to recruitment, workforce planning, learning, performance management, and employee support. In contemporary organisations, AI-enabled HRM is no longer limited to administrative automation; it is increasingly viewed as a strategic organisational capability that can reshape human capital management, improve decision quality, and strengthen organisational responsiveness (Mollah et al., 2024; Singh et al., 2025). AI-supported systems may enhance talent identification, workforce analytics, personalised development, and evidence-based managerial decision-making (Aydin and Turan, 2023; Huang et al., 2023).

At the same time, sustainable human resource management has expanded the role of HRM beyond short-term productivity by emphasising long-term organisational performance, employee well-being, inclusion, and environmental responsibility (Christina et al., 2025; Ramgolam et al., 2025). Within this perspective, HRM is expected to contribute to economic, social, and environmental goals through responsible workforce development, green skills, ethical employment practices, and sustainability-oriented organisational behaviour (Ogbeibu et al., 2024; Najam Shaikh et al., 2025).

Recent studies suggest that AI-enabled HRM can support sustainable HRM through efficient recruitment, improved workforce planning, green HRM practices, and sustainability-oriented decision-making (Khan et al., 2025; Koteczki et al., 2025). However, these outcomes are not guaranteed. AI-enabled HRM may also produce algorithmic bias, employee surveillance, reduced autonomy, job insecurity, technostress, and opaque decision-making when implemented without appropriate safeguards (Úbeda-García et al., 2025; Saiyed and Kumar, 2025). This creates a central conceptual tension: AI-enabled HRM may

* Corresponding author at: Department of Management Studies, Bhagat Phool Singh Mahila Vishwavidyalaya, Khanpur Kalan, Sonipat, India.
E-mail addresses: rimpysinghwal786@gmail.com (R. Singhwal), ibansalindia@gmail.com (I. Bansal).

https://doi.org/10.1016/j.sbr.2026.100246
Received 6 May 2026; Received in revised form 13 July 2026; Accepted 25 July 2026
Available online 26 July 2026
3051-0643/© 2026 Elsevier Ltd. All rights are reserved, including those for text and data mining, AI training, and similar technologies.

simultaneously enable sustainable value and generate risks that undermine employee trust, fairness, and organisational legitimacy.

This study addresses this tension by developing a conceptual framework of AI-enabled sustainable HRM grounded in the Resource-Based View and Socio-Technical Systems theory. The central argument is not that AI-enabled HRM automatically produces sustainable HRM outcomes. Rather, the paper argues that such outcomes are conditional: they depend on how AI-enabled HRM capability is embedded in HR routines, translated through HR practice transformation, employee experience and engagement, and decision-making quality, and shaped by digital readiness and ethical governance. The framework also recognises that AI-enabled HRM may generate negative pathways, including algorithmic bias, surveillance, autonomy loss, technostress, opaque decision-making, and employee distrust. By integrating these value-creating and value-constraining pathways, the paper explains when AI-enabled HRM may support sustainable HRM outcomes and when it may undermine them.

Research gap

Existing research on AI-enabled HRM has mainly developed in two directions. One stream views AI as a tool for HR efficiency, automation, workforce analytics, recruitment, learning, and performance management (Sova et al., 2023; Mollah et al., 2024; Singh et al., 2025). Another stream highlights ethical and employee-related risks, including algorithmic bias, surveillance, privacy concerns, opacity, autonomy loss, technostress, and weakened trust (Ogbeibu et al., 2024; Saiyed and Kumar, 2025; Úbeda-García et al., 2025). However, these two streams remain insufficiently integrated, leaving limited understanding of how AI-enabled HRM can simultaneously create sustainable value and generate risks that may constrain such value.

A key limitation is that prior studies do not clearly explain the mechanisms through which AI-enabled HRM influences sustainable HRM outcomes. HR practice transformation, employee experience and engagement, and decision-making quality are often discussed together, but their boundaries and interaction remain unclear. HR practice transformation refers to changes in HR processes and routines; decision-making quality concerns the transparency, explainability, consistency, and accountability of AI-supported HR decisions; and employee experience and engagement involve trust, fairness, autonomy, participation, well-being, and vulnerability. Clarifying these mechanisms is important because they may operate as parallel, reciprocal, or context-dependent pathways rather than as a simple linear chain.

Another gap concerns the conditional and governance-dependent nature of AI-enabled sustainable HRM. Existing studies often suggest that AI may support sustainable HRM, but they give less attention to the organisational conditions under which such outcomes emerge. Digital readiness, organisational culture, leadership support, and ethical governance may determine whether AI-enabled HRM supports responsible transformation or produces distrust, resistance, and perceived unfairness (Anwar et al., 2025; Bhasin and Krishna, 2025; Jangbahadur et al., 2025). Ethical governance also needs to be specified more clearly through safeguards such as bias audits, explainability, data minimisation, employee voice, appeal mechanisms, and human oversight.

The environmental dimension also remains underdeveloped. AI-enabled HRM is often linked to efficiency or social sustainability, while its environmental pathway is less clearly explained. Environmental sustainability should not be reduced to paperless HR or digital efficiency alone; it should be linked to green skill identification, sustainability-oriented recruitment and training, green performance indicators, workforce planning aligned with environmental goals, and employee eco-oriented behaviour (Ogbeibu et al., 2024; Najam Shaikh et al., 2025; Ali et al., 2025). Addressing these gaps, this study develops a conceptual framework grounded in the Resource-Based View and Socio-Technical Systems theory. It explains AI-enabled HRM as a conditional organisational capability whose sustainability effects depend on distinct but interrelated mechanisms, organisational readiness, ethical governance safeguards, negative pathways, and feedback from employee responses and sustainability performance (Barney et al., 2021; Bostrom and Heinen, 1977; Makarius et al., 2020).

Specifically, the study is guided by the following research questions:

RQ1: How does artificial intelligence function as a strategic organisational capability in reshaping HR processes to support sustainable HRM within contemporary organisations?
RQ2: Through what organisational mechanisms-such as changes in HR practices, employee experience, and data-driven decision-making-does AI-enabled HRM influence sustainable HRM outcomes?
RQ3: How do organisational conditions, including digital readiness and ethical governance, shape the effectiveness of AI-enabled HRM in achieving sustainable HRM outcomes?

Literature review

Artificial intelligence as a strategic capability in human resource management

Artificial intelligence has transformed HRM by enabling more predictive, data-driven, and responsive approaches to workforce planning, recruitment, employee development, and performance management. Organisations increasingly use AI-enabled systems to automate routine HR tasks, strengthen workforce analytics, and improve managerial responsiveness (Singh et al., 2025; Sova et al., 2023). This has shifted scholarly attention from AI as a technical application to AI-enabled HRM as a broader organisational capability.

However, existing literature remains divided in its assessment of AI-enabled HRM. Efficiency-oriented studies emphasise improvements in decision accuracy, productivity, recruitment speed, and workforce planning (Mollah et al., 2024; Singh et al., 2025). In contrast, critical studies highlight risks such as employee surveillance, algorithmic opacity, reduced trust, and weakened transparency in HR decision-making (Úbeda-García et al., 2025; Ogbeibu et al., 2024). These contrasting perspectives suggest that AI-enabled HRM cannot be evaluated only through performance gains, because its consequences extend to employee relations, fairness, and organisational legitimacy.

A further limitation is that AI is often conceptualised inconsistently across studies. Some research treats AI as a set of tools embedded in specific HR functions, while other work frames it as a strategic capability influencing broader organisational transformation (Sova et al., 2023; Singh et al., 2025). This variation makes it difficult to explain whether AI affects sustainable HRM outcomes directly or through organisational mechanisms. Therefore, the literature requires a clearer distinction between AI as functional automation and AI-enabled HRM as a strategic capability embedded in organisational systems.

However, conceptualising AI-enabled HRM as a capability should not imply that AI automatically creates sustainable value. Its effects depend on whether AI systems are integrated with HR expertise, human capital development, organisational learning, and responsible governance. This distinction is important because the same AI-enabled HRM practices may support efficiency and decision quality in one organisational context, but create distrust, perceived unfairness, or control-oriented HRM in another. Therefore, AI-enabled HRM should be understood as a conditional organisational capability rather than a universally beneficial technological solution.

AI-Enabled transformation of HR processes

AI-enabled HRM has changed the design and delivery of core HR processes by introducing predictive analytics, automation, and data-supported coordination into recruitment, learning, performance management, and workforce planning. AI-supported recruitment can improve candidate screening and selection efficiency, while analytics-

based learning systems can support personalised employee development and skill planning (Sova et al., 2023; Singh et al., 2025). These developments show that AI-enabled HR transformation involves more than the digitalisation of administrative tasks; it reshapes how HR activities are designed, connected, and evaluated.

Despite these advances, current research often examines HR functions separately. Recruitment, training, workforce analytics, and performance management are frequently studied as isolated AI applications rather than as interconnected elements of HR transformation. This limits understanding of how AI-enabled changes in one HR process may affect other organisational processes, employee responses, and sustainability outcomes. For example, AI-supported performance analytics may improve managerial information, but its organisational value depends on whether the process is transparent, accepted by employees, and aligned with responsible HR practices (Mollah et al., 2024; Úbeda-García et al., 2025).

From a socio-technical perspective, HR transformation should therefore be understood as the redesign of relationships among AI systems, HR professionals, managers, and employees. In this paper, HR practice transformation refers specifically to changes in HR structures, routines, workflows, and the delivery of HR services, including recruitment, learning, appraisal, workforce planning, and employee support. This mechanism should be distinguished from decision-making quality, which concerns the accuracy, transparency, explainability, consistency, and accountability of AI-supported HR decisions, and from employee experience and engagement, which concerns employees' perceptions of fairness, trust, autonomy, participation, well-being, and vulnerability. Clarifying these boundaries is necessary because these mechanisms may operate as parallel and mutually reinforcing pathways rather than as a fixed sequential chain.

Employee and organisational implications of AI-Enabled HRM

The growing use of AI-enabled HR systems has intensified debate about their implications for employees and organisational sustainability. AI-driven HR practices may support personalised learning, workforce planning, and data-informed talent decisions, but they may also alter the relational foundations of HRM by changing how employees receive feedback, experience evaluation, and interact with managerial systems (Singh et al., 2025; Úbeda-García et al., 2025).

Recent research on AI-mediated organisational communication is particularly relevant to this debate. Organisational communication is increasingly shifting from human-to-human interaction toward human–AI communication, where employees engage with digital agents, algorithmic feedback systems, automated platforms, and AI-supported decisions (Phan et al., 2026). In HRM, this shift affects recruitment, appraisal, training, employee feedback, and workforce analytics. Therefore, employee experience in AI-enabled HRM depends not only on system efficiency but also on communication transparency, interpretability, perceived fairness, and the availability of human oversight.

A further concern is the power asymmetry created by AI-enabled HRM in high-stakes employment domains. AI systems are increasingly used in recruitment, appraisal, promotion, monitoring, workforce allocation, and performance management, where employees may have limited control over how data are collected, how algorithmic evaluations are produced, or how decisions can be questioned. This can intensify employee vulnerability because AI makes employees more measurable and comparable, while the decision logic may remain opaque. In such contexts, employee experience depends strongly on procedural justice, including whether AI-supported HR decisions are explainable, contestable, and supported by human oversight.

The literature also shows that AI-enabled HRM may create tensions between technological optimisation and employee-centred outcomes. Systems designed to improve productivity and decision speed may simultaneously increase job insecurity, surveillance concerns, autonomy loss, or perceptions of unfairness when implemented without responsible safeguards (Thangaraju and Palani, 2024; Ogbeibu et al., 2024). These tensions indicate that employee experience and engagement should be treated as a distinct mechanism, not merely as a by-product of HR process efficiency. This mechanism helps explain why technologically advanced HR systems may fail to support sustainable HRM when employees perceive them as opaque, controlling, or insufficiently participatory. Therefore, employee voice, appeal mechanisms, explainability, and human oversight are not only ethical safeguards but also conditions for maintaining trust, autonomy, and procedural fairness in AI-enabled HRM (Table 1).

Sustainable human resource management outcomes

Sustainable human resource management extends HRM beyond short-term productivity by emphasising long-term organisational performance, employee well-being, inclusion, and environmental responsibility. In AI-enabled HRM, sustainability outcomes should be distinguished across economic, social, and environmental dimensions. Economic sustainability refers to productivity, adaptability, workforce planning effectiveness, and long-term organisational value creation (Khan et al., 2025; Mollah et al., 2024). Social sustainability concerns employee well-being, inclusion, fairness, skill development, meaningful work, and workforce stability in digitally mediated workplaces (Jangbahadur et al., 2025; Ramgolam et al., 2025).

Environmental sustainability requires more explicit treatment in AI-enabled HRM research because it should not be reduced to paperless HR processes or digital efficiency alone. A stronger environmental pathway lies in the ability of AI-enabled HRM to support people-centred environmental practices. AI-supported HR systems may help identify green competencies, align recruitment with sustainability-oriented skills, personalise green training, integrate environmental indicators into appraisal and reward systems, and encourage employee eco-oriented behaviour. These practices link AI-enabled HRM to environmental sustainability through employee capability development, green work behaviour, and sustainability-aligned HR systems rather than through automation alone (Ogbeibu et al., 2024; Najam Shaikh et al., 2025; Ali et al., 2025).

Ethical governance remains central to AI-enabled sustainable HRM, but it should be treated as a cross-cutting condition rather than as a substitute for economic, social, or environmental sustainability. Specific governance safeguards are needed for specific AI-HRM risks: bias audits can reduce algorithmic discrimination, explainability can address opaque decision-making, data minimisation can reduce privacy concerns, employee voice can limit autonomy loss, appeal mechanisms can address perceived unfairness, and human oversight can reduce over-reliance on algorithmic recommendations. A coherent sustainable HRM perspective therefore requires separating sustainability outcomes from governance conditions while recognising that ethical governance shapes the quality and legitimacy of economic, social, and environmental outcomes.

Methodology

This study follows a conceptual theory-building approach to develop an AI-enabled sustainable HRM framework. Since the paper is conceptual rather than empirical, its aim is not to test relationships statistically, but to organise fragmented literature, clarify theoretical relationships, and develop propositions for future empirical research.

The conceptual development followed five steps. First, literature was reviewed across the main domains relevant to AI-enabled sustainable HRM: AI-enabled HRM, sustainable HRM, employee experience and engagement, and environmental sustainability. These domains were selected because prior research shows that AI-enabled HRM can influence recruitment, learning, workforce analytics, employee engagement, decision-making, and sustainable performance, while also creating

Table 1
Prioritised future research agenda for AI-enabled sustainable HRM.

Priority	Research focus	Specific research question	Related propositions	Suggested variables	Methodological design	Possible empirical context
Priority 1	Core mechanisms	How do HR practice transformation, decision-making quality, and employee experience mediate the relationship between AI-enabled HRM capability and sustainable HRM outcomes?	P2–P5	AI-enabled HRM capability, HR practice transformation, decision-making quality, employee experience, economic/social sustainability	SEM or PLS-SEM	IT, banking, healthcare, hospitality
Priority 2	Boundary conditions	How do digital readiness and ethical governance shape the effectiveness of AI-enabled HRM implementation?	P7, P8a–P8e	Digital readiness, governance safeguards, HR transformation, decision quality, employee trust	Moderated mediation or multi-group SEM	Digitally mature vs low-maturity organisations
Priority 3	Negative AI-HRM pathways	How do algorithmic bias, surveillance, opaque decision-making, technostress, and distrust affect sustainable HRM outcomes?	P6a–P6e	Bias, surveillance, opacity, technostress, trust, autonomy, well-being, procedural justice	Longitudinal survey or mixed-method design	AI-based appraisal, monitoring, recruitment, platform work
Priority 4	Environmental sustainability	How does AI-enabled HRM support green skills, sustainability-oriented HR practices, environmental indicators, and eco-oriented behaviour?	P9	Green skills, green training, environmental KPIs, eco-oriented behaviour, environmental sustainability	Survey, case study, or comparative design	Manufacturing, logistics, energy, sustainability-oriented service firms
Priority 5	Feedback effects	How do employee responses and sustainability performance influence AI-HRM redesign, governance learning, and capability refinement?	P10a–P10c	Employee feedback, resistance, sustainability performance, AI-HRM redesign, governance learning	Longitudinal case study or process study	Organisations implementing AI-HRM in multiple phases
Priority 6	Multi-level effects	How do employee, team, and organisational factors jointly shape AI-enabled sustainable HRM outcomes?	P3–P5, P7	Employee trust, team communication, leadership support, HR analytics maturity, sustainability outcomes	Multi-level modelling	Large organisations using AI-supported HR platforms

ethical and employee-related risks such as algorithmic bias, surveillance, opacity, privacy concerns, and reduced trust (Huang et al., 2023; Mollah et al., 2024; Jangbahadur et al., 2025; Saiyed and Kumar, 2025; Úbeda-García et al., 2025).

Second, recurring concepts were organised into five analytical categories: AI-enabled HRM capability, organisational mechanisms, contextual conditions, sustainable HRM outcomes, and negative AI-HRM pathways. AI-enabled HRM capability refers to the integration of AI systems, HR analytics, data infrastructure, human capital, HR expertise, and organisational learning (Barney et al., 2021; Moderno et al., 2024; Singh et al., 2025). The organisational mechanisms include HR practice transformation, employee experience and engagement, and decision-making quality, which explain how AI-enabled HRM reshapes HR routines, employee responses, and managerial decisions (Mollah et al., 2024; Jangbahadur et al., 2025; Phan et al., 2026).

Third, the Resource-Based View and Socio-Technical Systems theory were used to integrate these concepts. RBV provides the capability logic by explaining how AI-enabled HRM becomes valuable when AI technologies are combined with human capital, HR routines, managerial capabilities, and organisational learning (Wright et al., 1994; Barney et al., 2021). STS theory provides the implementation logic by explaining how AI-enabled HRM outcomes depend on the alignment between technology, employees, HR processes, communication, organisational conditions, and governance arrangements (Bostrom and Heinen, 1977; Makarius et al., 2020). Together, these theories support the central argument that AI-enabled HRM is a conditional organisational capability rather than a direct technological solution.

Fourth, the framework was constructed by linking AI-enabled HRM capability with three distinct but interrelated mechanisms: HR practice transformation, employee experience and engagement, and decision-making quality. It also incorporates digital readiness and ethical governance as boundary conditions, negative pathways such as algorithmic bias, surveillance, autonomy loss, technostress, opaque decision-making, and employee distrust, and feedback from employee responses and sustainability performance.

Finally, the propositions were developed by translating the framework into directional and testable claims. These propositions explain how AI-enabled HRM may influence economic, social, and environmental sustainability outcomes, how organisational conditions shape these effects, how negative pathways may weaken sustainability outcomes, and how feedback may inform future AI-HRM redesign, governance learning, and capability refinement.

Contribution of the study

This study contributes to AI-enabled HRM and sustainable HRM literature by conceptualising AI-enabled HRM as a conditional organisational capability rather than as a direct technological route to sustainability. The paper argues that AI-enabled HRM may support sustainable HRM outcomes only when AI systems, HR analytics, human capital, HR routines, managerial capabilities, and governance arrangements are aligned with sustainability-oriented goals.

First, the study extends capability-based explanations of AI-enabled HRM by showing that AI does not create sustainable value in isolation. Its value depends on complementary organisational resources, including employee capabilities, HR expertise, organisational learning, digital readiness, and responsible governance. This extends RBV by explaining AI-enabled HRM as a capability whose effects are conditional rather than automatic.

Second, the study clarifies the mechanisms through which AI-enabled HRM may influence sustainable HRM outcomes. It distinguishes HR practice transformation, employee experience and engagement, and decision-making quality as separate but interrelated pathways. This distinction strengthens the internal logic of the framework by showing that AI-enabled HRM does not operate through a simple linear chain, but through mechanisms that may work in parallel and reinforce one another over time.

Third, the study integrates positive and negative AI-HRM pathways within the same framework. While AI-enabled HRM may improve efficiency, adaptability, and decision quality, it may also generate algorithmic bias, surveillance, autonomy loss, technostress, opaque decision-making, and employee distrust. This dual-pathway perspective explains why sustainable HRM outcomes depend not only on technological capability but also on procedural justice, employee voice, explainability, and ethical governance.

Fourth, the study strengthens the environmental sustainability pathway in AI-enabled HRM. Rather than linking environmental sustainability only to paperless HR or digital efficiency, the framework connects it to green skill identification, sustainability-oriented recruitment and training, environmental performance indicators, workforce

planning aligned with environmental goals, and employee eco-oriented behaviour.

Finally, the study provides a basis for future empirical research by developing propositions that specify mechanisms, boundary conditions, negative pathways, and feedback effects. The framework helps future studies examine not only whether AI-enabled HRM supports sustainable HRM outcomes, but also under what conditions, through which mechanisms, and with what possible unintended consequences.

Theoretical foundation

Resource-based view (RBV)

The Resource-Based View provides the strategic capability foundation for this study. RBV argues that sustained organisational advantage arises when firms possess valuable, rare, and strategically integrated resources and capabilities that are difficult for competitors to imitate (Barney, 2001; Barney et al., 2021). In AI-enabled HRM, this means that AI technologies do not create sustainable value merely through adoption. Their value depends on how they are combined with human capital, HR expertise, organisational knowledge, and managerial capabilities.

Within this perspective, AI-enabled HRM should be understood as a strategic organisational capability rather than a narrow automation tool. AI-supported HR systems may improve recruitment accuracy, workforce analytics, talent identification, and managerial responsiveness, but these benefits become strategically meaningful only when they are embedded in HR routines and aligned with long-term sustainability objectives (Mollah et al., 2024; Moderno et al., 2024). This helps explain why organisations using similar AI technologies may experience different outcomes.

RBV also highlights the continuing importance of human capital in AI-enabled workplaces. Although AI can automate routine HR activities, employee knowledge, creativity, adaptability, and collaborative capabilities remain central to sustainable value creation (Wright et al., 1994). Therefore, AI-enabled HRM should complement human capabilities rather than replace them. For this study, RBV explains why AI-enabled HRM can function as a strategic capability when technological resources are integrated with employee competencies, organisational learning, and sustainability-oriented HR practices. However, RBV alone does not fully explain how employees experience AI-enabled HRM or how governance, transparency, participation, and procedural justice shape its outcomes. This limitation creates the need to combine RBV with a socio-technical perspective.

Socio-technical systems (STS) theory

Socio-Technical Systems theory complements RBV by explaining how technological capabilities interact with human and organisational systems. STS theory argues that organisational effectiveness emerges from the joint optimisation of social and technical systems rather than from technology implementation alone (Bostrom and Heinen, 1977). In AI-enabled HRM, this perspective is important because AI systems operate within organisational contexts shaped by employees, managers, HR processes, workplace relationships, and governance structures.

STS theory helps explain why AI-enabled HRM outcomes depend on more than technical performance. AI may improve efficiency, prediction, and decision support, but its organisational effects are shaped by employee experience, trust, transparency, participation, and managerial interpretation (Makarius et al., 2020). For example, AI-supported recruitment or performance analytics may enhance decision speed, but employee acceptance depends on perceived fairness, explainability, and responsible implementation (Saiyed and Kumar, 2025).

This theory is also useful for examining the ethical and social risks of AI-enabled HRM. Algorithmic bias, surveillance, privacy concerns, reduced human interaction, and opaque decision-making are not only technical issues; they emerge from the way AI systems are designed, governed, and embedded in organisational practice (Bhasin and Krishna, 2025; Úbeda-García et al., 2025). STS theory therefore explains how HR transformation, employee experience, decision-making quality, and contextual conditions shape the sustainability implications of AI-enabled HRM. In this study, STS theory is therefore used to explain the implementation conditions and employee-facing consequences of AI-enabled HRM, while RBV explains the capability logic of AI-enabled HRM.

Integrating RBV and STS: toward a dynamic socio-technical capability perspective

The integration of RBV and STS theory provides the theoretical basis for understanding AI-enabled HRM as a conditional organisational capability. RBV explains why AI systems, HR analytics, data infrastructure, human capital, and organisational learning may become valuable when they are embedded in HR routines and managerial capabilities. STS theory explains how this value depends on the alignment between technological systems, employees, HR processes, communication, culture, and governance arrangements. Together, the two theories explain why AI-enabled HRM does not automatically produce sustainable HRM outcomes; its effects depend on both capability formation and responsible socio-technical implementation.

The two theories make distinct but complementary contributions. RBV provides the capability logic by explaining how AI-enabled HRM can support value creation, organisational adaptability, and long-term HR transformation. STS theory provides the implementation logic by showing that such value depends on socio-technical alignment, including employee trust, human oversight, ethical safeguards, leadership support, and organisational readiness. Recent research on AI-mediated organisational communication further strengthens this argument by showing that AI reshapes not only work processes but also communication relationships between employees, managers, and digital systems (Phan et al., 2026).

This integration also reveals a theoretical tension. RBV emphasises efficiency, strategic value, and capability development, whereas STS theory stresses human-centred alignment, employee participation, ethical governance, and responsible technological implementation. In AI-enabled HRM, this tension becomes visible when organisations use AI to improve speed, prediction, and control while increasing risks such as surveillance, autonomy loss, algorithmic bias, and reduced trust (Ogbeibu et al., 2024; Úbeda-García et al., 2025). The proposed framework therefore argues that sustainable HRM outcomes emerge when strategic AI capabilities are aligned with socio-technical conditions that protect employee well-being, fairness, transparency, and environmental responsibility. This tension is important because AI-enabled HRM may create economic value while weakening social sustainability if employees experience the system as biased, controlling, opaque, or difficult to challenge. The integrated RBV–STS perspective therefore treats sustainable HRM outcomes as conditional, not automatic.

This theoretical logic provides the foundation for the propositions developed in this study. RBV suggests that AI-enabled HRM contributes to sustainable outcomes when it is embedded in strategic HR routines, human capital development, and organisational learning. STS theory extends this logic by explaining how these outcomes depend on the quality of implementation, employee experience, governance, and contextual readiness. Together, the theories explain how AI-enabled HRM influences sustainability through HR transformation, employee experience and engagement, and decision-making quality, while also clarifying why these relationships may be strengthened or weakened by organisational conditions.

The integrated RBV–STS perspective contributes by connecting three elements that are often examined separately: AI-enabled HRM capability, socio-technical mechanisms, and governance conditions. It

explains why similar AI-enabled HRM systems may generate different outcomes across organisations. Where AI capability is supported by digital readiness, employee participation, transparent decision-making, and ethical governance, it may contribute to economic, social, and environmental sustainability. Where these conditions are weak, the same capability may intensify surveillance, distrust, autonomy loss, algorithmic bias, or procedural unfairness. This theoretical logic provides the basis for the framework and propositions developed in the next section.

Proposed conceptual framework

Fig. 1 presents a conceptual framework of AI-enabled sustainable HRM. The framework positions AI-enabled HRM as a conditional organisational capability consisting of AI systems, HR analytics, digital infrastructure, human capital, HR routines, and organisational learning. Grounded in RBV, the framework assumes that technological resources create value only when combined with complementary organisational and human resources (Wright et al., 1994; Barney et al., 2021; Moderno et al., 2024). Therefore, AI adoption alone is not expected to produce sustainable HRM outcomes; its effects depend on how AI tools are embedded in HR routines, used by skilled HR professionals and managers, and aligned with sustainability-oriented workforce goals.

The framework explains this relationship through three specific organisational mechanisms. HR practice transformation refers to changes in recruitment, learning, appraisal, workforce planning, and employee support. AI-enabled recruitment may improve candidate matching, AI-supported learning may identify skill gaps, and workforce analytics may support staffing forecasts (Huang et al., 2023; Mollah et al., 2024; Singh et al., 2025). This mechanism mainly links AI-enabled HRM capability with economic sustainability through productivity, adaptability, retention, and long-term workforce planning.

Decision-making quality refers to the accuracy, transparency, explainability, accountability, and human oversight of AI-supported HR decisions. This mechanism is important in recruitment, appraisal, promotion, and performance management, where AI-supported decisions affect employee opportunities and fairness perceptions. Explainable and reviewable decisions may improve consistency and procedural fairness, whereas opaque decisions may weaken trust and legitimacy (Saiyed and Kumar, 2025; Úbeda-García et al., 2025).

Employee experience and engagement refers to employees' trust, fairness perceptions, autonomy, participation, well-being, and vulnerability in AI-mediated HR processes. STS theory explains that technological systems produce outcomes through their interaction with employees, work practices, and governance arrangements (Bostrom and Heinen, 1977; Makarius et al., 2020). In AI-enabled HRM, employee experience depends on whether employees understand AI use, can raise concerns, and have access to human oversight. This is especially relevant because AI-mediated communication increasingly shapes feedback, HR interaction, and managerial decisions (Phan et al., 2026).

These mechanisms are treated as parallel but interrelated pathways, not as a fixed sequence. HR practice transformation captures process-level change, decision-making quality captures evaluative quality, and employee experience captures socio-psychological responses. For example, an AI-based appraisal system may redesign appraisal routines, but its sustainability value depends on explainability and employee perceptions of fairness. Employee feedback may also lead to HR process redesign or stronger governance safeguards. This clarification responds

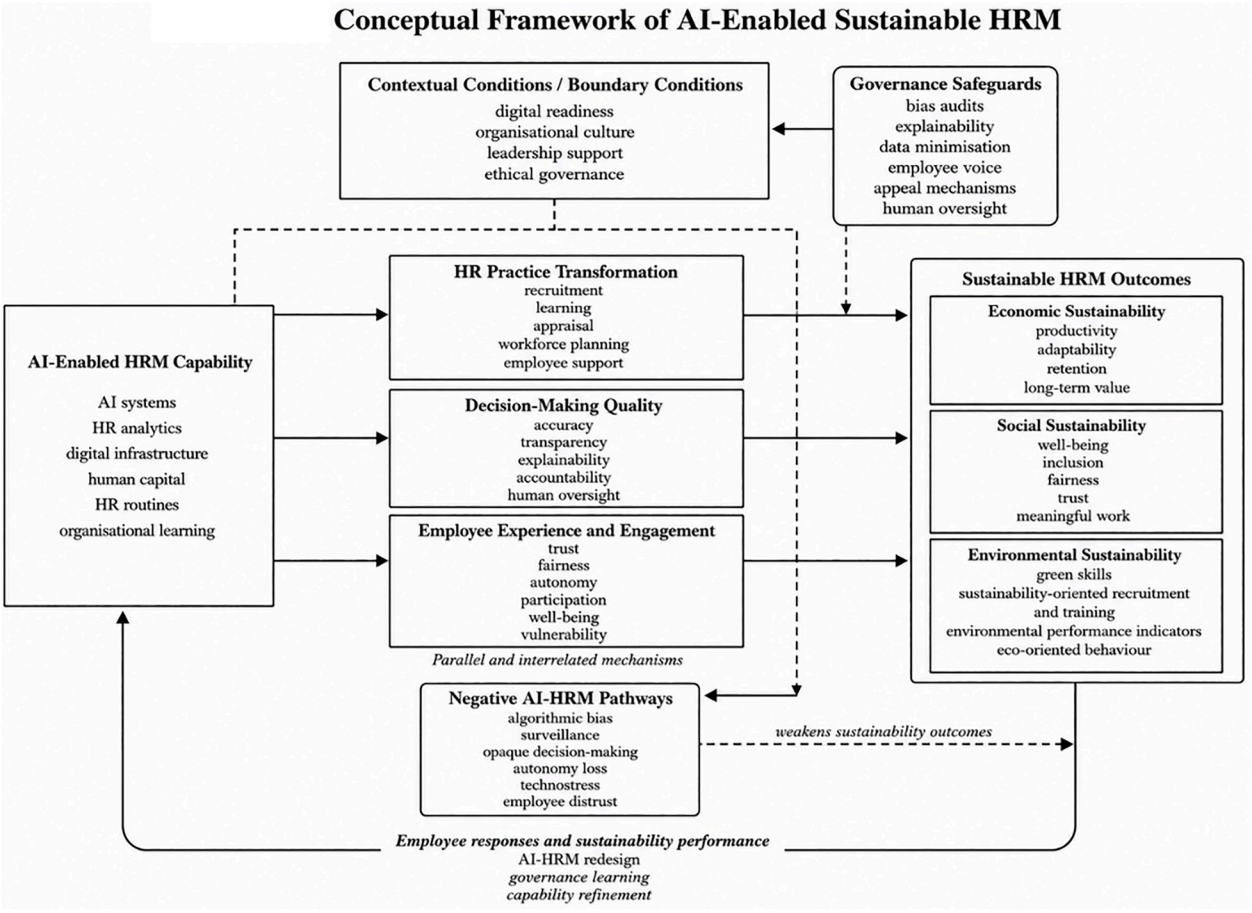


Fig. 1. Conceptual framework of AI-enabled sustainable HRM.
Source: Author's own work.

to the reviewers' concern that the mechanisms should not appear overlapping or purely linear.

Sustainable HRM outcomes are conceptualised across economic, social, and environmental dimensions. Economic sustainability includes productivity, adaptability, retention, and long-term organisational value. Social sustainability includes well-being, inclusion, fairness, trust, and meaningful work. Environmental sustainability includes green skill identification, sustainability-oriented recruitment and training, environmental performance indicators, workforce planning aligned with environmental goals, and employee eco-oriented behaviour. This pathway is important because environmental sustainability should not be reduced to paperless HR or digital efficiency. AI-enabled HRM may support environmental outcomes when HR analytics identify green competencies, recruitment prioritises sustainability-related skills, training develops eco-oriented capabilities, appraisal includes environmental indicators, and employees are encouraged to engage in green work behaviour (Ogbeibu et al., 2024; Ali et al., 2025; Najam Shaikh et al., 2025).

The framework also specifies negative AI-HRM pathways. Algorithmic bias may harm social sustainability by producing unfair recruitment, appraisal, promotion, or training decisions. Surveillance may reduce autonomy and trust. Opaque decision-making may weaken procedural justice when employees cannot understand or contest AI-supported decisions. Technostress may reduce well-being and performance. Employee distrust may weaken acceptance of AI-enabled HRM and limit its constructive use. These risks are conceptually different and should not be treated as one general negative effect (Ogbeibu et al., 2024; Saiyed and Kumar, 2025; Úbeda-García et al., 2025).

Contextual conditions shape whether AI-enabled HRM produces sustainable value or unintended harm. Digital readiness reflects data quality, infrastructure, and employee digital skills. Organisational culture shapes openness and participation. Leadership support provides resources, direction, and legitimacy. Ethical governance supports fairness, transparency, privacy protection, accountability, and responsible AI use (Anwar et al., 2025; Bhasin and Krishna, 2025; Jangbahadur et al., 2025). These conditions explain why similar AI-enabled HRM systems may produce different outcomes across organisations.

Governance safeguards are linked to specific risks. Bias audits address algorithmic discrimination; explainability addresses opaque decision-making; data minimisation addresses privacy concerns; employee voice addresses autonomy loss; appeal mechanisms address perceived unfairness; and human oversight reduces over-reliance on algorithmic recommendations. Thus, ethical governance is treated as a set of concrete safeguards rather than a broad ethical principle.

Finally, the feedback loop explains how the framework evolves over time. Negative employee responses such as distrust, resistance, perceived unfairness, or technostress may trigger AI-HRM redesign,

Table 2
Framework-specific theoretical and practical implications of AI-enabled sustainable HRM.

Framework component	Theoretical implication	Practical implication	Framework component	Theoretical implication
AI-enabled HRM capability	Extends RBV by explaining AI-enabled HRM as a conditional capability rather than a direct source of sustainable value.	Assess whether AI systems, HR analytics, human capital, HR routines, and organisational learning are aligned with sustainability-oriented HR goals.	AI-enabled HRM capability	Extends RBV by explaining AI-enabled HRM as a conditional capability rather than a direct source of sustainable value.
HR practice transformation	Explains how AI-enabled HRM influences sustainability through changes in recruitment, learning, appraisal, workforce planning, and employee support.	Use AI to redesign HR practices, not merely automate administrative tasks.	HR practice transformation	Explains how AI-enabled HRM influences sustainability through changes in recruitment, learning, appraisal, workforce planning, and employee support.
Decision-making quality	Clarifies that AI-supported HR decisions affect sustainability through accuracy, explainability, accountability, and human oversight.	Apply explainable decision rules, human review, and accountability procedures in recruitment, appraisal, promotion, and performance management.	Decision-making quality	Clarifies that AI-supported HR decisions affect sustainability through accuracy, explainability, accountability, and human oversight.
Employee experience and engagement	Extends STS logic by showing that employee trust, fairness, autonomy, participation, well-being, and vulnerability shape AI-HRM outcomes.	Create employee voice, feedback, and support mechanisms to address distrust, technostress, autonomy loss, and perceived unfairness.	Employee experience and engagement	Extends STS logic by showing that employee trust, fairness, autonomy, participation, well-being, and vulnerability shape AI-HRM outcomes.
Economic sustainability	Links AI-enabled HRM to long-term productivity, adaptability, retention, and workforce planning rather than short-term efficiency alone.	Evaluate AI-HRM outcomes through productivity, retention, adaptability, and workforce planning quality.	Economic sustainability	Links AI-enabled HRM to long-term productivity, adaptability, retention, and workforce planning rather than short-term efficiency alone.
Social sustainability	Shows that AI-enabled HRM may support or weaken fairness, inclusion, well-being, trust, and meaningful work.	Monitor employee well-being, inclusion, fairness perceptions, trust, and procedural justice after AI-HRM implementation.	Social sustainability	Shows that AI-enabled HRM may support or weaken fairness, inclusion, well-being, trust, and meaningful work.
Environmental sustainability	Strengthens the environmental pathway by linking AI-enabled HRM to green skills, sustainability-oriented HR practices, environmental indicators, and eco-oriented behaviour.	Use HR analytics to identify green competencies, support sustainability training, include environmental KPIs, and encourage employee eco-oriented behaviour.	Environmental sustainability	Strengthens the environmental pathway by linking AI-enabled HRM to green skills, sustainability-oriented HR practices, environmental indicators, and eco-oriented behaviour.
Negative AI-HRM pathways	Specifies that algorithmic bias, surveillance, opacity, technostress, autonomy loss, and distrust affect different sustainability outcomes.	Conduct periodic AI-HRM risk reviews to detect biased outcomes, excessive monitoring, opaque decisions, privacy concerns, and declining trust.	Negative AI-HRM pathways	Specifies that algorithmic bias, surveillance, opacity, technostress, autonomy loss, and distrust affect different sustainability outcomes.
Ethical governance safeguards	Explains governance as concrete safeguards rather than a broad ethical principle.	Use bias audits, explainability, data minimisation, employee voice, appeal mechanisms, and human oversight to reduce specific AI-HRM risks.	Ethical governance safeguards	Explains governance as concrete safeguards rather than a broad ethical principle.
Feedback loop	Positions AI-enabled sustainable HRM as an evolving process shaped by employee responses and sustainability performance.	Use employee feedback, sustainability indicators, and governance reviews to refine AI tools, HR processes, and oversight mechanisms.	Feedback loop	Positions AI-enabled sustainable HRM as an evolving process shaped by employee responses and sustainability performance.

Source: Author's own work.

stronger oversight, or greater participation. Sustainability performance data may show whether AI-enabled HRM is improving productivity, well-being, inclusion, retention, green skills, or eco-oriented behaviour. Governance learning may refine bias audits, explainability, appeal procedures, privacy safeguards, and human oversight. This feedback logic presents AI-enabled sustainable HRM as an evolving socio-technical process rather than a static input–output model (Bostrom and Heinen, 1977; Makarius et al., 2020; Phan et al., 2026).

Theoretical propositions

The propositions translate the framework into specific and testable claims. They do not assume that AI-enabled HRM automatically produces sustainable HRM outcomes; instead, they specify the mechanisms, conditions, risks, and feedback effects through which such outcomes may emerge (Table 2).

Proposition 1. *AI-enabled HRM capability will be positively associated with sustainable HRM outcomes when AI systems, HR analytics, human capital, HR routines, and organisational learning are aligned with sustainability-oriented HR goals.*

Proposition 2. *HR practice transformation will mediate the relationship between AI-enabled HRM capability and economic sustainability outcomes.*

Proposition 3. *Decision-making quality will mediate the relationship between AI-enabled HRM capability and sustainable HRM outcomes when AI-supported HR decisions are accurate, explainable, accountable, and subject to human oversight.*

Proposition 4. *Employee experience and engagement will mediate the relationship between AI-enabled HRM capability and social sustainability outcomes when employees perceive AI-enabled HRM as fair, participatory, autonomy-supportive, and supportive of well-being.*

Proposition 5. *HR practice transformation, decision-making quality, and employee experience and engagement will operate as parallel but interrelated mechanisms rather than as a fixed sequential chain.*

Proposition 6a. *Algorithmic bias will weaken social sustainability by reducing fairness, inclusion, and perceived equal opportunity in AI-supported HR decisions.*

Proposition 6b. *Surveillance will weaken social sustainability by reducing employee autonomy and trust.*

Proposition 6c. *Opaque decision-making will weaken procedural justice by limiting employees' ability to understand or challenge AI-supported HR decisions.*

Proposition 6d. *Technostress will reduce employee well-being and work performance in AI-enabled HRM contexts.*

Proposition 6e. *Employee distrust will weaken the positive relationship between AI-enabled HRM capability and sustainable HRM outcomes.*

Proposition 7. *Digital readiness will strengthen the relationship between AI-enabled HRM capability and HR practice transformation.*

Proposition 8a. *Bias audits will reduce the likelihood of algorithmic discrimination in AI-supported HR decisions.*

Proposition 8b. *Explainability will reduce the negative effect of opaque decision-making on procedural justice.*

Proposition 8c. *Data minimisation will reduce privacy concerns associated with AI-enabled HRM.*

Proposition 8d. *Employee voice and appeal mechanisms will reduce autonomy loss and perceived unfairness in AI-enabled HRM.*

Proposition 8e. *Human oversight will reduce over-reliance on algorithmic recommendations in HR decisions.*

Proposition 9. *AI-enabled HRM capability will be positively associated with environmental sustainability when HR analytics support green skill identification, sustainability-oriented recruitment and training, environmental performance indicators, and employee eco-oriented behaviour.*

Proposition 10a. *Negative employee responses, such as distrust, resistance, technostress, and perceived unfairness, will increase the likelihood of AI-HRM redesign and stronger governance intervention.*

Proposition 10b. *Sustainability performance feedback will inform future AI-HRM capability refinement across economic, social, and environmental outcomes.*

Proposition 10c. *Governance learning will strengthen future AI-HRM implementation by improving bias audits, explainability, data minimisation, appeal mechanisms, and human oversight.*

Discussion

The proposed framework advances AI-enabled sustainable HRM research by explaining AI-enabled HRM as a conditional organisational capability rather than as a direct technological route to sustainability. The framework suggests that AI-enabled HRM may contribute to sustainable HRM outcomes when AI systems, HR analytics, human capital, HR routines, and organisational learning are aligned with sustainability-oriented HR goals. At the same time, it recognises that the same capability may generate risks when implementation lacks transparency, employee participation, governance safeguards, or sufficient digital readiness. This interpretation extends RBV by showing that AI-enabled HRM capability creates value only when supported by complementary organisational, human, and governance resources.

A second implication concerns the mechanism-based logic of the framework. HR practice transformation, decision-making quality, and employee experience and engagement are treated as distinct but interrelated pathways. HR practice transformation explains how AI changes HR routines and service delivery; decision-making quality explains how AI affects the accuracy, explainability, accountability, and human oversight of HR decisions; and employee experience explains how employees respond in terms of trust, fairness, autonomy, participation, well-being, and vulnerability. This distinction helps avoid a broad or linear interpretation of AI-enabled HRM and provides a clearer basis for future empirical testing.

The framework also contributes to Socio-Technical Systems theory by showing that AI-enabled HRM outcomes emerge through the interaction between technical systems and social arrangements. AI systems influence not only HR efficiency but also communication, employee trust, workplace relationships, and managerial accountability. The inclusion of AI-mediated organisational communication strengthens this argument because employees increasingly interact with algorithmic feedback, automated decision platforms, and digital HR systems rather than only human managers (Phan et al., 2026). This suggests that AI-enabled HRM should be examined as a relational and communicative system, not only as an analytics or automation system.

The framework also highlights specific trade-offs in AI-enabled HRM. Efficiency gains may come at the cost of employee autonomy when AI systems intensify monitoring. Prediction may conflict with privacy when HR analytics rely on extensive employee data. Automation may weaken human judgement when managers over-rely on algorithmic

recommendations. These trade-offs are important because sustainable HRM cannot be assessed only through productivity or decision speed. It must also account for procedural justice, employee dignity, trust, inclusion, and well-being.

The framework also clarifies the environmental pathway of AI-enabled HRM. Environmental sustainability is not treated as a by-product of digitalisation or paperless HR. Instead, it is linked to people-centred HR processes, including green skill identification, sustainability-oriented recruitment and training, environmental performance indicators, workforce planning aligned with environmental goals, and employee eco-oriented behaviour. This framing strengthens the environmental dimension by showing how AI-enabled HRM can influence sustainability through employee capabilities and HR systems, not only through operational efficiency.

Ethical governance is discussed as a boundary condition, but the framework also recognises that governance may operate at multiple levels. It can function as an implementation process through bias audits, explainability, data minimisation, employee voice, appeal mechanisms, and human oversight. It can also operate as an organisational learning outcome when employee feedback and sustainability performance lead to stronger safeguards over time. This multi-level view avoids treating governance as a vague ethical principle or as a fixed moderator only.

Finally, the feedback logic of the framework positions AI-enabled sustainable HRM as an evolving process. Sustainable HRM outcomes and employee responses can inform future AI-HRM design, governance, and capability refinement. Positive outcomes may support further development of AI-enabled HRM, whereas distrust, fairness concerns, weak environmental alignment, or poor decision legitimacy may require redesign and stronger oversight. This dynamic view strengthens the conceptual contribution of the paper by showing that AI-enabled sustainable HRM is not a fixed technological outcome, but a continuously governed socio-technical process (Bostrom and Heinen, 1977; Makarius et al., 2020).

Limitations of the conceptual framework

This framework has several limitations. First, it is conceptual and does not empirically demonstrate that AI-enabled HRM produces sustainable HRM outcomes. Rather, it proposes conditions, mechanisms, risks, and feedback effects that require future empirical testing. Second, the relationships proposed in the framework may vary across industries, organisational size, national context, regulatory environment, and AI maturity. For example, AI-enabled HRM may operate differently in highly regulated sectors, digitally mature firms, SMEs, or labour-intensive organisations. Third, the framework distinguishes economic, social, and environmental sustainability outcomes, but these dimensions may involve trade-offs in practice. Efficiency gains may not always align with employee well-being or environmental responsibility. Finally, although the framework identifies governance safeguards, their effectiveness may depend on organisational commitment, employee participation, data quality, and managerial accountability. Future research should therefore test the framework across different contexts and examine whether the proposed mechanisms and safeguards work as expected.

Future research agenda

The proposed framework provides a basis for future empirical research on AI-enabled sustainable HRM. However, future research should not treat all relationships in the framework as equally urgent. Since the framework is conceptual and untested, the first priority is to validate the core mechanisms and boundary conditions. The second priority is to examine negative AI-HRM pathways, because these risks may directly undermine employee trust, fairness, autonomy, and well-being. The third priority is to test the environmental sustainability pathway, which remains less developed in AI-HRM research. Finally, longitudinal studies are needed to examine feedback effects involving employee responses, sustainability performance, AI-HRM redesign, and governance learning.

This prioritised agenda allows future research to move from basic validation to more complex longitudinal and multi-level testing. Initial studies should examine whether the proposed mechanisms and boundary conditions operate as expected. Subsequent research should test negative AI-HRM pathways, environmental sustainability mechanisms, and feedback effects over time. This sequence is important because the framework first requires empirical validation before its more dynamic and context-dependent relationships can be fully assessed.

Conclusion

This paper proposed a conceptual framework to explain how AI-enabled HRM may contribute to sustainable HRM outcomes under specific organisational and governance conditions. Rather than treating AI adoption as a direct route to sustainability, the framework positions AI-enabled HRM as a conditional organisational capability whose effects depend on HR practice transformation, decision-making quality, employee experience and engagement, digital readiness, and ethical governance.

The paper clarifies that AI-enabled HRM may support economic sustainability through improved HR processes, workforce planning, adaptability, and long-term value creation. It may support social sustainability when employees experience AI-supported HR practices as fair, transparent, participatory, and supportive of well-being. It may also support environmental sustainability when HR analytics are linked to green skill identification, sustainability-oriented recruitment and training, environmental performance indicators, and employee eco-oriented behaviour.

At the same time, the framework recognises that AI-enabled HRM may also generate negative pathways, including algorithmic bias, surveillance, autonomy loss, technostress, opaque decision-making, and employee distrust. These risks may weaken sustainable HRM outcomes if AI-enabled HRM is implemented without adequate safeguards. Therefore, bias audits, explainability, data minimisation, employee voice, appeal mechanisms, and human oversight are central to responsible AI-enabled HRM.

The paper does not empirically demonstrate that AI-enabled HRM produces sustainable HRM outcomes. Instead, it offers a theory-driven framework and propositions that require future empirical testing across different organisational, sectoral, and national contexts. By specifying mechanisms, boundary conditions, negative pathways, and feedback effects, the framework provides a basis for future research on when, how, and under what conditions AI-enabled HRM may contribute to sustainable HRM.

Declaration

I hereby declare that the research work entitled "**Artificial Intelligence and Sustainable Human Resource Management: A Conceptual Framework and Future Research Agenda**" is my original work and has been carried out by me under the guidance of Prof. Ipshita Bansal at the Department of Management Studies, Bhagat Phool Singh Mahila Vishwavidyalaya, Khanpur Kalan, Sonipat, Haryana, India. This work has not been submitted earlier, either in part or in full, for the award of any degree, diploma, or other academic recognition.

Funding

The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

CRediT authorship contribution statement

Rimpy Singhwal: Writing – review & editing, Writing – original draft. **Ipshita Bansal:** Supervision.

Declaration of competing interest

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

Acknowledgements

I would like to express my heartfelt gratitude to my research supervisor, Prof. Ipshita Bansal, for their invaluable guidance, continuous encouragement, and constructive feedback throughout this study. Their expertise and insights have been instrumental in shaping this research. I am also deeply thankful to Bhagat Phool Singh Mahila Vishwavidyalaya and the Department of Management Studies for providing the resources, facilities, and academic environment that supported the successful completion of this work. I sincerely acknowledge the support of my peers and colleagues, whose thoughtful suggestions and assistance enriched this research. Lastly, I extend my deepest appreciation to my family and friends for their constant motivation, patience, and unwavering support during this journey.

References

Ali, A., Yang, Q., Ali, A., Ali, Z., Noman, M., 2025. How and when AI-driven capabilities foster organisational sustainability: a moderated mediation analysis of digital literacy and green HRM. Int. J. Inf. Manage 85, 102956. https://doi.org/10.1016/j.ijinfomgt.2025.102956.

Anwar, B., Khan, N.W., Akram, F., 2025. The impact of AI-driven HRM on sustainable project performance: role of top management support as moderator and digital knowledge sharing as a mediator. Administrat. Manag. Sci. J. 4 (1), 73–82. https://doi.org/10.59365/amsj.4(1).2025.181.

Aydin, E., Turan, M., 2023. An AI-based shortlisting model for the sustainability of human resource management. Sustainability 15 (3), 2737. https://doi.org/10.3390/su15032737.

Barney, J.B., 2001. Resource-based theories of competitive advantage: a ten-year retrospective on the resource-based view. J. Manage. 27 (6), 643–650. https://doi.org/10.1177/014920630102700602.

Barney, J.B., Ketchen Jr., D.J., Wright, M., 2021. Resource-based theory and the value creation framework. J. Manage. 47 (7), 1936–1955. https://doi.org/10.1177/01492063211021655.

Bhasin, S., Krishna, K., 2025. The integration of artificial intelligence in human resource management for sustainable workplaces: exploring its impact, opportunities, and ethical challenges. Int. J. Res. Hum. Resour. Manag. 7 (2), 01–07. https://doi.org/10.33545/26633213.2025.v7.i2a.316.

Bostrom, R.P., Heinen, J.S., 1977. MIS problems and failures: a socio-technical perspective: part II: the application of socio-technical theory. MIS Quart. 1 (4), 11–28. https://doi.org/10.2307/249019.

Christina, J.L., Alamelu, R., Nigama, K., 2025. Synthesizing the impact of sustainable human resource management on corporate sustainability through multi-method evidence. Discov. Sustain. 6 (1), 666. https://doi.org/10.1007/s43621-025-01557-3.

Huang, X., Yang, F., Zheng, J., Feng, C., Zhang, L., 2023. Personalized human resource management via HR analytics and artificial intelligence: theory and implications. Asia Pac. Manag. Rev. 28 (4), 598–610. https://doi.org/10.1016/j.apmrv.2023.04.004.

Jangbahadur, U., Ahlawat, S., Rozera, P., Gupta, N., 2025. The effect of AI-enabled HRM dimensions on employee engagement and sustainable organisational performance: fusion skills as a moderator. Evid.-Based HRM 13 (1), 85–107. https://doi.org/10.1108/EBHRM-02-2023-0038.

Khan, A.J., Chaudhry, I.S., Iqbal, J., El Refae, G.A., 2025. Automation to sustainability: a systematic review of artificial intelligence applications in human resource management. Hum. Behav. Emerg. Technol. 2025, 7021656. https://doi.org/10.1155/hbe2/7021656.

Koteczki, R., Csikor, D., Balassa, B.E., 2025. The role of generative AI in improving the sustainability and efficiency of HR recruitment process. Discov. Sustain. 6 (1), 601. https://doi.org/10.1007/s43621-025-01484-3.

Makarius, E.E., Mukherjee, D., Fox, J.D., Fox, A.K., 2020. Rising with the machines: a sociotechnical framework for bringing artificial intelligence into the organization. J. Bus. Res. 120, 262–273. https://doi.org/10.1016/j.jbusres.2020.07.045.

Moderno, O.B.D.S., Braz, A.C., Nascimento, P.T.D.S., 2024. Robotic process automation and artificial intelligence capabilities driving digital strategy: a resource-based view. Bus. Process Manag. J. 30 (1), 105–134. https://doi.org/10.1108/BPMJ-08-2022-0409.

Mollah, M.A., Rana, M., Amin, M.B., Sony, M.A.A.M., Rahaman, M.A., Fenyves, V., 2024. Examining the role of AI-augmented HRM for sustainable performance: key determinants for digital culture and organizational strategy. Sustainability 16 (24), 10843. https://doi.org/10.3390/su162410843.

Najam Shaikh, S., Sohu, J.M., Shaikh, S., Zahra Kherazi, F., Soomro, S., 2025. Artificial intelligence adoption, green HRM, and employee behavior: driving environmental sustainability in SMEs with organizational culture as a moderator. Sage Open 15 (4), 21582440251392673. https://doi.org/10.1177/21582440251392673.

Ogbeibu, S., Emelifeonwu, J., Pereira, V., Oseghale, R., Gaskin, J., Sivarajah, U., Gunasekaran, A., 2024. Demystifying the roles of organisational smart technology, artificial intelligence, robotics, and algorithm capability: a strategy for green human resource management and environmental sustainability. Bus. Strategy. Environ. 33 (2), 369–388. https://doi.org/10.1002/bse.3495.

Phan, T.A., Nguyen, T.P.Y., Tran, H.P., 2026. From Human communication to Human–AI communication: mapping the intellectual structure of AI-mediated organizational communication. Int. J. Bus. Commun., 23294884261455815 https://doi.org/10.1177/23294884261455815.

Ramgolam, G., Ramphul, N., Chittoo, H., 2025. The role of sustainable human resource management practices to achieve sustainable employee performance: literature review and future research directions. Learn. Organ. 32 (6), 885–903. https://doi.org/10.1108/TLO-01-2025-0014.

Saiyed, S., Kumar, V., 2025. Green AI hiring and ethical risks: investigating the impact of algorithmic bias on sustainable human capital development and SDGs compliance. Strateg. Bus. Res. 1, 100018. https://doi.org/10.1016/j.sbr.2025.100018.

Singh, R., Joshi, A., Dissanayake, H., Nainanayake, D., Kumar, V., 2025. Harnessing artificial intelligence and human resource management for circular economy and sustainability: a conceptual integration. Sustainability 17 (15), 7054. https://doi.org/10.3390/su17157054.

Sova, O., Bieliaieva, N., Antypenko, N., Drozd, N., 2023. Impact of artificial intelligence and digital HRM on resource consumption within a sustainable development perspective. In: E3S Web of Conferences, 408. EDP Sciences, 01006. https://doi.org/10.1051/e3sconf/202340801006.

Thangaraju, K., Palani, P., 2024. Integrating sustainability into AI-driven HRM practices: examining employee engagement and organizational performance in the IT industry. Pak. J. Life Soc. Sci. 22 (2). https://doi.org/10.57239/PJLSS-2024-22.2.001008.

Úbeda-García, M., Marco-Lajara, B., Zaragoza-Sáez, P.C., Poveda-Pareja, E., 2025. Artificial intelligence, knowledge and human resource management: a systematic literature review of theoretical tensions and strategic implications. J. Innov. Knowl. 10 (6), 100809. https://doi.org/10.1016/j.jik.2025.100809.

Wright, P.M., McMahan, G.C., McWilliams, A., 1994. Human resources and sustained competitive advantage: a resource-based perspective. Int. J. Hum. Resour. Manag. 5 (2), 301–326. https://doi.org/10.1080/09585199400000020.