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AI-Enabled Sustainable Human Resource Management: Employee Well-Being, Ethical Governance, Organizational Resilience, and Sustainable Development

B. Bahar¹, Baharuddin Semmaila², Baso Amang³, Aryati Arfah⁴, Muh.Arif⁵, T. Tenriwaru⁶

^{1,2,3} Doctoral of Management Study Program, Faculty of Economics and Business, Universitas Muslim Indonesia, Makassar, Indonesia. Email: dbaharzazg799@gmail.com¹, baharuddin.semmaila@umi.ac.id², basoamang@umi.ac.id³, aryati.arfah@umi.ac.id⁴, muh.arif@umi.ac.id⁵, tenriwaru@umi.ac.id⁶

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ABSTRACT

Artificial intelligence has moved from the periphery of human resource management to its operational core, and its integration with sustainable HRM is now a strategically significant but contested field. This systematic literature review synthesises peer-reviewed, Scopus- and Web of Science-indexed research, with emphasis on 2020–2026 and retention of seminal theoretical sources, to examine how AI-enabled sustainable HRM shapes employee well-being, ethical governance, organizational resilience, and contributions to the Sustainable Development Goals (SDGs 3, 5, 8, 9, 10, and 16). Theoretically, the review appraises Job Demands–Resources, Conservation of Resources, Social Exchange, Dynamic Capabilities, Stakeholder, and Institutional perspectives, retaining only those warranted by the evidence. The synthesis identifies a consistent dual-process pattern: AI resources raise engagement, job satisfaction, and productivity, whereas AI demands generate technostress, exhaustion, work–family conflict, and job insecurity. Ethical governance emerges as a precondition rather than a compliance add-on, and organizational resilience depends on intellectual capital while being attenuated by environmental dynamism. The review also documents a fragmented theoretical base, heavy reliance on cross-sectional designs, inconsistent operationalisation of resilience, algorithmic management, and sustainable HRM, and thin organizational-level and SDG-outcome evidence. Its contribution is an explicitly exploratory integrated framework linking AI-enabled sustainable HRM to SDG contributions through the mutually conditioning pillars of well-being, governance, and resilience, with specified propositions, moderators, and boundary conditions.

Keywords: AI-enabled Sustainable HRM, Employee Well-Being, Ethical Governance, Organizational Resilience, Sustainable Development Goals.

I. Introduction

Artificial intelligence has moved from the periphery of human resource management to its operational core, reshaping recruitment, performance evaluation, compensation analysis, training, and workforce planning (Votto et al., 2021). This diffusion is increasingly framed as AI-enabled Sustainable HRM the integration of machine learning, predictive analytics, and digital automation into HR systems that pursue simultaneously economic performance and social, environmental, and human sustainability (Belás et al., 2024; Essien et al., 2025). The strategic stakes are substantial: AI-augmented HRM has assumed strategic importance



for achieving both HRM-domain outcomes and broader organisational outcomes tied to sustainable competitive advantage (Prikshtat et al., 2023), while HRM practices themselves shape whether sustainability agendas translate into real changes in business performance, society, and the environment (Belás et al., 2024). Yet the field is contested rather than consensual. Proponents argue that AI increases productivity, reduces workload, and reduces bias in decision-making; critics warn of technostress, job replacement anxiety, surveillance, and the dehumanisation of workplace relationships (Chuang et al., 2025; Essien et al., 2025). Empirical evidence confirms this duality: AI efficacy and generative AI can enhance productivity, engagement, and job satisfaction, whereas AI technostress increases exhaustion, work–family conflict, and lowers job satisfaction even while sustaining output (Chuang et al., 2025). Documented harmful forms of practice biased decision-making, data privacy violations, and efficiency reduction emerge where technological, individual, and organisational factors converge after adoption (Roppelt et al., 2025). Workplace surveillance scholarship has long documented similar tensions between managerial control and employee interests (Kayas, 2023). This divergence of outcomes, rather than a simple balance of benefits and harms, is what makes AI-enabled SHRM a strategically significant and unresolved field.

Four constructs anchor this review. AI-enabled SHRM denotes the strategic deployment of AI applications across HR functional areas, including HR management and information systems, to advance human and organisational sustainability (Prikshtat et al., 2023; Votto et al., 2021). Employee well-being encompasses engagement, job satisfaction, autonomy, job security, exhaustion, work–family conflict, and technostress outcomes that AI adoption influences through both resource-enhancing and demand-intensifying pathways (Chiu et al., 2021; Chuang et al., 2025). Ethical governance refers to the principles, mechanisms, and accountabilities that constrain AI use: transparency in algorithmic decision-making, explainable AI, data privacy and security, informed consent, employee autonomy, accountability, and human oversight (Berman et al., 2024; Jaturat et al., 2026; Olaniyan et al., 2023). Organizational resilience captures the capacity of firms to respond to challenges and adversity by being agile, recovering rapidly, and learning from disruptive experience (Dwivedi et al., 2021; Mhlanga & Dzingirai, 2024); strategic HRM practices are a principal mechanism through which resilient behaviour is developed among employees and, consequently, across organisations (Rehman et al., 2021). SDG contribution denotes AI's measurable alignment with the United Nations Sustainable Development Goals, a relationship with documented imbalance in coverage across goals (Nasir et al., 2022).

The review is delimited to peer-reviewed Scopus- and Web of Science-indexed literature, with emphasis on 2020–2026, retaining seminal theoretical sources where necessary. Its guiding research questions are: (1) How does AI-enabled SHRM shape employee well-being, and through which mechanisms? (2) What ethical governance arrangements are proposed or evidenced for responsible AI in HRM? (3) How does AI-enabled SHRM contribute to organisational resilience? (4) Which SDGs are credibly linked to this evidence, and where is the linkage asserted rather than demonstrated? (5) How do Job Demands–Resources, Conservation of Resources, Social Exchange, Dynamic Capabilities, Stakeholder, and Institutional theories explain these relationships?. Methodologically, the review follows a sequential systematic literature review procedure identifying, determining, retrieving, synthesising, and reporting with a review panel establishing conceptual boundaries and resolving disagreements at each stage (Hina et al., 2021). Literature sampling follows prioritised scoping, searching, screening, and reporting steps adapted from Cochrane and PRISMA recommendations for management research (Gusenbauer & Gauster, 2024). Synthesis is thematic and critical rather than article-by-article, examining configurations of consensus, contradiction, and unresolved questions rather than summarising individual studies. Existing reviews in the field have already identified a weak theoretical base, disproportionate attention to routine HR functions such as recruitment and selection, sparse sector- and country-specific evidence, and minimal linkage to organisational-level outcomes (Prikshtat et al., 2023); the present review responds to these gaps by centring theoretically grounded, multi-level outcomes.

The manuscript proceeds as follows. It first characterises AI-enabled sustainable HRM, then examines the theoretical foundations. Subsequent sections analyse employee well-being, ethical governance, and organisational resilience in turn, followed by integration with the SDGs (Giordino et al., 2025; Nahar, 2024). It

then identifies research gaps and future directions, advances an integrated conceptual framework AI-enabled SHRM → employee well-being + ethical governance + organizational resilience → SDG contributions and concludes with implications for theory and practice.

II. Literature Review and Hypothesis Development

2.1. AI-Enabled Sustainable HRM

AI-enabled Sustainable HRM (hereafter AI-enabled SHRM) can be defined as the integration of artificial intelligence applications across the HR function in a manner explicitly oriented toward simultaneous economic, social, and environmental sustainability outcomes, rather than toward cost reduction or administrative efficiency alone. The distinction matters because the broader literature on AI in HRM and the narrower sustainable HRM literature have largely developed in parallel. Prikshat et al.'s systematic review of 56 articles published in 35 peer-reviewed academic journals between October 1990 and December 2021 positions AI-augmented HRM as having "assumed strategic importance for achieving HRM domain-level outcomes and organisational outcomes for a sustainable competitive advantage" (Prikshat et al., 2023). This framing is the closest the reviewed corpus comes to an explicit strategic-level conceptualisation, yet the sustainable dimension remains implicit: competitive advantage is framed economically, with social and ecological outcomes left largely untheorised. Where the sustainability linkage is asserted more directly, as in the overview treatment of AI and digital HRM's contribution to sustainable development and the SDGs (Adanma & Ogunbiyi, 2024), the argument is programmatic rather than evidentiary. AI-enabled SHRM therefore currently functions more as an aspirational integration than as a settled construct with a cumulative empirical base.

a. Strategic Framing Versus Tactical Concentration

The critical tension in this literature is between a strategic, multilevel framing and a prevailing concentration on routine, procedure-level functions. Votto et al. explicitly anchor their analysis in tactical HRM/HRIS (Votto et al., 2021), and Deepa et al.'s systematic review and bibliometric analysis, drawing on the Dynamic Capabilities View, found that recruitment and selection was the single function with the broadest use of AI applications (Deepa et al., 2024). Rathore's bibliometric treatment similarly centres on automating and enhancing recruitment and selection procedures and their presumed effects on turnover and organisational performance (Rathore, 2023). Prikshat et al. name this concentration directly as a research gap, alongside unequal distribution of prior research in terms of a smaller number of sector- and country-specific studies, an absence of sound theoretical bases or frameworks, and significantly less empirical research, concluding that there is minimal research evidence linking HRM to organisational-level outcomes (Prikshat et al., 2023). Their proposed multilevel framework — connecting contextual variables through HRM-level to organisational-level outcomes and ultimately to operational and financial performance — is therefore a corrective agenda rather than a synthesis of existing findings (Prikshat et al., 2023). Crucially, no source in the reviewed corpus supplies organisational-level outcome evidence that would populate that framework, and the literature is silent on whether AI-enabled SHRM produces measurable sustainability outcomes at the firm level. This is the section's central unresolved question.

b. Sectoral, Geographic, and Theoretical Imbalance

The evidence base is geographically and sectorally skewed. A substantial share of applied work originates in the United States (Olaniyan et al., 2023; Popo-Olaniyan et al., 2022), with further contributions from Indian industrial contexts (Neelayapalem, 2026) and Scandinavian HR service organisations (Trocin et al., 2021), and a growing body of commentary on the Global South. Yet the latter literature is overwhelmingly diagnostic of constraint rather than of implementation: economic, infrastructural, and educational disparities and the digital divide limit widespread AI adoption in developing countries, compounded by shortages of

skilled AI talent and ethical complexity around algorithmic bias (Aderibigbe et al., 2023). In developing regions specifically, the Fourth Industrial Revolution disrupts traditional jobs and creates new ones requiring specialised skills, producing workforce skills gaps that HR must address through reskilling and upskilling, while limited digital access, unreliable internet connectivity and power grids, and cultural norms shape both adoption and employee responses to change (Ogedengbe et al., 2023). Theoretically, deep engagement is sparse: affordance theory underpins the analysis of how AI affordances are actualised in Scandinavian HR services (Trocin et al., 2021); the Dynamic Capabilities View frames managerial competencies for AI adoption (Deepa et al., 2024); and sociotechnical systems theory is invoked to argue that AI systems must integrate emergent technology with employees' knowledge, capabilities, and well-being to enhance organisational effectiveness (Marvi et al., 2025).

c. Sociotechnical Assumptions and the Efficiency–Sustainability Tension

AI-enabled SHRM carries embedded sociotechnical assumptions that deserve scrutiny. The dominant claim is that automation of routine work is a win–win: efficiency gains release human capacity for strategic and relational work (Okatta et al., 2024; Popo-Olaniyan et al., 2022). This optimism rests on an assumed substitutability of task and role. A sociotechnical perspective on automation in workforce management foregrounds instead the potential displacement of traditional roles, requiring proactive skill development and retraining, and a shift toward more collaborative work in which human expertise complements technological capability (Popoola et al., 2024). The distinction between automation and augmentation is decisive here: reactions to automated decisions differ across situations in which remaining human decision control exists, and system design choices such as transparency are important but under-researched (Langer & Landers, 2021). The literature further acknowledges, without resolving, limited understanding of how employees actually collaborate and engage with AI systems and of the theoretical mechanisms through which such collaboration affects engagement (Marvi et al., 2025). Organisational capability conditions compound the tension: leadership readiness, workforce adaptability, process maturity, data governance capability, and organisational learning culture collectively determine whether AI initiatives generate meaningful value, and organisations with unresolved capability impairments struggle to scale AI beyond pilot stages (Neelayapalem, 2026).

2.2. Theoretical Foundations

The theoretical scaffolding of AI-enabled Sustainable HRM is best characterized as fragmented rather than cumulative. A systematic review of 56 articles published across 35 peer-reviewed journals between October 1990 and December 2021 concluded that the most consequential gap in HRM scholarship is the "absence of sound theoretical base/frameworks," compounded by minimal evidence linking HRM to organizational-level outcomes (Priksat et al., 2023).

a. Job Demands–Resources Theory

JD-R offers the strongest and most consistently validated explanatory logic in this domain. Its core mechanism is a balance between demands — defined as "physical, psychological, social, or organizational aspects of the job that require sustained physical and/or psychological effort" — and resources that mitigate those demands (Yang et al., 2025). In digital settings, JD-R has been explicitly extended to incorporate digital job demands and resources, with a study of 898 white-collar employees confirming that the model provides a holistic lens for classifying both the "dark side" and "bright side" of digitization in a theoretically structured way (Scholze & Hecker, 2024). The most direct AI application models AI demands (technostress) and AI resources (efficacy and generative AI) against productivity, job satisfaction and work–family conflict, with engagement and exhaustion as mediators; a three-wave survey of 600 gender-balanced participants found that AI efficacy enhanced engagement and job satisfaction, whereas AI technostress increased exhaustion

and work–family conflict while still contributing to productivity, and that generative AI mitigated technostress (Chuang et al., 2025).

b. Conservation of Resources Theory

COR complements JD-R by extending the resource concept beyond job-related factors to "objects, conditions, personal characteristics, and energies" (Yang et al., 2025), and by explaining why resource deficits alone generate stress — employees also suffer from the effort required to acquire resources to bridge the gap between demands and available resources (Yang et al., 2025). Its mechanism is well-suited to algorithmic stressors: employees seek to obtain, retain, protect and foster valuable resources, and when stressors deplete them, employees protect what remains through coping mechanisms that can diminish motivation and job satisfaction (Albashiti et al., 2021). COR also explains why employees resort to defensive routines when resources are lacking (Yang et al., 2025). Yet the theory carries acknowledged temporal indeterminacy: the "timeframe in which resource processes play out" is unclear, it may not be possible to acquire resources indefinitely, and those starting from depleted positions risk "loss spirals" that inhibit the buffering effect of resources (Wallace & Coughlan, 2022).

c. Social Exchange Theory

SET supplies the reciprocity logic underpinning perceived organizational support and its attitudinal returns. Its canonical operationalization models POS as an antecedent of psychological empowerment, which in turn predicts work engagement and service-oriented organizational citizenship behaviour, tested on 242 frontline hotel employees (Meira & Hançer, 2021). The theory has been extended to human–AI collaboration, where the relationship is framed as "governed by reciprocity," such that AI empathy signals relational investment and triggers a psychological obligation to reciprocate through effort, trust and engagement (Marvi et al., 2025).

d. Dynamic Capabilities Theory

DCV explains how organizations and, notably, employees reconfigure competencies under change. Dynamic capabilities are defined as higher-order routines conferring upon management "a set of decision options for producing significant outputs of a particular type," and as a higher-order capability explaining competitive advantage in highly changing markets (Chatterjee et al., 2021). HR capabilities have been framed as a form of dynamic capability that integrates, builds and reconfigures HR-related competencies such as learning and reskilling — while the field concedes "no consensus with regard to which domain-specific dynamic capabilities are of particular relevance" (Soluk et al., 2023). This specification problem is visible in AI-HRM applications: DCV has been used to derive managerial cognitive capability, managerial human capital and managerial social capital as coding categories for the competencies HR managers require to adopt AI (Deepa et al., 2024).

2.3. Stakeholder Theory

Stakeholder theory explains why firms adopt socially responsible HR practices to secure support. Guided by the theory, corporations empower board members to negotiate with and incorporate stakeholders in wealth creation, providing social amenities, ethical and safe-working conditions and green marketing (Awa et al., 2024). In HR specifically, evaluations by 157 CSR experts on approximately 30 multinational companies produced a strong positive relationship between CSR practices focused on employees and organizational legitimacy (Del-Castillo-Feito et al., 2021). Stakeholder theory is therefore well-supported as an account of sustainable HR strategy, but its application is often fused loosely with CSR, agency, ecological modernization and institutional theory rather than deployed distinctly (Awa et al., 2024).

2.4. Institutional Theory

a. Employee Well-Being

The well-being consequences of AI-enabled Sustainable HRM are best understood as a dual-process phenomenon in which the same technological substrate that raises productivity and engagement simultaneously generates demands that deplete psychological resources. This duality is not merely rhetorical. Organizations adopt well-being-oriented policies precisely because the employment relationship rests on mutual beliefs, attitudes, and expectations, and technology may "increase the efficiency and rewards of those who remain employed, but may also lead to contradictory effects on the well-being of employees and the security of employment" (Cramarenco et al., 2023). Indeed, technology should not be permitted to "dehumanize" or "control" working life in ways that displace the basic interactions sustaining psychological well-being and skill development (Cramarenco et al., 2023). Because psychological well-being is a composite of interpersonal functioning and self-referential outcomes such as self-confidence and individual development, the same AI deployment can register as a resource in one employee's appraisal and as a demand in another's (Cramarenco et al., 2023).

b. The gain pathway: engagement, productivity, and enriched job content

The most robust evidence for positive well-being effects comes from studies that model AI as a job resource. In a three-wave survey of 600 gender-balanced employees working with AI across industries, both AI efficacy and generative AI use raised productivity, with AI efficacy additionally enhancing engagement and job satisfaction through reduced exhaustion (Chuang et al., 2025). This finding that AI can elevate engagement and satisfaction while productivity rises is echoed in field evidence: access to a generative AI conversational assistant across 5,172 customer-support agents raised issues resolved per hour by 15% on average and improved the experience of work, with customers behaving more politely and less likely to demand escalation (Brynjolfsson et al., 2025). Randomized experimental evidence reinforces the productivity claim, showing a 40% reduction in average task time and an 18% increase in output quality among 453 professionals, alongside reduced inequality between workers (Noy & Zhang, 2023). These gains plausibly translate into well-being by lowering time pressure and cognitive load, though the effect is heterogeneous—less experienced and lower-skilled workers improved in both speed and quality, whereas the most experienced saw only small speed gains and small quality declines (Brynjolfsson et al., 2025).

c. The harm pathway: technostress, exhaustion, and eroded meaningfulness

Countervailing evidence is equally strong and considerably more textured. AI technostress increased exhaustion, exacerbated work-family conflict, and lowered job satisfaction among the 600 employees studied, even while contributing to productivity—demonstrating that productive and harmful effects can co-occur within the same individual (Chuang et al., 2025). This is consistent with earlier warnings that technological overload, invasion, and complexity act as techno-stressors, producing behavioral stress and work-family conflict (Cramarenco et al., 2023). Skill mismatch functions as a parallel stressor: as AI adoption drives upskilling and reskilling demands, the mismatch between an employee's skills and job requirements increases dissatisfaction (Cramarenco et al., 2023). Affective well-being, encompassing anxiety-comfort, boredom-enthusiasm, and fatigue-vigor dimensions, is tightly linked to work-family conflict, job satisfaction, and burnout (Cramarenco et al., 2023). AI awareness—employees' anticipation of being displaced—maps directly onto these dimensions.

d. Divergence, contingency, and unresolved questions

The literature converges on the conclusion that AI's well-being effects are contingent and dual-sided rather than uniformly positive or negative (Chuang et al., 2025; Yang et al., 2025). Divergence across studies is attributable to at least four factors. First, appraisal: challenge appraisal of AI improves service performance via job crafting, whereas hindrance appraisal harms it via job insecurity, with AI knowledge strengthening both

paths (He et al., 2023). Second, individual and leadership resources. Defensive routines mediate the technostress–performance relationship, and digital leadership buffers the negative impact of technostress creators among 221 salespeople and their managers (Yang et al., 2025); resource depletion under COR theory explains why employees resist adoption to conserve resources (Yang et al., 2025). AI literacy and psychological resilience jointly mediate and moderate the work–stress–burnout relationship among 411 university teachers, with model fit superior when both operate as multiple mediators (Yin et al., 2025). A techno growth mindset similarly mitigates powerlessness and its behavioral consequences (Wang et al., 2025). Third, the design of governance: generative AI mitigated technostress in one study, a benefit not observed for AI efficacy as measured (Chuang et al., 2025), while surveillance outcomes turned positive only when employees controlled the monitoring (Kayas, 2023)—implying that governance quality, not technology per se, determines valence. Fourth, measurement heterogeneity: well-being is operationalized variously as affective well-being, psychological well-being, work–family conflict, burnout, and quality of life, which complicates cross-study comparison (Cramarenco et al., 2023).

2.5. Ethical Governance

a. The Bias Paradox: Optimism Versus the Automation of Discrimination

The governance literature is organized around a structural tension that no single study has resolved. In algorithmic hiring, one narrative is optimistically focused on replacing biased recruiter decisions, while the opposing narrative pessimistically points to the automation of discrimination; whether—and, more importantly, which types of—algorithmic hiring can be less biased and more beneficial to society than low-tech alternatives remains unanswered, to the detriment of trustworthiness (Fabris et al., 2024). This is not merely a rhetorical framing: it marks the field's central unresolved governance question. The optimistic case rests on the premise that machines can be purged of human prejudice, yet the evidence shows bias can arise from biased training data, flawed algorithms, and the human decision-making processes that influence algorithm design and implementation (Callari et al., 2024). Bias is therefore socio-technical in origin, and cannot be engineered away at the model layer alone.

b. Transparency, Explainability, and Their Limits

Transparency is the most frequently invoked governance remedy and the most contested. The trustworthy-AI literature frames transparency as a triad comprising traceability, explainability, and open communication about an AI system's limitations, positioned as the foundation on which those using or affected by systems can trust that design, development, and use are lawful, ethical, and robust (Stahl et al., 2023). In the workplace specifically, transparency is linked to worker autonomy, the right to intervene, the regulation of skill grading and the ruling of organization and production processes, and is seen as a means to detect non-democratic practices such as discrimination and even to identify the workplace conditions enabling discrimination in the first place (Graziani et al., 2022).

c. Accountability Architectures and the Human-Oversight Problem

Governance is defined as the practice of establishing and implementing policies, procedures, and standards for the proper development, use, and management of the infosphere, encompassing regulatory, financial and economic, and individual and societal impacts, including rules to ensure human rights, data governance, and lawful surveillance (Ashok et al., 2021). Operationalizing this definition has led to audit-based architectures. Independent audit of AI systems has been proposed as a pragmatic mechanism embodying three governance principles—prospective risk assessments, operation audit trails, and system adherence to jurisdictional requirements—as a response to assurance challenges that are otherwise burdensome and unenforceable (Falco et al., 2021). The trustworthy-AI literature converges on a seven-requirement architecture—human agency and oversight; robustness and safety; privacy and data governance; transparency; diversity, non-discrimination and fairness; societal and environmental well-being; and

accountability—sustained over lawful, ethical, and robust pillars, with responsibility realized through auditing processes subject to the challenges posed by regulatory sandboxes (Díaz-Rodríguez et al., 2023). Impact assessment represents a parallel instrument. The first systematic review of AI impact assessments examined a population of 181 documents, identified 38 actual AI-IAs, and found some convergence between them but no full agreement on content, structure, and implementation, proposing a baseline implementation process usable as a critical yardstick by regulators and external observers (Stahl et al., 2023). The immaturity of these instruments is significant: organizations could be required to publicly disclose information about each automated decision system, including purpose, reach, potential internal use policies, and implementation timeline, yet few organizations are explicitly mandated to disclose anything about the systems they have in place or plan to use, leaving impacted communities, the public, and governments to rely on journalists, researchers, and public records requests (Stahl et al., 2023).

d. Divergent Judgments and the Unresolved Enforcement Gap

Worker participation and consultation rights are asserted as being of particular importance where AI algorithms make workplace decisions, with democracy essential to enabling employees to create optimal working conditions and transparency required to determine whether an algorithm is performing non-democratic practices (Graziani et al., 2022). Yet the evidence on how third parties actually judge algorithmic versus human agents conflicts. Experimental work found interpersonal justice perceptions stronger for the human agent, with participants perceiving human agents as offering more voice and automated agents as more consistent in decision-making, and with informational justice impaired only for the human decision agent when no explanation was given (Schlicker et al., 2021).

2.6. Organizational Resilience

a. From SHRM to Adaptive Capability: Framing the Link

Organizational resilience is routinely invoked as the organizational-level payoff of AI-enabled SHRM, yet the construct itself remains contested. Resilience has been defined as the firm's ability to survive, recover and even grow after disruption, as responsiveness and reinvention to ensure business continuity, and as proactive anticipation and adaptation that generates new capabilities (Martín-Rojas et al., 2023). A parallel stream treats it as a psychological or behavioral attribute that can be developed by capitalizing on the cumulative psychological strengths of human capital (Martín-Rojas et al., 2023). This plurality is not merely semantic: a bibliometric analysis of 469 Scopus-indexed articles found the field fragmented across themes such as crisis management, innovation, dynamic capabilities, sustainability and change management, with no unifying architecture (Mhlanga & Dzingirai, 2024). Scholars also disagree on whether adaptability is a constituent of resilience or a separate phenomenon (Mhlanga & Dzingirai, 2024), and evidence from the German Mittelstand confirms that no uniform conceptualization has emerged because resilience is rooted in psychology, ecology, management and organizational studies, requiring definition in light of the specific context analyzed (Bürgel et al., 2022).

b. Workforce Adaptability, Reskilling and Human Capital

The most direct SHRM-to-resilience pathway runs through human capital. SHRM practices—training, employee participation, employment security, job design, performance-oriented appraisal, internal career opportunities and profit sharing—enhance employees' knowledge, skills and abilities, which in turn help build a resilient attitude and support sustainable performance, since organizational survival presupposes resilience (Rehman et al., 2021). SHRM is positioned as a strategic collaborator in designing growth strategies through recruitment, selection, training, compensation and shared ownership, and resilient organizations are said not merely to absorb shocks but to anticipate change and build the future rather than defend the past (Rehman et al., 2021). The mechanism is theoretically distinctive because HR capabilities can themselves be read as a form of dynamic capability: they support the integration, building and reconfiguration of HR-related

competencies such as learning, reskilling and change in the face of dynamic shifts in the HR domain (Soluk et al., 2023).

c. Organizational Learning, Knowledge and Ambidexterity

Adaptive capability depends on how learning is organized. Self-renewal—the systemic ability to create and maintain different knowledge environments—leads to continuous improvement and ultimately enhances organizational resilience, while firms that diagnose environmental conditions accurately, renew themselves and develop new capabilities are better able to prosper under threat (Martín-Rojas et al., 2023). A configurational study of 19 resilient Italian public services found that the three effective configurations of enabling factors for resilience stem from human-based and continuous learning processes addressed through knowledge-based adaptive approaches (Casalegno et al., 2023). AI complicates rather than simply augments this process.

d. Digital Capabilities, Literacy and Agility

Digital resources function as dynamic capabilities enabling firms to navigate complex and uncertain environments. Digital literacy equips entrepreneurs to leverage technological tools, adapt to technological change and implement new business models; digital accessibility is a significant driver of resilience because equitable access to infrastructure, platforms and information allows faster response to market shifts; and human capital—education, professional experience, problem-solving capability—enables strategic decision-making and operational flexibility (Shatila et al., 2025).

e. AI Capacities and Dynamic Capabilities Under Turbulence

The AI-specific contribution is best specified through dynamic capabilities micro-foundations. AI capacities are conceptualized as perceptive, predictive and prescriptive, enabling firms to automate and augment data-driven analysis and decisions (Sjödin et al., 2023), and their commercialization rests on three dynamic capabilities—value discovery (sense), value realization (seize) and value optimization (reconfigure)—each comprising routines such as customer intelligence and ecosystem value exploration (Sjödin et al., 2023). Survey evidence from 487 SME managers and owners indicates that environmental turbulence influences the implementation of both dynamic capabilities and AI, which act as mediators between disruptive elements and enhanced firm performance (Dhaheri et al., 2024).

f. Is Resilience an Antecedent, Mediator or Outcome?

The literature offers three mutually inconsistent positions. As an antecedent, resilience enables adoption of complex technologies: from a resource-based view, the flexibility and capability to adapt found in resilient organizations is warranted to implement and fully leverage disruptive technologies, so organizational resilience becomes a key enabler of AI and blockchain adoption, whereas organizations with lower resilience find these technologies riskier and less likely to succeed (Rodríguez-Espíndola et al., 2022). As a mediator, production-system resilience channels the effect of AI capacity onto operational performance, with multi-wave data from 305 manufacturing firms showing that resilience significantly mediates this relationship and that human–organization–technology fit moderates the AI-capacity-to-resilience path (Wang et al., 2025). As an outcome or dynamic capability in itself, service innovation and organizational resilience are confirmed as key dynamic capabilities that address a changing business landscape, with digital tools (social media platforms) and external networks as drivers of service innovation, evidenced across 343 Spanish service firms and 12 managerial interviews (Garrido-Moreno et al., 2024). These positions are difficult to reconcile within a single model, and their coexistence suggests that resilience is being measured at different levels and moments rather than that one specification is correct.

g. Institutional Context and Durability

Institutional context is a persistent blind spot. Studies of technology adoption for risk management explicitly combine institutional theory, the resource-based view and the technology acceptance model, and conclude that organizational and supply-chain resilience research has emphasized leadership, strategy, resource capacity and human resource capability as facilitators of restructuring operations while largely neglecting the effect of resilience on successful adoption of emergent technologies (Rodríguez-Espíndola et al., 2022). Digital-enabled resilience is also contingent: creating adaptive capacity through digital technologies during COVID-19 depended on resource constraints, socioemotional wealth and the presence of non-family managers, with interaction effects showing crisis resilience varying by level of pre-crisis digitalization and globalization exposure (Bürgel et al., 2022).

h. SDG Integration

The proposition that AI-enabled SHRM advances the Sustainable Development Goals is increasingly asserted, yet the SDG framework itself offers weak external discipline. It is, in the assessment of the most comprehensive review of its political impact, "a non-legally binding and loose script, purposefully designed to provide much leeway for actors to interpret the goals differently and often according to their interests," with little evidence that the UN system functions as a conductor aligning actors around shared targets (Biermann et al., 2022). SDG claims attached to workplace AI must therefore be read as institutional and discursive constructions as much as measured outcomes. This section maps SDGs 3, 5, 8, 9, 10, and 16 to the mechanisms established in the preceding sections and assesses whether those claims are substantiated or aspirational.

i. Substantiated or Aspirational? Measurement and Attribution

Table 2. Evidentiary status of SDG linkages to AI-enabled sustainable HRM.

SDG	Proposed mechanism	Evidentiary status
3	Algorithmic burnout detection; personalised wellness	Demonstrated prediction ($R^2 = 0.9567$) but offset by AI-awareness burnout and technostress
5	Gender-inclusive AI design; reduced physical task barriers	Enabling in part; persistent bias; institutionally contingent
8	Upskilling/reskilling; employee technical assistance	Strong on skill demand; employment effects inconclusive and speculative
9	Human-centric human-machine collaboration; digital infrastructure	Conceptual alignment; infrastructure precondition established
10	Optimal IT education to reduce skill premium	Counter-evidence dominates: within-country inequality and polarization increase
16	Transparency, accountability, auditing, participation rights	Requirements measurable and validated; disclosure motives remain institutional

Two unresolved problems limit the field. First, measurement: there exists no consensus or science-based method for assessing SDG performance, bringing the risk of cherry-picking and arbitrary target-setting among the 17 goals (Gebara et al., 2023). Second, attributing a firm-level SDG contribution specifically to AI-enabled SHRM remains unsupported; as one analysis of multinational communications found, only approximately 2.7% of communications concerned innovation and SDGs, firms predominantly used assertive organizational impression-management tactics, and messaging concentrated on goals with positive externalities (Frutos-Bencze et al., 2024). Until AI-enabled SHRM contributions are tied to systematic, science-based indicators rather than selective disclosure, SDG-washing remains a credible risk, and the strongest defensible claim is that these contributions are conditional on governance, education design, and institutional context.

2.7. Research Gaps and Future Research

Table 3. Consolidated research agenda: gaps, evidence, directions, and theoretical lenses.

Gap	Key evidence	Future direction	Theoretical lens
Fragmented, atheoretical base	(Nhan & Thu, 2026; Prikshat et al., 2023; Vera et al., 2025)	Integrative multilevel models bridging platform, governance, and organizational streams	Institutional Theory; Dynamic Capabilities
Untested mediators/moderators	(Hai et al., 2025; Verma & Singh, 2022)	Model boundary conditions (digital job demands, perceived substitution crisis) within one framework	JD-R; COR
Unclear causal direction	(Chiu et al., 2021; Tomprou & Lee, 2021)	Experiments and longitudinal process studies across adoption phases	Social Exchange; psychological contract
Cross-sectional dominance	(Verma & Singh, 2022; Zoonen et al., 2023)	ESM, multi-wave, mixed-method, multi-source designs	—
Inconsistent constructs	(Bürgel et al., 2022; Jaturat et al., 2026; Rehman et al., 2021)	Context-specific resilience measures; standardized AI responsibility instrument	—
Thin SDG and organizational outcome evidence	(Nahar, 2024; Nasir et al., 2022; Prikshat et al., 2023)	System-dynamics forecasting; goal-targeted outcome studies	Technology Enactment
Governance principles–practice gap	(Ashok et al., 2021; Kayas, 2023; Tan et al., 2021)	Implementation-level studies of transparency, accountability, surveillance policy	Stakeholder Theory
Understudied populations/contexts	(Aderibigbe et al., 2023; Kuhn et al., 2021; Shamim et al., 2023)	Gig, precarious, and developing-economy samples	Institutional Theory

The overarching unresolved question is whether ethical governance should be theorized as an antecedent condition enabling well-being benefits, a mediator transmitting AI-SHRM effects, or a moderator determining when those effects turn negative. The coexistence of documented benefits and dark-side mechanisms—GenAI collaboration raising work alienation on the one hand (Hai et al., 2025) and algorithmic agents reducing perceived breach on the other (Tomprou & Lee, 2021)—cannot be reconciled without designs capable of testing competing causal orderings across levels and contexts.

2.8. Integrated Conceptual Framework

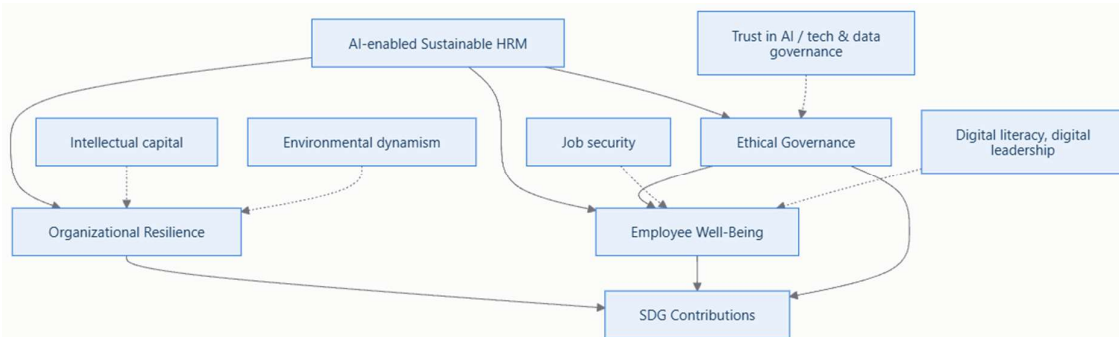


Figure 1. Integrated conceptual framework linking AI-enabled sustainable HRM to SDG contributions through employee well-being, ethical governance, and organizational resilience.

Table 4. Testable propositions, theoretical anchors, and evidence status

Proposition	Path	Theoretical anchor	Evidence status
P1	AI-SHRM → well-being is dual (resources raise engagement; demands raise exhaustion)	JD-R	Supported (Chuang et al., 2025; Scholze & Hecker, 2024)
P2	Engagement and exhaustion mediate AI-SHRM → job satisfaction and work-family outcomes	JD-R	Supported (Chuang et al., 2025)
P3	Job security positively moderates AI-SHRM → engagement and performance	Boundary crossing/self-regulation	Supported (Prentice et al., 2023)
P4	Digital leadership and goal orientation buffer technostress; resource scarcity triggers defensive routines	COR	Supported (Yang et al., 2025)
P5	AI-SHRM → transparency, XAI, fairness auditing, privacy and consent → trust	Governance design	Supported (Falke et al., 2026; Nwachukwu et al., 2025; Olaniyan et al., 2023)
P6	Governance quality moderates AI-SHRM → well-being via trust and perceived fairness	COR (resource gain/loss)	Partially supported; exploratory (Falke et al., 2026; Olaniyan et al., 2023)
P7	Digital capability → resilience is mediated by intellectual capital and weakened by environmental dynamism	Dynamic capabilities	Supported (Ahmed et al., 2022; Rodríguez-Espíndola et al., 2022)
P8	Well-being + governance + resilience → SDG contributions	Stakeholder/institutional	Partially supported: SDG5, SDG8, SDG10 (and SDG4 training) (Giordino et al., 2025); SDG3, 9 and 16 remain inferential

Level-of-analysis assumptions follow Hillebrand et al.'s call to move from tasks to organisational context, individual to collective agency, local to systemic interaction, and micro to multilevel outcomes

(Hillebrand et al., 2025), consistent with the multilevel HRM platform proposed by Prikshat et al. (Prikshat et al., 2023); trust, job security, engagement and technostress are specified at the individual level, governance mechanisms and intellectual capital at the organisational level, and SDG contributions at the societal level. Boundary conditions are environmental turbulence and dynamism (Ahmed et al., 2022; Garrido-Moreno et al., 2024) and institutional legitimacy pressures (Del-Castillo-Feito et al., 2021). The recommended figure is a path diagram with four labelled blocks (AI-SHRM antecedent; three pillar mediators; SDG outcomes), solid arrows for theoretically grounded and empirically supported paths, and dashed arrows for the exploratory relationships P6 and P8, with moderators entering as arrows terminating on paths rather than on constructs.

III. Conclusion

This review argues that AI-enabled sustainable HRM influences SDG-related outcomes through three interconnected pathways: employee well-being, ethical governance, and organizational resilience. The evidence indicates a dual impact of AI adoption. AI-related demands, such as technostress, can increase exhaustion, work–family conflict, and reduce job satisfaction, while AI resources, including AI efficacy and generative AI, can enhance productivity, engagement, and satisfaction (Chuang et al., 2025; Scholze & Hecker, 2024). Similar contingencies appear in organizational resilience, where digital capabilities and innovation can strengthen agility and resilience, but their effects depend on environmental conditions and organizational resources (Ahmed et al., 2022; Garrido-Moreno et al., 2024). Thus, AI's contribution to sustainable HRM is conditional rather than uniformly beneficial.

The literature generally agrees that the Job Demands–Resources and Conservation of Resources theories help explain how AI-related demands and resources affect employees, while ethical governance requires transparency, fairness, privacy, explainability, and accountability (Yang et al., 2025; Li et al., 2022). Sustainable HRM further positions employee well-being and retention as foundations of organizational resilience (Essien et al., 2025). However, important contradictions remain concerning algorithmic hiring bias, AI's effects on employment, and its contribution to different SDGs across developed and developing countries (Fabris et al., 2024; Haidegger et al., 2023; Nahar, 2024). Methodologically, the literature is also dominated by cross-sectional and single-country studies, limiting causal inference and leaving the positive and negative consequences of AI insufficiently resolved.

The review contributes by integrating AI-enabled sustainable HRM with employee well-being, ethical governance, and organizational resilience while emphasizing contextual contingencies. It supports an augmentative rather than substitutive approach to AI, requiring human oversight, employee reskilling, AI literacy, privacy protection, ethical audits, and stakeholder participation (Olaniyan et al., 2023; Pero & Verhagen, 2023). Nevertheless, the framework remains a synthesizing heuristic because of limited longitudinal evidence, inconsistent measurement, and restricted SDG coverage. Future research should therefore employ longitudinal and multi-level designs to examine how AI demands, resources, governance, and organizational capabilities jointly shape sustainable HR outcomes and SDG contributions over time.

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