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# Human-Centered Artificial Intelligence in Human Resource Management: An Integrative Review and Research Agenda

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**Abstract**

**Purpose:** This study synthesizes recent AI-HRM research and develops a Human-Centered AI-HRM Value Framework that integrates AI applications, employee experiences, organizational capabilities, and responsible governance to explain how AI creates strategic value while safeguarding fairness, trust, autonomy, and employee well-being.

**Research Methodology:** A structured integrative review examined 46 peer-reviewed journal articles published from 2017 to August 2026. Academic discovery searches were combined with publisher verification and snowballing. Studies were coded by HR function, AI role, employee mechanism, organizational capability, risk, and outcome, with synthesis focused on convergent mechanisms and boundary conditions.

**Results:** Six themes emerged: strategic augmentation, recruitment and selection, people analytics and performance, employee reactions, algorithmic work design, and responsible governance. Benefits are strongest when AI augments consequential human judgment; opaque automation can trigger injustice, distrust, dehumanization, reduced autonomy, resistance, and adverse attraction or retention outcomes.

**Conclusions:** Sustainable AI-HRM value depends on high-quality data, HR analytics capability, explainability, meaningful human review, employee voice, and accountable governance. The framework shows that AI-HRM value is contingent on how automation authority is configured for different HR decisions and organizational contexts.

**Limitations:** The review is limited to English-language peer-reviewed journals and does not estimate a pooled effect across all HR outcomes.

**Contributions:** This study extends Socio-Technical Systems Theory and Organizational Justice Theory by proposing a Human-Centered AI-HRM Value Framework integrating AI capabilities, employee well-being, and responsible governance.

**Keywords:** *Algorithmic HRM, Artificial Intelligence, Employee Outcomes, Human Resource Management, People Analytics*

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## 1. Introduction

Artificial intelligence is changing the architecture of Human Resource Management (HRM) from a function centered on administrative processing toward one increasingly supported by prediction, recommendation, automation, and generative assistance (Ridwan, Sustiyatik, & Jauhari, 2025). Across recruitment, workforce planning, performance management, learning, and retention, AI systems can screen information at a scale that is difficult for human decision makers to reproduce, while people analytics can link workforce data with strategic outcomes. This technological expansion has made AI-HRM a management issue rather than merely an information-technology issue because the quality of algorithmic decisions affects who enters the organization, how employees are evaluated, what opportunities they receive, and whether they experience the employment relationship as legitimate (Pan & Froese, 2023; Tambe, Cappelli, & Yakubovich, 2019; Vrontis et al., 2022).

The strategic promise is substantial. Earlier work on workforce and people analytics argued that data can strengthen evidence-based HR decisions and connect human-capital investments with organizational performance when analytical capability is combined with business understanding (Huselid, 2018; Marler & Boudreau, 2017; McIver, Lengnick-Hall, & Lengnick-Hall, 2018; Tursunbayeva, Lauro, & Pagliari, 2018). More recent AI-HRM research extends this logic by showing that intelligent systems can support talent matching, decision consistency, personalized development, and organizational learning. However, strategic value does not arise automatically from installing a tool. It depends on data quality, HR capability, task fit, managerial interpretation, and the extent to which AI is assimilated into broader HR routines rather than used as an isolated technology (Bastida, García, Taín, & Araujo, 2025; Prikshat, Malik, & Budhwar, 2023; Ratnawati et al., 2026).

This distinction between technological possibility and realized management value is important because the HR domain contains decisions that are socially consequential and frequently ambiguous. Employee performance, potential, leadership readiness, cultural contribution, and future learning ability cannot always be reduced to stable historical labels. Tambe et al. (2019) therefore caution that the promise of AI in HR must be considered alongside small-data constraints, complex causal relationships, legal and ethical obligations, and employee reactions. Cheng and Hackett (2021) similarly argue that algorithmic HRM requires clear conceptualization because algorithms can assist, recommend, rank, or make decisions, and these roles carry different implications for accountability and human discretion.

Research on applicant and employee reactions makes those implications visible. Algorithmic decisions are not evaluated solely by their predictive accuracy; people also judge whether the procedure is understandable, whether relevant personal information was considered, whether they had an opportunity to express themselves, and whether the organization can be held accountable. Studies of automated interviews, AI-based selection, and algorithmic decision making show that acceptance varies with decision stakes, the amount and type of information provided, perceived chance to perform, and the presence of human involvement (Acikgoz, Davison, Compagnone, & Laske, 2020; Köchling, Wehner, & Warkocz, 2023; Langer, König, & Fitili, 2018; Langer, König, & Papathanasiou, 2019; Mirowska & Mesnet, 2022). The 2026 meta-analysis by Moritz, Pomrehn, Steinmetz, and Wehner (2026) consolidates this concern by showing that reactions to algorithmic HR decisions are a systematic organizational issue rather than an isolated design problem.

At the same time, the employee side of AI-HRM has expanded beyond selection. Algorithmic management can allocate tasks, monitor work, evaluate performance, schedule labor, and recommend actions. Such systems may improve coordination and consistency, but they can also redesign jobs in ways that restrict autonomy, intensify monitoring, or separate workers from meaningful managerial interaction. Parent-Rocheleau and Parker (2022) conceptualize algorithms as work designers, while Meijerink and Bondarouk (2023) emphasize the duality through which algorithmic management can simultaneously create and destroy value. Empirical evidence from European organizations further suggests that the relationship between algorithmic practices and workplace well-being is contingent on how those practices reshape control, resources, and employee experience (Kinowska & Sienkiewicz, 2023).

The ethical debate has consequently moved from a narrow concern with bias to a broader governance question. Bias and discrimination remain critical because training data may reproduce historical inequality, proxies can encode sensitive characteristics, and seemingly neutral optimization targets can generate unequal outcomes (Hunkenschroer & Luetge, 2022; Köchling & Wehner, 2020). Yet responsible AI-HRM also requires transparency, privacy, explainability, accountability, opportunities for appeal, and clarity about which decisions should remain meaningfully human. Research on dignity and procedural justice shows that an outcome can be technically consistent while still being experienced as inappropriate if the decision process fails to recognize the person behind the data (Bankins, Formosa, Griep, & Richards, 2022; Newman, Fast, & Harmon, 2020).

Generative AI broadens the challenge again. Large language models can draft job advertisements, summarize interviews, create personalized learning materials, assist HR service delivery, and support managerial communication. These applications lower the cost of producing and processing language but can also introduce hallucination, privacy, security, contextual insensitivity, and new forms of hidden standardization. Budhwar et al. (2023) therefore, call for HRM scholarship to examine generative AI not only as a productivity tool but also as a technology that may alter employment relationships, HR roles, work design, and stakeholder expectations. This implies that the next phase of AI-HRM research should integrate strategic value creation with employee-centered and governance perspectives.

Despite the rapid growth of literature, the field remains fragmented across several conversations: people analytics focuses on evidence and strategic contribution; algorithmic HRM examines decision structures and managerial control; applicant-reaction research emphasizes fairness, trust, and organizational attraction; work-design research considers autonomy and well-being; and responsible-AI studies address ethics and governance. Existing reviews have provided important maps of AI in HRM (Bujold et al., 2024; Pan & Froese, 2023; Pereira, Hadjielias, Christofi, & Vrontis, 2023; Vrontis et al., 2022), but recent evidence on AI resistance, organizational dehumanization, augmentation, and meta-analytic employee reactions creates an opportunity for a more integrated management framework (Bastida et al., 2025; Golgeci, Ritala, Arslan, McKenna, & Ali, 2025; Moritz et al., 2026; Shin, Choi, & Kim, 2025).

This review contributes an integrated socio-technical value logic rather than another inventory of AI applications. It links organizational and technological antecedents to AI design choices; these choices shape employee mechanisms justice, trust, autonomy, dignity, privacy, and AI readiness which influence HR and organizational outcomes. Governance conditions affect these relationships throughout. By treating human agency and governance as sources of value creation, the framework connects research streams often examined separately.

Accordingly, this study addresses three questions.

The review extends prior work in three ways: it links strategic value to employee-centered mechanisms; distinguishes automation from augmentation and identifies decision stakes, job characteristics, organizational climate, workforce diversity, and institutional context as boundary conditions; and translates the synthesis into six propositions and a governance-oriented framework. It thus explains not only where AI is used in HRM, but why outcomes differ across decisions and settings.

***RQ1.*** *Through which HR functions and mechanisms does AI create or erode value?*

***RQ2.*** *Which design and governance conditions shape employee reactions to AI-enabled HR decisions?*

***RQ3.*** *How can organizations combine analytical efficiency with meaningful human agency?*

The article contributes by synthesizing 46 peer-reviewed journal studies published between 2017 and August 2026, developing six research propositions, and presenting a Human-Centered AI-HRM Value Framework that connects organizational antecedents, AI design choices, employee mechanisms, outcomes, and governance. The framework positions augmentation, justice, explainability, autonomy, and accountability as central management variables rather than secondary ethical considerations.

## 2. Literature Review and Hypotheses Development

### *2.1 Conceptual Boundaries: AI-HRM, Algorithmic HRM, and People Analytics*

AI-HRM is best understood as an umbrella for HR activities in which artificial intelligence contributes to sensing, prediction, recommendation, content generation, interaction, or decision execution. This definition is broader than a single class of machine-learning model and narrower than generic digital HRM because the distinctive feature is computational inference or automated decision support. Algorithmic HRM overlaps with AI-HRM but places greater emphasis on rule-based or data-driven systems that structure managerial decisions, while people analytics refers to the systematic analysis of workforce data for evidence-based decisions (Suryawan, Yusuf, Suhendah, Krisna, & Kamar, 2025). Meijerink, Boons, Keegan, and Marler (2021) show that algorithmic HRM benefits from cross-disciplinary integration because the same technical system can simultaneously function as an analytics tool, a control mechanism, and a mediator of the employment relationship.

Conceptual clarity is important because the level of automation changes the social meaning of the technology. An algorithm that summarizes information for a recruiter has a different role from a system that independently rejects applicants, and a dashboard that detects turnover risk differs from an automated intervention that changes schedules or development opportunities. Langer and Landers (2021) distinguish decision automation from augmentation and argue that consequences depend on whether AI replaces or supports human judgment. In HRM, this distinction is particularly consequential because employees often expect contextual interpretation, interpersonal treatment, and an identifiable locus of accountability for high-stakes decisions.

People analytics provides the capability foundation for many AI-HRM systems. Marler and Boudreau (2017) found that the evidence base for HR analytics was growing but still underdeveloped, while Tursunbayeva et al. (2018) highlighted both value propositions and conceptual ambiguity. Subsequent research has emphasized that analytics creates value through organizational routines, decision quality, and managerial use rather than through dashboards alone (Greasley & Thomas, 2020; McCartney & Fu, 2022a). This leads to a core distinction in the present review: AI-HRM is a socio-technical management system whose outcomes depend on the interaction between technology, HR capability, employee interpretation, and governance.

### *2.2 Strategic Augmentation and HR Capability*

The strategic HRM literature suggests that technology creates advantage when it strengthens difficult-to-imitate organizational capabilities rather than merely automating common administrative tasks (Lestary, Meilita, Marhaini, & Wa, 2026). Applied to AI-HRM, this means that value is likely to arise when AI improves the speed, scope, and consistency of analysis while humans contribute causal reasoning, contextual knowledge, relational judgment, and ethical accountability. The workforce-analytics literature makes a similar argument: analytics can improve organizational performance when HR professionals translate evidence into decisions that are connected with strategy and when those decisions are embedded in credible organizational processes (Huselid, 2018; McCartney & Fu, 2022a; McIver et al., 2018).

AI assimilation therefore requires more than technical adoption. Prikshat et al. (2023) conceptualize AI-augmented HRM as a multilevel process involving antecedents, assimilation, and consequences, while Pan, Froese, Liu, Hu, and Ye (2022) show that contextual factors influence organizational adoption of AI in recruitment. HR professionals also need analytical competencies that bridge data literacy with consulting, business, communication, and ethical judgment (McCartney et al., 2021).

Organizations with weak capability may automate existing poor practices at greater speed, whereas capable organizations can use AI to question assumptions, test alternatives, and allocate human attention to decisions that require interpretation.

Recent work strengthens the augmentation argument. Bastida et al. (2025) explicitly frame the HR journey as a movement from automation to augmentation and emphasize the balance between algorithmic efficiency and human-centered workforce development. This is compatible with evidence that high-stakes decisions often attract more negative reactions when human discretion is absent or when employees cannot understand how the decision was reached (Langer et al., 2019; Moritz et al., 2026). Thus, augmentation is not simply a transitional compromise; it can be a deliberate design principle that preserves organizational learning and accountability.

> *$P_1$:* AI-HRM configurations that emphasize human-AI augmentation, rather than full automation of consequential decisions, will be associated with stronger employee acceptance and more sustainable HR value creation

***2.3 AI in Recruitment and Selection: Efficiency, Fairness, and Applicant Experience***

Recruitment and selection are the most visible AI-HRM applications because they combine high data volume with repeated classification decisions. AI can assist sourcing, résumé screening, candidate matching, interview scheduling, conversational support, and assessment. Pillai and Sivathanu (2020) show that organizations adopt AI for talent acquisition because of expected efficiency and decision benefits, while Pan et al. (2022) demonstrate that adoption depends on contextual conditions rather than technological attributes alone. From the employer perspective, standardized systems may reduce processing time and increase consistency; from the applicant perspective, however, the experience depends on whether the technology provides a fair opportunity to demonstrate relevant qualities.

Applicant-reaction studies reveal a persistent tension between consistency and social legitimacy. Langer et al. (2018) show that information about novel selection technologies can shape reactions, while Langer et al. (2019) find that acceptance of highly automated interviews is influenced by decision stakes. Automated evaluation may also alter impression-management behavior and the sense that anyone is genuinely listening (Langer, König, & Hemsing, 2020). In a related experiment, Langer et al. (2020) demonstrate that organizational context matters for reactions to highly automated interviews. These studies imply that user communication cannot compensate for every design problem, but it can clarify the purpose, limits, and decision role of the system.

Fairness perceptions are equally important. Acikgoz et al. (2020) find that justice perceptions influence responses to AI in selection, and Köchling et al. (2023) show that affective reactions are related to whether applicants feel able to demonstrate their skills. Mirowska and Mesnet (2022) find that some applicants may prefer familiar human evaluation even when AI is presented as a sophisticated alternative. At the broader level, Köchling and Wehner (2020) show that discrimination and fairness risks can emerge throughout recruitment and development when algorithms reproduce biased data or use proxies that disadvantage particular groups.

These findings suggest that the efficiency of AI selection is strategically incomplete unless applicant experience is treated as an outcome. Rejected applicants are also customers, future applicants, referrers, and members of the labor market. A system that is accurate but experienced as arbitrary can damage organizational attractiveness and trust. Therefore, selection design should combine validation, job relevance, understandable communication, accessibility, bias monitoring, and a channel for human review.

> *$P_2$:* Perceived procedural and interactional justice will mediate the relationship between the intensity of AI involvement in recruitment and applicant outcomes such as trust, organizational attractiveness, and job-pursuit intentions

### *2.4 Transparency, Human Oversight, and the Limits of Algorithmic Reduction*

Transparency is frequently proposed as a remedy for algorithm aversion, but the literature suggests that the issue is more complex than simply revealing technical detail. Employees need information that is meaningful for the decision context: what data are used, why those data are relevant, how the system contributes to the decision, what limitations exist, and how an individual can challenge an error. Langer and König (2023) frame opacity as a multi-stakeholder problem because developers, HR professionals, managers, applicants, employees, and regulators require different forms of transparency. Technical explainability that is incomprehensible to a candidate may satisfy documentation requirements without improving perceived legitimacy.

Organizational justice research provides a useful mechanism. Lee (2018) shows that algorithmic decisions can influence fairness, trust, and emotion, particularly when automated systems perform tasks for which people expect human judgment. Newman et al. (2020) introduce the concept of algorithmic reductionism: even when algorithms are intended to remove human bias, people may perceive the procedure as unfair if it reduces a complex person to a limited set of measurable attributes. Bankins et al. (2022) extend this concern to dignity, finding that worker reactions to human and AI decision makers depend on the perceived justice of the process and the recognition of human standing.

Human oversight can address some of these concerns, but only when it is substantive. A nominal human-in-the-loop who routinely accepts recommendations does not provide meaningful review. Effective oversight requires authority to disagree, access to contextual information, accountability for the final decision, and documented escalation rules. It also requires interface design that avoids automation bias and prompts managers to consider evidence beyond the algorithmic score. In this sense, explainability and oversight are complementary: explanation makes review possible, and review makes accountability credible.

> *$P_3$:* Explainability and meaningful human review will weaken the negative effects of perceived algorithmic opacity and reductionism on fairness, trust, and acceptance of AI-enabled HR decisions

### *2.5 People Analytics, Performance Management, and Organizational Learning*

Beyond hiring, AI-HRM is increasingly connected with performance data, workforce planning, learning recommendations, retention models, and internal labor-market decisions (Baja, Suroso, Zulganef, & Brahmana, 2026). The value proposition is that large and diverse data sources can help managers detect patterns that are difficult to observe through informal judgment alone. Workforce analytics research argues that this capability can strengthen the link between human-capital decisions and organizational strategy (Huselid, 2018; Simón & Ferreiro, 2018). At the same time, the analytics literature consistently warns that correlation does not automatically establish a useful intervention and that model outputs must be interpreted through business and causal reasoning.

McCartney and Fu (2022a) explain that HR analytics affects organizational performance through mechanisms involving evidence, decision making, and organizational context. Their systematic review of people-analytics debates also shows that the field continues to face gaps between promise and realized practice (McCartney et al., 2021). Greasley and Thomas (2020) add a political and epistemological critique: metricized HRM does not merely describe performance; it can change what the organization values by privileging what is measurable. This matters for AI because model objectives become embedded priorities. If the target is narrow, the system may improve the metric while displacing less measurable aspects of cooperation, learning, creativity, or citizenship.

The practical implication is that AI performance systems should be designed as learning systems rather than automated scorekeepers. Managers need to test whether predictions are stable across groups and time, whether measures capture relevant dimensions of work, and whether recommendations improve decisions when compared with credible alternatives. HR analysts also need competencies that allow them to explain uncertainty and limitations instead of presenting scores as

facts (McCartney et al., 2021). Used this way, AI can expand managerial attention without turning the employment relationship into a purely metric exchange.

> *$P_4$:* HR analytics capability and evidence-based decision routines will mediate the relationship between AI-HRM adoption and organizational performance, such that technological adoption without complementary capability will produce weaker or inconsistent value

### *2.6 Algorithmic Work Design, Autonomy, Well-Being, and Dehumanization*

AI-HRM does not only evaluate workers; it can structure how work is performed. Algorithmic systems may assign tasks, prioritize workflows, set schedules, monitor activity, provide real-time feedback, and recommend corrective action. Parent-Rocheleau and Parker (2022) argue that these systems act as work designers because they influence core job characteristics. This perspective moves the analysis beyond accuracy and efficiency toward autonomy, feedback quality, skill use, social interaction, and perceived control. The consequences are inherently dual. Meijerink and Bondarouk (2023) show that algorithmic management can create value by improving coordination and information while simultaneously restricting autonomy or intensifying control. Kinowska and Sienkiewicz (2023) provide evidence that algorithmic management practices are associated with workplace well-being in ways that depend on the specific configuration of practices. The management question is therefore not whether an organization uses algorithms, but how algorithmic rules redistribute resources, discretion, and voice.

Resistance is another critical mechanism. Golgeci et al. (2025) conceptualize AI resistance as a process that can arise from technological, individual, relational, and organizational sources. Resistance should not automatically be interpreted as irrational reluctance; it can signal a perceived threat to competence, identity, privacy, fairness, or employment security. Employee participation, training, role clarity, and visible boundaries on AI authority can convert some resistance into constructive learning. Conversely, a top-down implementation that frames concerns as obstacles may amplify distrust and defensive behavior.

Recent experimental evidence also introduces organizational dehumanization as a mechanism. Shin et al. (2025) find that AI involvement in promotion and performance-evaluation contexts can increase perceived organizational dehumanization and trigger negative employee reactions. This finding is particularly important for HRM because relational signals are part of the employment exchange. When a consequential decision is delegated to an impersonal system, employees may infer that the organization values them primarily as data points. A human-centered design must therefore protect not only decision quality but also the symbolic meaning of being heard and recognized.

> *$P_5$:* The effects of algorithmic management on employee well-being and retention will be mediated by perceived autonomy, organizational support, and dehumanization, while employee participation in AI design and implementation will buffer adverse effects

### *2.7 Responsible AI-HRM Governance*

Responsible AI-HRM governance is the organizational infrastructure that converts ethical principles into repeatable managerial controls. Reviews of AI recruiting and HRM ethics consistently identify bias, privacy, transparency, accountability, explainability, and human oversight as recurring concerns (Bujold et al., 2024; Hunkenschroer & Luetge, 2022; Köchling & Wehner, 2020). Rodgers, Murray, Stefanidis, Degbey, and Tarba (2023) further show that ethical decision pathways in algorithmic HRM should be treated as part of strategic choice rather than as a compliance activity added after deployment. Varma, Dawkins, and Chaudhuri (2023) similarly argue that people-management applications require critical ethical assessment because AI can reshape power and responsibility inside organizations.

A governance system should begin before procurement. Organizations need to define the decision purpose, assess whether AI is appropriate for the task, determine the minimum necessary data, validate job relevance, and establish performance and fairness thresholds. During deployment,

governance should include documentation, access controls, bias and drift monitoring, incident management, vendor accountability, and channels for employee questions and appeal. After deployment, organizations should periodically reassess whether the technology still serves the original objective and whether observed efficiency gains are accompanied by unintended human costs.

Governance is also a capability for responsible experimentation. Tambe et al. (2019) recommend causal reasoning and experimentation because HR data are often observational and complex. Rather than immediately scaling an opaque model, organizations can pilot AI on lower-stakes decisions, compare augmented and non-augmented workflows, measure both efficiency and employee reactions, and use the results to refine the design. Such experimentation makes the business case more credible and allows organizations to detect harm before it becomes institutionalized.

> *$P_6$:* Responsible AI-HRM governance including bias auditing, data minimization, accountability, meaningful appeal, and continuous monitoring will positively moderate the relationship between AI-HRM use and sustainable employee and organizational outcomes

### *2.8 Integrative Framework*

The six propositions converge on a Human-Centered AI-HRM Value Framework. The framework begins with organizational and technological antecedents such as data quality, HR analytics capability, task characteristics, and regulatory context. These antecedents shape AI-HRM design choices, especially the balance between automation and augmentation, the degree of explainability, and the presence of human oversight and employee voice. Design choices influence employee mechanisms including justice, trust, autonomy, dignity, privacy perceptions, and AI readiness which in turn affect HR and organizational outcomes. Responsible governance surrounds the process because accountability, auditing, and appeal are required at every stage. The model also recognizes boundary conditions such as decision stakes, job design, organizational climate, workforce diversity, and national institutions.

## 3. Research Methodology

### *3.1 Review Design and Scope*

This study uses a structured integrative literature review. An integrative approach was selected because the research question spans conceptual reviews, field studies, experiments, meta-analytic evidence, and management frameworks across HRM, organizational behavior, information systems, and business ethics. The purpose was not to calculate one pooled effect across heterogeneous outcomes, but to identify convergent mechanisms and boundary conditions that explain when AI-HRM produces strategic and employee value. The review window covers January 2017 to 13 August 2026, capturing the expansion from people analytics and early automated selection to algorithmic management, generative AI, AI resistance, and recent meta-analytic evidence.

### *3.2 Search Strategy and Study Selection*

Academic discovery searches were conducted using combinations of the terms “artificial intelligence,” “human resource management,” “algorithmic HRM,” “algorithmic management,” “people analytics,” “AI recruitment,” “automated interview,” “employee fairness,” “algorithmic justice,” “employee trust,” “AI resistance,” “workplace well-being,” and “organizational dehumanization.” Discovery was supplemented by publisher-level verification on journal platforms and by backward and forward snowballing from influential reviews and core empirical studies. Searches were iteratively refined until additional queries primarily reproduced already identified conceptual streams.

For reproducibility, the core search concepts were operationalized as Boolean combinations of three blocks: technology terms such as “artificial intelligence,” “generative AI,” algorithmic HRM, algorithmic management, people analytics, intelligent automation, and AI recruitment; HR/work terms such as “human resource management,” HRM, recruitment, selection, performance management, workforce planning, learning, employee monitoring, and workplace management; and employee/governance terms such as fairness, justice, trust, autonomy, well-being, resistance,

dehumanization, transparency, explainability, privacy, and governance. The discovery process was intentionally broad at the first stage and narrowed during screening to retain studies with substantive HRM or employee implications. Because the original review record did not retain database-level hit counts, this revision does not retrospectively invent database names or initial-result numbers; publisher verification and backward/forward snowballing remain explicitly reported as complementary retrieval routes.

Studies were included when they were peer-reviewed journal articles; were written in English; were published within the review window; and explicitly examined or theorized AI, algorithms, advanced analytics, or intelligent automation in an HRM or workplace-management context. Articles were excluded when they were purely technical without a meaningful HR or employee outcome, focused only on customer-facing AI, were non-peer-reviewed commentary, or duplicated an earlier journal version. The final analytic corpus comprised 46 journal articles. All bibliographic details and DOI links were checked against publisher or journal records where available.

Screening first assessed relevance to AI, algorithms, or advanced analytics in HRM/workplace management, then applied peer-review, language, publication-date, and substantive-relevance criteria. Duplicates and ineligible publication types were removed. Borderline studies received full-text assessment, and backward/forward citation chasing identified additional studies. The final corpus comprised 46 articles. Because initial identification and screening counts were not retained, the selection flow reports only the verified final corpus.

### *3.3 Coding and Synthesis*

Each article was coded in a structured matrix using six dimensions: HR function (recruitment, performance, analytics, work design); role of AI (decision support, recommendation, automation, or interaction); level of analysis (applicant, employee, HR professional, organization); focal mechanism (justice, trust, autonomy, dignity, capability, resistance); outcome; and governance implication. A deductive starting framework based on strategic HRM, organizational justice, and work design was combined with inductive coding for themes that became prominent in recent literature, particularly dehumanization, opacity, augmentation, and resistance.

The synthesis followed three passes. The first pass mapped the evolution and conceptual architecture of the literature. The second compared findings within major HR functions and employee mechanisms. The third examined contradictions and boundary conditions, prioritizing explanations that were supported across more than one research stream. Recent meta-analytic and systematic-review evidence was used to test whether conclusions drawn from individual studies were consistent with broader patterns. Because themes overlap, the synthesis treats the same article as relevant to more than one mechanism when appropriate.

### *3.4 Review Quality and Reproducibility*

Quality was assessed pragmatically using methodological transparency, clarity of constructs, relevance to HRM, and the appropriateness of evidence for the claim being synthesized. Greater interpretive weight was given to peer-reviewed empirical studies, systematic reviews, and meta-analyses with clear methods, while conceptual articles were used primarily to define mechanisms and develop propositions. The protocol, search concepts, inclusion rules, coding dimensions, and complete reference list are reported in the article so that future researchers can update the review as the AI-HRM literature evolves.

The review protocol and eligibility criteria used to identify the studies are summarized in Table 1.

Table 1. Review protocol and inclusion criteria

| Study-selection stage | Evidence reported in the review |
|---|---|
| Identification | Academic discovery search + publisher-level verification + backward/forward snowballing |

| Study-selection stage | Evidence reported in the review |
|---|---|
| Initial relevance screening | Records checked against AI/algorithm/advanced-analytics and HRM/workplace relevance |
| Eligibility assessment | Peer-reviewed English journal article; 2017–13 August 2026; substantive HRM/workplace-management focus |
| Exclusion | Purely technical studies without HR outcomes; customer-only AI; non-peer-reviewed commentary; duplicate journal versions |
| Included corpus | 46 peer-reviewed journal articles |

The coding dimensions and key methodological specifications are presented in Table 2.

Table 2. Review dimensions and methodological specifications

| Dimension | Specification |
|---|---|
| Review type | Structured integrative literature review |
| Review period | January 2017–13 August 2026 |
| Discovery channels | Academic discovery search, publisher-level verification, backward/forward snowballing |
| Core search concepts | AI + HRM; algorithmic HRM; people analytics; AI recruitment; automated interview; fairness; trust; resistance; well-being; dehumanization |
| Inclusion criteria | Peer-reviewed English journal articles with explicit AI/algorithm/advanced-analytics relevance to HRM or workplace management |
| Exclusion criteria | Purely technical studies without HR outcomes; customer-only AI; non-peer-reviewed commentary; duplicate journal versions |
| Analytic corpus | 46 peer-reviewed journal articles |
| Coding dimensions | HR function; AI role; level of analysis; employee mechanism; outcome; governance implication |

## 4. Results and Discussions

### *4.1 Architecture and Evolution of the Evidence*

The literature reveals three overlapping phases. The first phase is capability-oriented and is anchored in people and workforce analytics. It asks whether HR can produce decision-relevant evidence and contribute to organizational performance (Huselid, 2018; Marler & Boudreau, 2017; McIver et al., 2018; Tursunbayeva et al., 2018). The second phase focuses on automated decisions, especially recruitment and selection, and brings applicant reactions, procedural justice, and algorithmic bias to the center of the debate (Acikgoz et al., 2020; Langer et al., 2018; Langer et al., 2019; Newman et al., 2020). The third phase expands to algorithmic work design, generative AI, organizational dehumanization, and governance, showing that AI-HRM affects ongoing employment relationships rather than only entry decisions (Budhwar et al., 2023; Golgeci et al., 2025; Meijerink & Bondarouk, 2023; Shin et al., 2025).

Across these phases, the unit of analysis has shifted from the HR function to a wider socio-technical system. Earlier research often asked whether analytics could improve decisions; recent research asks who retains discretion, how employees interpret the process, which institutional safeguards are needed, and what happens when algorithms become routine managers. This evolution is theoretically important because it connects strategic HRM outcomes with organizational justice and work design. The same system that raises process efficiency can also reduce trust or autonomy if design choices signal surveillance, reductionism, or a lack of human concern.

The evidence also suggests that debates should avoid a simple pro-AI versus anti-AI dichotomy. Positive and negative effects frequently coexist. Standardization may reduce some forms of arbitrary human inconsistency while creating new data-driven biases. Automated scoring may speed decisions while weakening applicant opportunity to perform. Real-time monitoring may provide useful

feedback while increasing perceived control. Predictive retention models may help managers intervene early while raising privacy concerns. The key analytical question is therefore configuration: what combination of technology, human judgment, employee voice, and governance is used for a particular HR decision?

Contradictions across studies reveal boundary conditions rather than simple inconsistency. Standardized recruitment can reduce arbitrary human variation yet make applicants feel reduced to narrow metrics. Performance analytics can support early intervention while encouraging metric gaming; algorithmic coordination can improve efficiency while limiting autonomy if workers cannot override recommendations. AI-HRM outcomes therefore depend on decision stakes, information asymmetry, human discretion, employee voice, and how authority, explanation, participation, and governance are configured.

Representative studies, their research contexts, and contributions to the synthesis are summarized in Table 3.

Table 3. Representative evidence in the AI-HRM literature

| Study | Context | Design | Main contribution to synthesis |
|---|---|---|---|
| Marler and Boudreau (2017) | People analytics | Evidence review | Analytics has strategic potential but requires stronger evidence and integration with HR decision making. |
| Lee (2018) | Algorithmic management | Empirical | Fairness, trust, and emotion depend on task and perceptions of algorithmic decision authority. |
| Tambe et al. (2019) | AI-HRM | Conceptual/managerial | HR AI faces causal, data, accountability, and employee-reaction challenges. |
| Langer et al. (2019) | Automated interviews | Experimental | Acceptance of highly automated interviews varies with decision stakes. |
| Acikgoz et al. (2020) | AI selection | Empirical | Organizational justice perceptions are central to reactions to AI-based selection. |
| Newman et al. (2020) | HR decisions | Experimental | Algorithmic reductionism can make bias-reduction procedures appear unfair. |
| Köchling and Wehner (2020) | Recruitment/ development | Systematic review | Algorithmic discrimination and fairness risks occur across HR decision stages. |
| Meijerink et al. (2021) | Algorithmic HRM | Integrative | Algorithmic HRM spans cross-disciplinary mechanisms and changes managerial decision structures. |
| Langer and Landers (2021) | Decision automation | Review | Automation and augmentation create different worker and observer reactions. |
| Bankins et al. (2022) | HR decision making | Empirical | Justice and dignity perceptions differ between human and AI decision makers. |
| Parent-Rocheleau and Parker (2022) | Algorithmic management | Conceptual | Algorithms reshape work design and core job characteristics. |
| McCartney and Fu (2022b) | People analytics | Systematic/empirical synthesis | Organizational value depends on evidence-based routines and capability, not technology alone. |
| Budhwar et al. (2023) | Generative AI | Perspectives | Generative AI extends HR opportunities while increasing uncertainty, privacy, bias, and work-design questions. |
| Kinowska and Sienkiewicz (2023) | Algorithmic management | Empirical | Algorithmic practices have contingent relationships with workplace well-being. |
| Bujold et al. (2024) | Responsible AI-HRM | Review | Empirical responsible-AI research emphasizes fairness, transparency, privacy, and accountability. |

| Study | Context | Design | Main contribution to synthesis |
|---|---|---|---|
| Bastida et al. (2025) | AI-HRM strategy | Integrative model | Sustainable transformation requires a shift from automation toward augmentation and workforce development. |
| Golgeci et al. (2025) | AI resistance | Integrative review | Resistance develops through a multi-stage process and requires targeted organizational responses. |
| Shin et al. (2025) | Promotion/performance | Three experiments | AI involvement can increase organizational dehumanization and negative employee reactions. |
| Moritz et al. (2026) | Algorithmic HR decisions | Meta-analysis | Across 53 studies and 73 samples, algorithmic decision making generates systematic system- and organization-related reactions. |

### *4.2 Recruitment and Selection Outcomes*

Recruitment is the clearest domain in which operational efficiency and stakeholder legitimacy must be managed simultaneously. Adoption studies indicate that organizations are attracted to AI because of expected gains in speed, scalability, and matching (Pan et al., 2022; Pillai & Sivathanu, 2020). Yet applicant-reaction studies show that higher automation is not uniformly preferred. The effect depends on how the assessment is framed, the stakes of the decision, the opportunity to demonstrate skills, and whether human judgment remains visible (Köchling et al., 2023; Langer et al., 2018; Langer et al., 2019).

Fairness is a recurring mechanism. Acikgoz et al. (2020) demonstrate the relevance of justice perceptions in AI selection, while Newman et al. (2020) show why reducing human bias does not automatically create a fair procedure: candidates may object when a complex person is represented through a narrow set of measurable indicators. Bankins et al. (2022) add that dignity and perceived treatment matter when comparing human and AI decision makers. These findings imply that predictive validity and fairness perception are related but distinct criteria. A system should be evaluated on both.

The recent meta-analysis by Moritz et al. (2026), covering dozens of studies and samples, strengthens the conclusion that reactions to algorithmic decision making in HRM are systematic and meaningful. For management practice, the implication is to define a maximum acceptable level of automation by decision stakes. Low-stakes administrative decisions may tolerate greater automation, while consequential hiring, promotion, termination, and compensation decisions require stronger human review, clearer explanation, and appeal. This tiered approach operationalizes Proposition 1 and Proposition 3 and offers a practical way to align system design with stakeholder expectations.

Applicant reactions are not peripheral acceptance issues; they link AI design to organizational attraction and legitimacy. This reconciles efficiency gains with negative reactions to high automation: processing speed benefits the organization, while justice and opportunity to demonstrate skills shape how applicants interpret the employment relationship.

### *4.3 Strategic Analytics and Performance Value*

The evidence on people analytics supports a conditional rather than deterministic business case. Analytics can improve decision quality when HR professionals combine statistical evidence with business knowledge and when managers actually use that evidence in resource-allocation decisions (Huselid, 2018; McCartney & Fu, 2022a). Organizations also need analyst competencies that translate models into credible narratives and interventions (McCartney et al., 2021). This supports Proposition 4: AI is more likely to improve performance when it is embedded in complementary capabilities.

However, the literature also warns against metric substitution. Greasley and Thomas (2020) show that analytics is not politically neutral because measures define what becomes visible and valuable.

McCartney and Fu (2022b) similarly identify continuing debates about the gap between the promise and reality of people analytics. In AI-enabled performance management, these concerns become more acute because a model can continuously rank, predict, and recommend. If employees do not understand which behaviors drive outcomes, the system may encourage gaming or defensive compliance instead of learning.

A stronger design is developmental rather than punitive. AI can identify skill gaps, patterns of workload, or coaching opportunities, but the interpretation should occur in a conversation that allows employees to provide context and challenge inaccurate data. Such an approach preserves the scale advantage of analytics while protecting the relational function of management. It also creates better data: when employees can correct errors and explain anomalies, the organization can learn where the model is weak. Human involvement is therefore not only an ethical safeguard; it can improve the quality of the socio-technical system.

Analytics capability is interpretive and relational, not merely technical. Organizations create value when managers question model outputs, integrate contextual knowledge, and use employee feedback to correct weak measures. The pathway is therefore AI capability → evidence interpretation → managerial action → learning, rather than AI adoption automatically producing performance.

### *4.4 Employee-Centered Mechanisms: Justice, Trust, Autonomy, and Dignity*

A central result of the review is that employee-centered mechanisms explain why technically similar systems can produce different organizational outcomes. Justice and trust are especially important because HR decisions communicate organizational values. Lee (2018) shows that algorithmic management affects fairness, trust, and emotion, while Acikgoz et al. (2020); Newman et al. (2020), and Bankins et al. (2022) demonstrate related justice concerns in HR contexts. These reactions can extend beyond the system to the organization itself, influencing attraction, commitment, and willingness to accept decisions.

Autonomy becomes more salient when algorithms move from occasional decisions to continuous management. Parent-Rocheleau and Parker (2022) show that algorithmic systems can influence core job characteristics, and Meijerink and Bondarouk (2023) emphasize their dual effects on value creation and autonomy. Kinowska and Sienkiewicz (2023) demonstrate that algorithmic management practices are connected with workplace well-being, supporting the argument that implementation should be evaluated through work-design outcomes rather than efficiency alone. An organization can therefore improve an operational metric and still damage the conditions that sustain long-term performance.

Dignity and dehumanization add a relational layer that classic acceptance models often miss. Employees do not only ask whether a system is useful or easy to use; they infer what the system says about how the organization sees them. Shin et al. (2025) provide evidence that AI involvement in HR decisions can increase organizational dehumanization and negative reactions. This mechanism is consistent with Bankins et al. (2022), who highlight dignity in algorithmic HR decisions. Together, these studies suggest that human-centered AI-HRM must preserve recognition, voice, and relational accountability even when the underlying analytics are sophisticated.

Resistance should be interpreted in this context. Golgeci et al. (2025) show that AI resistance develops through a process involving multiple antecedents. Management responses that rely only on training may fail when resistance is driven by distrust, identity threat, or concerns about fairness. A more effective approach begins with diagnosis: is the concern about capability, job security, surveillance, lack of transparency, poor fit, or the absence of meaningful participation? Different causes require different interventions. This supports Proposition 5 and positions employee voice as both an implementation mechanism and an information source for governance.

Resistance, autonomy, and dehumanization are connected mechanisms. Resistance can result from poor design and signal threats to identity, fairness, privacy, or employee voice. These reactions

provide evidence about socio-technical fit and should inform governance monitoring rather than be treated only as implementation obstacles.

### *4.5 Governance as a Value-Creation Capability*

The review indicates that governance should be treated as a strategic capability, not merely a legal constraint. Ethical reviews identify a recurring set of risks bias, privacy, opacity, accountability, and insufficient human oversight but the managerial contribution lies in converting those risks into operating controls (Bujold et al., 2024; Hunkenschroer & Luetge, 2022; Rodgers et al., 2023; Varma et al., 2023). Governance can increase trust, improve data discipline, clarify vendor responsibilities, and make experimentation safer. It can therefore support innovation rather than oppose it.

A practical governance cycle includes five stages. First, organizations classify the use case by decision stakes and potential impact. Second, they define lawful and job-relevant data and a clear outcome objective. Third, they validate model performance and subgroup fairness before deployment. Fourth, they implement transparency, human review, access controls, and appeal. Fifth, they monitor drift, incidents, employee reactions, and unintended work-design effects after deployment. Each stage should have an accountable owner. High-stakes applications should also have a documented fallback process for cases in which the model is uncertain or an individual challenges the input data.

This governance cycle helps reconcile competing objectives. For example, an organization may accept slightly slower selection if human review substantially improves fairness perception for borderline cases. Conversely, it may fully automate low-stakes scheduling recommendations if employees can override them and the system demonstrably reduces administrative burden. The purpose is not to maximize human involvement everywhere; it is to allocate human judgment where it creates contextual, relational, or ethical value. This interpretation supports Proposition 6 and the augmentation principle in Proposition 1.

The theoretical contribution of governance is consequently broader than risk mitigation. Governance determines where organizational discretion resides, how errors become visible, and whether employee voice can influence system correction. It functions as a boundary-spanning capability connecting technical reliability, HR decision quality, and institutional legitimacy.

### *4.6 Human-Centered AI-HRM Value Framework and Managerial Implications*

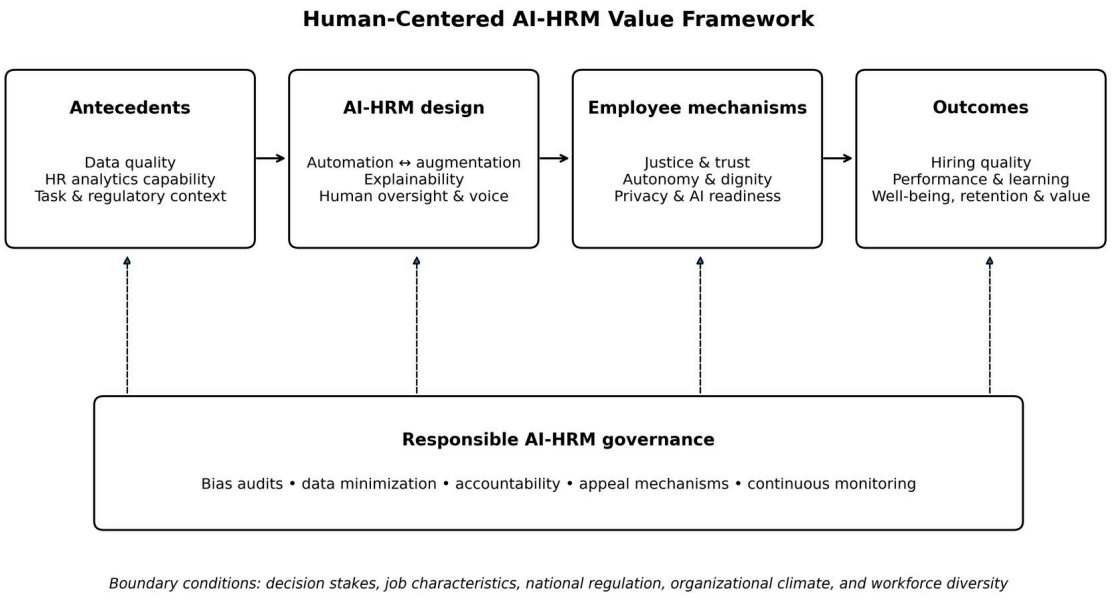



Figure 1. Human-centered AI-HRM value framework

Figure 1 summarizes the framework: organizational and technological antecedents—including data quality, HR capability, task suitability, and regulatory context—shape design choices about automation, augmentation, explainability, human oversight, and employee voice. These choices influence justice, trust, autonomy, dignity, privacy, and AI readiness, which in turn affect HR and organizational outcomes. Governance spans all layers, while decision stakes, job characteristics, institutions, organizational climate, and workforce diversity shape the relationships.

For managers, the framework implies that AI-HRM investment decisions should be evaluated with a balanced scorecard of technical, HR, and employee outcomes. Technical indicators include predictive validity, error rates, robustness, latency, and drift. HR indicators include time-to-hire, quality of hire, internal mobility, learning uptake, performance improvement, and retention. Employee indicators include fairness, trust, perceived autonomy, explainability, privacy concern, and perceived dehumanization. A system that improves only the technical layer should not be considered fully successful.

Implementation should also be staged. Organizations can begin with assistive use cases that summarize information or recommend options, evaluate whether managers use recommendations appropriately, and then decide whether greater automation is justified. Employee representatives and end users should be involved before scaling because they can identify contextual variables that model developers may overlook. HR professionals should be trained to challenge algorithmic outputs, not merely operate the interface. Procurement contracts should specify access to validation information, incident handling, data ownership, and audit rights so that accountability is not outsourced to vendors.

Implementation should reflect organizational context. Large, data-rich organizations can support formal validation, monitoring, governance, and specialist HR-analytics roles; smaller organizations may need simpler assistive tools, stronger vendor checks, and proportionate controls. Regulated or high-accountability sectors require stronger documentation, audits, human review, and appeal, while low-stakes administration may allow more automation with override and monitoring. Priorities also vary by industry: recruitment-intensive sectors should emphasize applicant fairness; monitored operations should protect autonomy, workload, and privacy; and knowledge-intensive organizations should preserve expertise and learning. Across HR functions, recruitment and promotion need robust justice and appeal, performance management needs contextual interpretation, learning should remain developmental, and routine scheduling can allow more automation when employees retain meaningful override options.

Finally, managers should communicate limits as clearly as benefits. Overstating AI objectivity creates unrealistic expectations and may worsen reactions when errors appear. A credible message explains what the system does, what it does not do, which data are considered, where humans intervene, and how employees can seek review. Such communication aligns with the evidence on transparency and justice and reinforces the principle that responsible AI is a continuing managerial relationship rather than a one-time technology deployment.

The recommended management responses and associated controls for different HR contexts are outlined in Table 4.

Table 4. Managerial implementation matrix for responsible AI-HRM

| Context / HR function | Preferred AI-HRM approach | Priority controls |
|---|---|---|
| High-stakes recruitment, promotion, compensation, termination | Augmentation with substantive human review | Explainability, opportunity to perform, bias testing, documented appeal, accountable decision owner |
| Performance management and development | Developmental analytics with contextual manager interpretation | Data-quality checks, uncertainty communication, employee correction, autonomy safeguards |

| Context / HR function | Preferred AI-HRM approach | Priority controls |
|---|---|---|
| Learning and internal mobility | Recommendation/augmentation with employee choice | Transparency, skills relevance, privacy, human override |
| Scheduling and routine administration | Greater automation where stakes are low | Override, monitoring, accessibility, incident handling |
| Large, data-rich organizations | Scaled analytics plus formal AI governance capability | Model validation, drift monitoring, audit rights, specialist HR-analytics roles |
| Small or resource-constrained organizations | Proportionate assistive tools and stronger vendor controls | Data minimization, vendor due diligence, simple review protocols, clear accountability |
| Highly regulated or high-accountability industries | Conservative automation and enhanced auditability | Documented decisions, subgroup fairness, human review, appeal, regulatory alignment |
| Knowledge-intensive industries | Augmentation focused on expertise, learning, and decision support | Preserve professional discretion, challenge model outputs, monitor deskilling and dehumanization |

The operational governance cycle, including managerial actions and minimum evidence requirements, is summarized in Table 5 .

Table 5. Five-stage governance cycle for responsible AI-HRM

| Stage | Managerial action | Minimum evidence/control |
|---|---|---|
| 1. Define the decision | Classify stakes, purpose, affected stakeholders, and whether AI is appropriate. | Decision charter; risk tier; accountable owner |
| 2. Validate data and model | Test job relevance, predictive performance, subgroup fairness, and data minimization. | Validation report; bias metrics; data inventory |
| 3. Configure authority | Choose automation vs. augmentation; specify human override and uncertainty thresholds. | Human-review protocol; escalation rules |
| 4. Design employee experience | Provide understandable notice, opportunity to perform, explanation, and accessible review. | Communication template; appeal channel |
| 5. Monitor in operation | Track model drift, errors, fairness, employee reactions, autonomy, and unintended work effects. | Monitoring dashboard; incident log |
| 6. Reassess and learn | Compare realized benefits and human costs; pause, redesign, or scale based on evidence. | Periodic governance review; documented actions |

## 5. Conclusions

### *5.1 Conclusion*

This review synthesized 46 peer-reviewed studies and developed a Human-Centered AI-HRM Value Framework that treats AI-HRM as a socio-technical configuration. It connects strategic HR value with justice, trust, autonomy, dignity, privacy, and AI readiness, while positioning augmentation, explainability, human review, employee voice, and governance as core design conditions. The six propositions indicate that sustainable value depends on augmenting rather than indiscriminately automating consequential decisions, supporting justice and meaningful review, building analytics capability, protecting autonomy and dignity, and aligning technical performance with human and organizational outcomes through governance. In practice, automate according to decision stakes, preserve human authority where contextual or ethical judgment matters, and evaluate technical, HR,

and employee outcomes together. The framework supports context-sensitive implementation and future empirical testing rather than offering a universal prescription.

### *5.2 Research Limitations*

The study has four limitations. First, the review focuses on English-language peer-reviewed journal articles and may underrepresent research published in other languages, practitioner reports, or jurisdiction-specific legal analyses. Second, the integrative design synthesizes heterogeneous methods and outcomes; it does not provide a single pooled effect size. Third, the field is developing rapidly, especially in generative AI, so specific tools and use cases can change faster than peer-reviewed evidence. Fourth, much empirical work remains concentrated in recruitment, scenario experiments, and selected occupational contexts, which limits generalization to long-term employment relationships and smaller organizations. These limitations mean that the framework should be treated as a theory-building synthesis that requires continued empirical testing.

### *5.3 Suggestions and Directions for Future Research*

Future studies should test the six propositions with longitudinal and multi-level designs. Research is particularly needed on whether human-AI augmentation produces better long-term decisions than either human-only or highly automated approaches, and whether the benefits differ across hiring, promotion, compensation, scheduling, performance management, and learning. Field experiments can compare alternative explanation formats, review thresholds, and appeal mechanisms while measuring both accuracy and employee reactions.

A second priority is work design. Researchers should examine how AI changes autonomy, skill variety, feedback, workload, managerial relationships, and identity over time. The dehumanization mechanism identified in recent research should be tested across industries and cultures, including whether relational leadership or employee participation can buffer adverse effects. Third, responsible-AI governance should be treated as an organizational capability that can be measured and linked to outcomes. Comparative research across regulatory environments could determine which governance practices increase trust without creating unnecessary administrative burden.

Finally, generative AI requires research beyond productivity. Studies should examine data leakage, hallucination, authorship, bias in generated HR content, employee surveillance through conversational systems, and the redistribution of expertise between HR professionals and AI assistants. Future scholarship will be strongest when it reports technical performance together with organizational justice, work-design, and strategic outcomes, allowing researchers and managers to evaluate whether AI is not only efficient but also legitimate and sustainable.

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## Author Contributions

AJ contributed to the conceptualization, methodology, literature search and study selection, coding and synthesis, framework development, and writing of the original draft, as well as reviewing and editing the manuscript. GDP contributed to the literature search and study selection, validation of the synthesis, and reviewing and editing the manuscript. All authors reviewed and approved the final manuscript.

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