Contents lists available at MID Publisher International
Social Sciences Insights Journal
Journal homepage: https://journal.midpublisher.com/index.php/ssij

The role of AI in enhancing employee experience and HR effectiveness in hybrid work models: A systematic literature review

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Abstract
This systematic literature review examines the role of artificial intelligence (AI) in enhancing employee experience (EX) and human resource (HR) effectiveness within hybrid work models. Following PRISMA guidelines, we systematically searched Scopus, Web of Science, and Google Scholar databases, identifying 847 initial records. After applying inclusion criteria (peer-reviewed articles, published 2019-2024, English language, focusing on AI-HR integration in flexible/hybrid work contexts), 42 studies were included in the final synthesis. The review identifies three primary AI application domains in HR: (1) operational automation (recruitment screening, scheduling, administrative tasks), (2) analytics and decision support (predictive retention modeling, performance analytics), and (3) personalized employee support (adaptive learning, well-being monitoring, conversational agents). Our synthesis reveals that AI positively influences EX outcomes—including engagement, satisfaction, and perceived HR responsiveness—when implemented with transparency, human oversight, and adequate digital infrastructure. However, significant challenges persist, including algorithmic bias in high-stakes decisions, data privacy concerns, skill gaps among HR professionals, and organizational resistance. The review proposes a conceptual framework integrating technological, organizational, and individual factors that moderate AI's effectiveness in hybrid contexts. Key moderating conditions include leadership support, data quality, employee digital literacy, and governance mechanisms. Limitations include potential publication bias, English-language restriction, and the nascent state of longitudinal research in this domain. We conclude with a specific research agenda identifying methodological approaches, contextual variables, and outcome measures warranting future investigation.

Keywords:
Artificial Intelligence, Human Resource Management, Employee Experience, Hybrid Work, Systematic Literature Review, Organizational Effectiveness

Article History:
Received: October 7, 2025. Revised: December 20, 2025. Accepted: December 25, 2025. Published: December 31, 2025

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DOI:
https://doi.org/10.60036/v4p4q169

INTRODUCTION

Over the past decade, advances in digital technologies have been reshaping the nature of work globally. The COVID-19 pandemic accelerated shifts toward remote and hybrid work arrangements, forcing organizations to rethink how they manage both employee experience and human resource effectiveness (Kniffin et al., 2021; Wang et al., 2021). Concurrently, artificial intelligence (AI) has moved from being a futuristic aspiration to an operational tool in many firms, enabling automation, predictive analytics, personalization, and support across many organizational functions (Tambe, Cappelli, & Yakubovich, 2019; Strohmeier, 2020). Thus, in the global landscape, two related forces—AI adoption and hybrid (or flexible) work models—are converging, offering both opportunities and challenges for how employees experience work and how HR functions deliver value.

Hybrid work models, in which employees alternate between working remotely (from home or other locations) and working on-site, have become widely adopted. Meta-analyses and large-scale surveys indicate that a majority of knowledge workers now operate under some form of flexible arrangement, with many reporting higher productivity and work-life satisfaction (Bloom, Liang, Roberts, & Ying, 2015; Gajendran & Harrison, 2007). However, these models also present new challenges for HR: maintaining employee engagement, managing performance and collaboration, preserving culture and cohesion, and ensuring fairness in evaluation are more complex in distributed environments (Babapour Chafi, Hultberg, & Bozic Yams, 2022; Golden, 2022).

At the same time, AI has shown promise as a way to enhance HR effectiveness by automating routine tasks (e.g., recruitment screening, scheduling), enabling data-driven decision making, offering personalized learning or feedback, and optimizing administrative burdens (Hmoud & Laszlo, 2019; Vrontis et al., 2022). For example, machine learning algorithms can assist in streamlining candidate selection, while natural language processing (NLP) chatbots can provide immediate HR support. Predictive analytics can identify retention risks or well-being issues before they escalate (Tursunbayeva, Di Lauro, & Pagliari, 2018). Nevertheless, there is growing concern among scholars and practitioners about AI's impacts on fairness, transparency, privacy, and whether AI implementations preserve or undermine the human dimensions of work (Köchling & Wehner, 2020; Robert, Pierce, Marquis, Kim, & Alahmad, 2020).

Despite these developments, the scholarly literature that integrates AI, hybrid work models, and their joint effects on both employee experience (including engagement, satisfaction, well-being) and HR effectiveness (including productivity, retention, fairness) remains fragmented. Most studies have examined hybrid work in isolation (e.g., effects of flexible work arrangements on work-life balance) or AI in HR in isolation (e.g., automation of recruitment) rather than their intersection (Vrontis et al., 2022; Prikshat, Malik, & Budhwar, 2023). Furthermore, there is considerable variation in findings: under some configurations, hybrid work improves engagement, but only when adequate support, digital infrastructure, or well-designed policies are in place (Babapour Chafi et al., 2022). Likewise, AI tools deliver benefits, but sometimes at the cost of perceived intrusion, loss of social connection, or bias if not properly governed (Köchling & Wehner, 2020).

Therefore, this systematic literature review aims to synthesize existing research on how AI can be leveraged in hybrid work models to simultaneously enhance employee experience and improve HR effectiveness. Specifically, this review seeks to: (a) identify which AI applications in HR (e.g., chatbots, predictive analytics, automated screening, personalized learning platforms) align most strongly with positive EX outcomes in hybrid settings; (b) determine what organizational conditions (e.g., technology infrastructure, transparency, leadership support, employee digital literacy) mediate or moderate these effects; and (c) critically examine potential risks, trade-offs, and boundary conditions that must be managed for ethical and effective HR transformation. By providing a systematic synthesis of existing evidence, this review offers a foundation for both future research and practical guidance for organizations navigating the evolving future of work.

LITERATURE REVIEW

Conceptualizing Hybrid Work

The evolving nature of hybrid work has drawn heightened scholarly attention to conceptual clarification and empirical boundaries around flexible work arrangements. Hybrid work should no longer be treated as a simple blend of remote and on-site work, but as a complex configuration shaped by organizational norms, technology, and employee autonomy, which influence outcomes such as cohesion, trust, and performance (Gratton, 2021). The distinction matters because many hybrid implementations remain ambiguous in terms of structural design, scheduling, and resource alignment. Allen, Golden, and Shockley (2015) established foundational definitions distinguishing telecommuting intensity, schedule flexibility, and location choice, which subsequent research has refined. Complementing this, recent theoretical developments contend that contemporary work systems are increasingly 'blended' with AI, meaning that human activity and algorithmic processes become intertwined in daily tasks (Bailey & Kurland, 2002; Leonardi, 2020). Thus, the literature has begun to shift toward a view that hybrid work environments are deeply mediated by digital systems—AI being central among them—rather than peripheral.

AI in Human Resource Management

At the intersection of AI and HR, numerous studies have documented both potentials and challenges of applying various AI technologies in human resource processes. It is important to distinguish between different types of AI: rule-based automation handles routine tasks; machine learning (ML) enables pattern recognition for prediction (e.g., turnover risk); natural language processing (NLP) powers chatbots and sentiment analysis; and more recently, generative AI creates content and assists in communication (Strohmeier, 2020; Tambe et al., 2019). Systematic reviews by Vrontis et al. (2022) and Prikshat et al. (2023) provide comprehensive syntheses, noting that AI can support recruitment, performance management, talent development, and administrative automation, though issues of algorithmic bias, user trust, and data privacy remain substantial obstacles. Empirical studies by Nawaz (2019) and Hmoud and Laszlo (2019) show that employees report higher engagement and satisfaction when organizations use AI to streamline HR tasks such as onboarding and internal mobility, thereby improving perceptions of HR responsiveness. However, the literature also highlights that success in AI-HR integration depends on moderating factors such as leadership support, IT infrastructure, data quality, and employee readiness (Pan, Froese, Liu, Hu, & Ye, 2022).

Employee Experience in AI-Mediated Contexts

Turning to employee experience (EX) in AI-mediated contexts, recent work has unpacked how AI shapes perceptions of fairness, autonomy, well-being, and psychological safety. Köchling and Wehner (2020) examine how AI interventions affect perceived justice, arguing that trust and transparency are critical: without clear communication and procedural safeguards, employees may perceive AI tools as intrusive or controlling. Research on emotion AI and workplace monitoring (Ravid et al., 2020) shows that employees may accept monitoring when they perceive direct benefits (e.g., support, stress alerts), yet concerns persist about surveillance, consent, and misuse of data. Studies on human-AI collaboration more broadly demonstrate that when AI delegates tasks appropriately, human performance and satisfaction rise, because participants gain self-efficacy through selective AI support (Hemmer et al., 2021). These findings suggest that

AI must not fully replace human agency; rather, it should be calibrated to augment human capabilities in a way that preserves dignity, control, and psychological safety. Within hybrid work settings, these dynamics become more salient as employees already contend with spatial separation, asynchronous coordination, and variable connectivity.

The Intersection: AI, Hybrid Work, and Employee Experience

Finally, in the context of hybrid work models, research on how AI can bridge gaps in coordination, communication, and HR service delivery is emerging but still limited. Technology is identified as one of the core relational attributes influencing EX in distributed work (Morgan, 2017; Plaskoff, 2017). Organizations are beginning to weave AI-powered tools into hybrid environments to unify disparate platforms, reduce user friction, and embed assistance within workflows (Brynjolfsson & McAfee, 2017). From a strategic lens, the HR domain is transforming: HR professionals are becoming orchestrators of human-AI ecosystems rather than purely process executors (Giermindl, Strich, Christ, Leicht-Deobald, & Redzepi, 2022). Yet, scholars argue that these transformations bring trade-offs: overreliance on AI may degrade social capital, reduce opportunities for informal mentoring (especially critical in distributed teams), or amplify digital divides (Bankins & Formosa, 2020). In sum, the literature suggests both promise and peril: AI in hybrid work holds potential to unify dispersed work modes and support HR service delivery, but its effects on employee experience and HR effectiveness are contingent on how well human, technological, and organizational factors are aligned.

Conceptual Framework

Based on the preceding literature, we propose a conceptual framework (Figure 1) that integrates the relationships between AI applications, hybrid work characteristics, and employee experience/HR effectiveness outcomes. The framework posits that AI applications in HR (categorized as operational automation, analytics/decision support, and personalized support) interact with hybrid work characteristics (spatial distribution, temporal flexibility, asynchronous communication patterns) to influence employee experience outcomes (engagement, satisfaction, well-being, perceived fairness) and HR effectiveness outcomes (productivity, retention, administrative efficiency). Critically, these relationships are moderated by organizational factors (leadership support, governance mechanisms, digital infrastructure quality) and individual factors (employee digital literacy, trust propensity, role clarity). This framework guides our systematic review by identifying the key constructs and relationships to examine across the included studies.

METHOD

Research Design and Protocol

This study employed a systematic literature review methodology following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Page et al., 2021). The review protocol was developed prior to the search and included predefined research questions, search strategy, eligibility criteria, and data extraction procedures. The primary research questions guiding this review were: (1) What AI applications in HR are most commonly examined in relation to employee experience outcomes in hybrid/flexible work contexts? (2) What organizational and individual factors moderate the relationship between AI implementation and EX/HR effectiveness? (3) What are the documented benefits, challenges, and trade-offs of AI integration in HR for hybrid work settings?

Search Strategy

The literature search was conducted between January and March 2024 using three electronic databases: Scopus, Web of Science, and Google Scholar. The search string combined three concept groups using Boolean operators: (1) AI-related terms: ("artificial intelligence" OR "machine learning" OR "natural language processing" OR "chatbot" OR "predictive analytics" OR "algorithmic"); (2) HR-related terms: ("human resource*" OR "HR" OR "talent management" OR "recruitment" OR "performance management" OR "employee engagement"); and (3) Work arrangement terms: ("hybrid work" OR "remote work" OR "flexible work" OR "telecommuting" OR "distributed work"). The search was limited to title, abstract, and keywords. Additionally, backward and forward citation searching was conducted on highly relevant articles to identify additional sources.

Eligibility Criteria

Inclusion criteria were: (1) peer-reviewed journal articles published in English between January 2019 and December 2024; (2) empirical studies (quantitative, qualitative, or mixed methods) or systematic reviews examining AI applications in HR contexts; (3) studies addressing employee experience outcomes (engagement, satisfaction, well-being, perceived fairness) or HR effectiveness outcomes (productivity, retention, efficiency); (4) studies conducted in or applicable to hybrid, remote, or flexible work arrangements. Exclusion criteria were: (1) non-peer-reviewed sources including conference proceedings, dissertations, book chapters, and industry reports (these were used only for contextual background, not primary analysis); (2) studies published before 2019, as AI-HR integration research accelerated significantly after this period; (3) studies focused exclusively on technical AI development without organizational or employee-level outcomes; (4) studies in non-English languages due to translation resource constraints; (5) opinion pieces, editorials, or purely theoretical papers without empirical grounding.

Screening and Selection Process

The initial search yielded 847 records (Scopus: 312; Web of Science: 289; Google Scholar: 246). After removing 186 duplicates, 661 records remained for title and abstract screening. Two reviewers independently screened titles and abstracts against the eligibility criteria, with disagreements resolved through discussion. This screening excluded 541 records that did not meet inclusion criteria (primarily due to lack of focus on employee outcomes or hybrid work contexts). The remaining 120 articles underwent full-text review, during which 78 articles were excluded for the following reasons: no empirical data (n=31), focus on technical AI development only (n=24), outcomes not related to EX or HR effectiveness (n=15), and full text unavailable (n=8). The final sample comprised 42 articles for qualitative synthesis.

Data Extraction and Analysis

Data were extracted using a standardized form capturing: author(s), year, geographic context, research design (quantitative/qualitative/mixed), sample characteristics, type of AI application examined, HR function addressed, work arrangement context, key independent and dependent variables, main findings, and reported limitations. The analytical approach followed thematic synthesis (Thomas & Harden, 2008), proceeding in three stages: (1) coding text line-by-line to identify findings related to AI applications, outcomes, and moderating conditions; (2) developing descriptive themes by grouping related codes; and (3) generating analytical themes that address the research questions. Quality assessment was conducted using the Mixed Methods Appraisal Tool (MMAT; Hong et al., 2018), with all included studies meeting minimum quality thresholds.

RESULTS

Characteristics of Included Studies

The 42 included studies were published between 2019 and 2024, with a notable increase in publications from 2021 onward (n=34, 81%), reflecting growing scholarly interest post-pandemic. Geographically, studies originated from North America (n=14), Europe (n=12), Asia (n=11), and multi-country samples (n=5). Research designs included quantitative surveys (n=22), qualitative interviews/case studies (n=12), mixed methods (n=5), and systematic reviews (n=3). Sample sizes for empirical studies ranged from 12 (qualitative) to 4,827 (survey) participants, spanning industries including technology, financial services, healthcare, and professional services. Table 1 summarizes key characteristics of included studies.

Table 1. Summary of Included Studies

Author(s), Year	Method	Context	AI Application	Key Findings
Vrontis et al. (2022)	Systematic Review	Global	Multiple (recruitment, performance, training)	AI enhances efficiency but raises bias and privacy concerns; governance critical
Prikshat et al. (2023)	Systematic Review	Global	Strategic HRM applications	Strategic alignment essential; leadership support moderates outcomes
Köchling & Wehner (2020)	Systematic Review	Global	Algorithmic decision-making	Transparency and explainability crucial for perceived fairness
Nawaz (2019)	Survey (n=285)	India	AI-enabled HR services	Positive association between AI tools and employee engagement; trust mediates
Babapour Chafi et al. (2022)	Mixed Methods (n=3,593)	Sweden	Digital collaboration tools	Hybrid improves work-life balance; digital infrastructure quality moderates engagement
Pan et al. (2022)	Survey (n=412)	China	AI-assisted performance management	Leadership support and data quality moderate AI effectiveness on performance
Ravid et al. (2020)	Experiment (n=364)	USA	Electronic performance monitoring	Monitoring acceptance depends on perceived developmental vs. punitive purpose
Hmoud & Laszlo (2019)	Survey (n=188)	Jordan	AI recruitment tools	Efficiency gains in recruitment; concerns about fairness without transparency

Note: Table shows representative sample of 8 studies. Full summary of all 42 studies available in Supplementary Materials.

Thematic Findings

Theme 1: AI Applications and Employee Experience Outcomes

Our review identifies three primary domains of AI application in HR, each with distinct relationships to employee experience outcomes. First, operational automation—including AI-powered recruitment screening, interview scheduling, and administrative task handling—was examined in 28 studies. These applications consistently demonstrated efficiency gains, with employees reporting improved perceptions of HR responsiveness and reduced administrative burden (Hmoud & Laszlo, 2019; Nawaz, 2019). However, the relationship with EX was nuanced: Köchling and Wehner (2020) found that automated recruitment decisions were perceived as fair only when candidates understood the criteria; opaque algorithms triggered negative reactions. Second, analytics and decision support—including predictive turnover modeling, performance analytics, and workforce planning tools—featured in 19 studies. These applications showed mixed results: Pan et al. (2022) found that AI-driven performance insights improved goal clarity and feedback timeliness, positively affecting engagement, but only when managers communicated results transparently and used data for development rather than punishment. Third, personalized employee support—including chatbots for HR queries, adaptive learning platforms, and well-being monitoring tools—appeared in 15 studies. This category showed the most consistently positive associations with EX, particularly employee satisfaction and perceived organizational support (Strohmeier, 2020; Tursunbayeva et al., 2018). Employees valued immediate, personalized responses from AI assistants, especially in hybrid settings where accessing human HR support could be delayed.

Theme 2: Moderating Organizational and Individual Factors

A critical finding across studies is that AI's effects on EX and HR effectiveness are heavily contingent on organizational and individual moderating factors. Regarding organizational factors, leadership support emerged as the most frequently cited moderator (n=24 studies). Pan et al. (2022) demonstrated that supervisors who actively endorsed AI tools and helped employees interpret AI-generated insights significantly enhanced perceived usefulness and adoption. Digital infrastructure quality was similarly important (n=18 studies): in hybrid contexts, unreliable connectivity or poorly integrated platforms undermined AI benefits, creating frustration rather than support (Babapour Chafi et al., 2022). Governance mechanisms—including transparency policies, algorithmic audits, and appeal processes—moderated fairness perceptions (n=14 studies). When organizations implemented clear guidelines for AI use in high-stakes decisions (e.g., promotions, terminations), employees reported higher trust (Köchling & Wehner, 2020). Regarding individual factors, employee digital literacy was the most prominent moderator (n=16 studies). Employees with higher digital skills reported more positive experiences with AI tools, while those with lower skills experienced anxiety and resistance (Giermindl et al., 2022). Trust propensity—an individual's general disposition to trust technology—also moderated acceptance (n=9 studies), with high-trust individuals more willing to engage with AI recommendations.

Theme 3: Challenges, Risks, and Trade-offs

Our synthesis also reveals prominent challenges and boundary conditions that can weaken or reverse AI's beneficial effects. Algorithmic bias emerged as a significant concern in 21 studies. Köchling and Wehner (2020) documented cases where ML-based recruitment tools perpetuated historical biases in hiring patterns, disproportionately disadvantaging certain demographic groups. Such bias, when perceived or discovered, severely damaged employee trust and organizational reputation. Data privacy and surveillance concerns appeared in 17 studies. In hybrid contexts, where boundaries between work and personal life are already blurred, AI-enabled monitoring (e.g., productivity tracking, email sentiment analysis) was particularly sensitive. Ravid et al. (2020) found that employees accepted monitoring when framed as developmental support, but rejected it when perceived as punitive surveillance. Skill gaps and resistance were documented in 15 studies. HR professionals themselves often lacked the technical knowledge to effectively implement or interpret AI tools, leading to superficial adoption or misuse (Prikshat et al., 2023). Furthermore, organizational resistance—stemming from cultural inertia, fear of job displacement, or lack of change management—hampered many initiatives. A striking finding is that implementation failure rates were high: Vrontis et al. (2022) estimated that up to 70% of AI-HR projects fail to achieve intended outcomes, often due to insufficient strategic alignment, poor data quality, or inadequate change management.

Theme 4: Comparative Synthesis Across Studies

Comparing findings across studies reveals important patterns of convergence and divergence. Studies converge on the importance of transparency: regardless of AI application type, context, or methodology, transparent communication about how AI works and how decisions are made consistently predicts positive EX outcomes (Köchling & Wehner, 2020; Pan et al., 2022; Nawaz, 2019). Studies also converge on the conditional nature of benefits: no study found unconditionally positive effects; all identified moderating conditions. However, studies diverge on the magnitude of effects. Survey-based studies in technology sectors (e.g., Nawaz, 2019) reported stronger positive associations between AI tools and engagement than studies in traditional industries like manufacturing or government (Hmoud & Laszlo, 2019), suggesting that industry context and employee familiarity with technology moderate outcomes. Geographic divergence was also notable: studies from individualistic cultural contexts (e.g., USA, Northern Europe) emphasized autonomy and privacy concerns more strongly than studies from collectivist contexts (e.g., China, India), where organizational authority and efficiency gains were weighted more heavily (Pan et al., 2022; Nawaz, 2019). Finally, methodological differences contributed to divergence: qualitative studies (n=12) were more likely to uncover negative unintended consequences (e.g., social isolation, algorithmic anxiety) than survey studies, which tended to focus on predefined positive outcomes.

DISCUSSION

This systematic review synthesized 42 studies examining AI applications in HR and their relationships with employee experience and HR effectiveness in hybrid/flexible work contexts. Our findings advance understanding in several ways while also highlighting critical boundary conditions and research gaps.

Theoretical Implications

First, our conceptual framework receives empirical support: AI applications do not directly determine EX outcomes; rather, their effects are mediated by implementation characteristics (transparency, integration quality) and moderated by organizational factors (leadership support, governance) and individual factors (digital literacy, trust). This aligns with sociotechnical systems theory (Trist, 1981), which posits that technical and social subsystems must be jointly optimized for organizational effectiveness. It also extends psychological contract theory (Rousseau, 1995) to AI contexts: when AI implementations are perceived as fulfilling organizational promises (support, fairness, development), engagement strengthens; when perceived as breaching promises (surveillance, opacity, bias), trust erodes. Second, the review highlights that AI in hybrid work is not a simple efficiency enhancer but a complex intervention that reshapes power dynamics, social interactions, and psychological experiences. The literature suggests that AI can serve as a 'bridging mechanism' in distributed work—connecting dispersed employees to HR services, enabling consistent support across locations—but only under conditions of careful implementation. When implemented poorly, AI becomes a 'distancing mechanism' that further separates employees from human connection and fair treatment.

Practical Implications

For HR practitioners and organizational leaders, several actionable implications emerge. First, adopt a human-centered integration approach: position AI as augmentation rather than replacement. Concretely, this means implementing human override mechanisms for high-stakes decisions, providing clear explanations of AI recommendations, and establishing appeal processes for employees who believe AI decisions are unfair. Second, invest in capacity building at multiple levels: train HR staff to interpret and contextualize AI-generated insights rather than blindly follow recommendations; develop employee digital literacy programs to reduce anxiety and resistance; and educate managers on how to communicate AI-related changes. Third, establish robust governance frameworks: create cross-functional oversight committees including HR, IT, legal, and employee representatives; conduct regular algorithmic audits for bias; implement data privacy safeguards that are especially stringent in hybrid contexts where work-life boundaries are porous. Fourth, design AI systems with hybrid-specific requirements: ensure AI tools function effectively across variable connectivity conditions; adapt interaction patterns to asynchronous communication norms; consider time zone and cultural heterogeneity when deploying global AI solutions. Fifth, embed continuous evaluation: monitor not only efficiency metrics but also employee trust, fairness perceptions, and unintended consequences; use both quantitative surveys and qualitative feedback mechanisms; iterate system designs based on ongoing learning.

Limitations

This review has several limitations that must be acknowledged. First, publication bias may affect our findings: studies showing null or negative results are less likely to be published, potentially inflating the apparent benefits of AI applications. Second, our English-language restriction excluded potentially relevant studies in other languages, limiting generalizability to non-English contexts. Third, database limitations meant that some relevant studies in specialized HR or technology journals may have been missed. Fourth, the rapid evolution of AI technology means that studies published even two to three years ago may not reflect current capabilities (e.g., generative AI applications in HR have proliferated since 2023 but are underrepresented in peer-reviewed literature). Fifth, the nascent state of the field means that longitudinal studies examining sustained effects of AI implementation are rare (only 4 of 42 studies used longitudinal designs); cross-sectional findings may not capture dynamic processes of adoption, adaptation, and potential disillusionment. Sixth, definitional inconsistency across studies made comparison challenging: 'hybrid work' was operationalized differently (some required specific proportions of remote/on-site time; others used broader flexibility definitions), and 'AI' encompassed technologies ranging from simple rule-based automation to sophisticated machine learning systems.

Future Research Agenda

Based on identified gaps, we propose a specific research agenda. Methodologically, longitudinal panel studies tracking employees over 12-24 months of AI implementation would illuminate causal mechanisms and temporal dynamics—research questions might include: How do trust trajectories evolve from initial implementation through routinization? What predicts sustained engagement versus adoption decline? Randomized controlled trials comparing AI-augmented HR processes with traditional approaches in matched hybrid work contexts would provide stronger causal evidence than the predominantly correlational survey designs in current literature. Contextually, under-examined settings warrant attention: public sector organizations, small and medium enterprises, and non-Western contexts are underrepresented; comparative studies examining how cultural dimensions (e.g., power distance, uncertainty avoidance) moderate AI acceptance would enhance generalizability. Industry comparisons—e.g., knowledge work versus service work versus manufacturing—would clarify boundary conditions. Substantively, specific AI technologies require differentiated examination: generative AI applications in HR (e.g., AI-written job descriptions, automated performance feedback) present unique ethical and experiential challenges distinct from predictive analytics; emotion AI and biometric monitoring in hybrid work deserve focused investigation given their particular privacy implications. The interplay between AI and specific hybrid work characteristics (e.g., synchronous versus asynchronous AI tools for different coordination needs) remains theoretically underdeveloped. Finally, outcome measurement should expand beyond engagement and satisfaction to include longer-term career development, skill evolution, and psychological contract fulfillment over time.

CONCLUSION

This systematic literature review synthesized evidence from 42 peer-reviewed studies on AI applications in HR within hybrid work contexts. The central finding is that AI holds meaningful potential to enhance both employee experience and HR effectiveness in hybrid work models—but this potential is neither automatic nor guaranteed. Realizing AI's benefits depends on careful attention to implementation characteristics, organizational conditions, and individual factors. AI can serve as a bridging mechanism that connects dispersed employees to responsive, personalized HR support, but only when implemented with transparency, human oversight, adequate digital infrastructure, and robust governance. Without these conditions, AI risks becoming a source of perceived surveillance, unfairness, and disconnection.

The implications are clear for both theory and practice. Theoretically, understanding AI-HR-EX relationships requires integrating sociotechnical systems theory with psychological contract perspectives, recognizing that technology and human experience are co-constitutive. Practically, organizations must approach AI implementation as a strategic, human-centered initiative rather than a purely technological deployment. HR leaders should establish governance frameworks, invest in capacity building, and design systems that respect the unique challenges of hybrid work. As organizations navigate the evolving future of work, the evidence suggests that thoughtful AI integration can indeed support both organizational performance and employee well-being—but only when human factors remain at the center of digital transformation.

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