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Impact of AI on Global HRM

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DECLARATATION

I, Muhammad Hashaam Younas Kiyani declare that this dissertation has been composed by myself, that the work contained herein is entirely my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or qualification, in whole or in part, except as specified.

Signature: HASHAAM

Date: 10/29/2025

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CHAPTER 1: INTRODUCTION

1.1 Background and Problem Statement

Artificial Intelligence (AI) has emerged as a transformative force across all domains of organizational management, with Human Resource Management (HRM) being no exception. For example, according to Kaushal et al (2021) and Venugopal et al (2024), AI-powered tools are now increasingly embedded in HR practices such as recruitment, onboarding, training, performance evaluation, and employee retention. These tools, as these authors noted, enhance efficiency by automating repetitive tasks, enabling predictive analytics, and facilitating real-time decision-making. Furthermore, AI-driven applicant tracking systems (ATS), chatbots for candidate communication, and machine learning algorithms for performance prediction are also seen to have reshaped how HR functions are performed (Cai et al., 2024).

Despite its advantages, the integration of AI into HRM raises complex challenges. According to Fenwick et al. (2024) and Budhwar et al. (2022), Key among these are concerns include potential algorithmic bias, transparency and data privacy issues, and fairness in use.

Studies have shown that employees often perceive AI-based decisions, particularly in recruitment and performance management, as less fair than those made by humans (Cai et al., 2024). Moreover, the rapid technological change has outpaced the development of ethical and regulatory frameworks to ensure responsible AI use (Ncube et al., 2025).

While several conceptual frameworks such as the AIHRMI (Artificial Intelligence in Human Resource Management Integration) model have been proposed (Kaushal et al., 2021) with regards to effective integration of AI in HRM, much of the literature lacks empirical validation and cross-industry comparison on the actual impact of AI on HRM. Existing research is often sector-specific or conceptual in nature, leaving significant gaps in understanding how AI-HRM integration manifests across different organizational contexts (Alshahrani et al., 2025; Rana & Kumar, 2025).

1.2 Research Aim

This dissertation aims to explore the transformative impact of Artificial Intelligence on Human Resource Management by examining its influence on recruitment, training, performance evaluation, and employee retention, while also investigating how HRM strategies facilitate or hinder AI adoption.

1.3 Research Objectives

1. To identify the key HR functions being transformed by AI technologies.
2. To evaluate the benefits and challenges associated with AI integration in HRM.
3. To evaluate how HR strategies influence the successful implementation of AI.
4. To analyze the ethical implications and employee perceptions related to AI-HRM systems.

1.4 Research Questions

1. How is AI transforming core HRM functions
2. What are the perceived benefits of AI adoption in HRM?
3. What ethical and trust-related concerns emerge from the use of AI in HR processes?

1.5 Significance / Relevance of the Study

This study contributes to both academic literature and practical HRM by providing a comprehensive synthesis of AI's evolving role in HRM. As organizations increasingly rely on intelligent systems for decision-making, understanding their implications on workforce management, equity, and organizational performance becomes critical (Chowdhury et al., 2022; Glikson & Woolley, 2020). The study also addresses existing research gaps by providing cross-sector insights, incorporating bibliometric trends, and proposing a refined conceptual model that can guide ethical AI implementation in HRM.

1.6 Brief Research Methodology

This dissertation adopts a qualitative research design through a Systematic Literature Review (SLR), following the PRISMA protocol. Data will be sourced from peer-reviewed databases such as Scopus, Web of Science, and ScienceDirect. The study

applies bibliometric and content analysis methods, including co-citation and keyword co-occurrence mapping, to identify research trends, key contributors, and emerging themes (Rana & Kumar, 2025). Thematic synthesis will then be used to construct a conceptual framework that integrates findings on AI-HRM transformation.

1.7 Structure of the Rest of the Project

- **Chapter 2: Literature Review** – Critically reviews the existing literature, identifies themes, and presents the conceptual framework.
- **Chapter 3: Research Methodology** – Outlines research design, data collection procedures, and analytical methods, along with ethical considerations.
- **Chapter 4: Findings and Discussion** – Presents and analyzes the findings of the systematic literature review and bibliometric analysis.
- **Chapter 5: Conclusions and Recommendations** – Summarizes main findings, responds to research questions, and offers practical and theoretical recommendations for future research and implementation.

AI-HRM Integration Framework

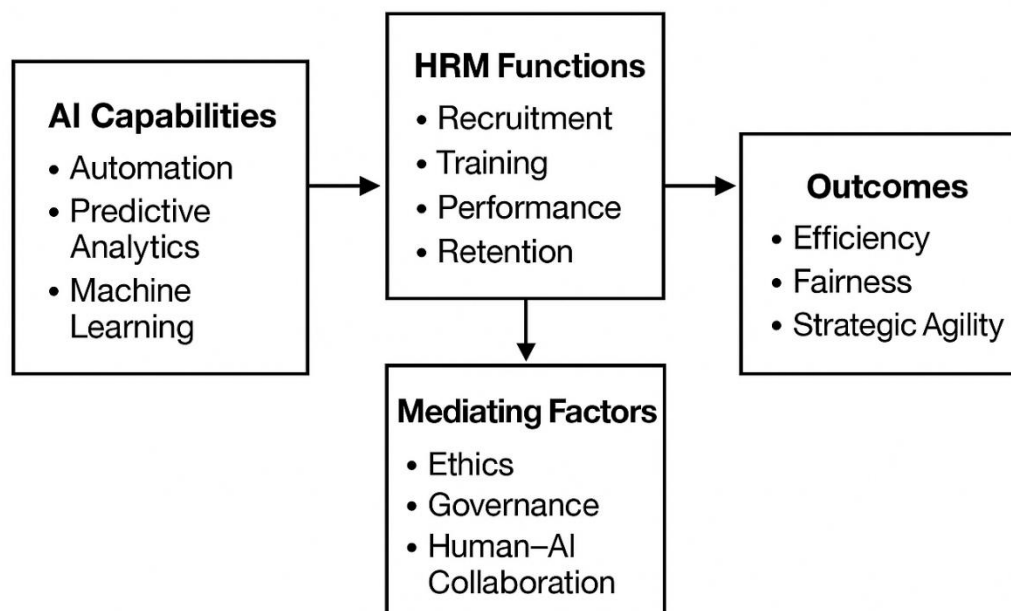


Figure 1.1: Proposed AI-HRM Integration Framework, Developed by the researcher (2025), adapted from concepts discussed in Kaushal et al. (2021), Fenwick et al. (2024), and Rana & Kumar (2025)

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

Artificial Intelligence (AI) has become one of the most influential technological forces shaping modern Human Resource Management (HRM), reflecting a shift from traditional, administrative HR practices to digitally enabled, strategic HRM functions. Scholars such as Tambe et al. (2019) and Budhwar et al. (2022) highlight that AI now integrates deeply within recruitment, training, performance evaluation, and employee engagement systems, enabling efficiency, precision, and data-driven decision-making. This transformation has sparked extensive debate, as the opportunities presented by AI coexist with substantial concerns related to ethics, fairness, trust, and organisational readiness (Glikson & Woolley, 2020; Bankins & Formosa, 2023). The growth of AI in HRM is therefore not only a technological development but a fundamental shift in how organisations manage people, requiring critical academic analysis.

Understanding AI's influence requires acknowledging the dual nature of its impact. Scholars such as Raisch and Krakowski (2021) describe AI as operating within an “automation–augmentation paradox,” where technology can simultaneously automate tasks and enhance human capabilities. This dynamic is central to debates about whether AI should replace or complement human judgement. Raisch and Fomina (2024) further argue that hybrid intelligence—where humans and AI collaborate—offers the most balanced approach to HRM innovation. However, despite these theoretical advancements, practical implementation remains challenging because organisations struggle to align technological capabilities with ethical and human-centred decision making (Berente et al., 2021; Malik et al., 2022). This chapter builds on these discussions by critically reviewing AI's role across four central HR domains—recruitment, training and development, performance management, and employee retention and engagement—before presenting a conceptual integration framework.

This chapter is structured as a **Systematic Literature Review (SLR)**, using peer-reviewed academic studies selected through a structured, transparent and replicable process. The review systematically analyses research on Artificial Intelligence (AI) in

Human Resource Management (HRM) in order to identify key themes, contradictions, knowledge gaps and future research opportunities. This structured approach strengthens the academic rigour of the chapter and ensures that conclusions are grounded in high-quality scholarly evidence.

2.2 Critical Review of Research Areas

Theme	Key Findings	Supporting Authors	Risks / Critiques
AI in Recruitment	Automation, improved job–candidate matching	Tambe et al. (2019); Budhwar et al. (2022)	Bias, fairness concerns (Bandara et al., 2025)
AI in Training & Development	Personalised learning and adaptive training systems	Dima et al. (2024); Li et al. (2023)	Surveillance and data privacy concerns (Citrin & Davison, 2022)
AI in Performance Management	Predictive analytics and continuous performance feedback	Gill et al. (2023); Selvamohana et al. (2025)	Stress, opacity, and reduced autonomy (Rahman, 2021; Anthony, 2021)
AI in Retention & Engagement	Attrition prediction, chatbots, sentiment analysis	Li & Greer (2023); Căvescu & Popescu (2025)	Depersonalisation and weakened human connection (Escobar-Rodríguez & Romero-Alonso, 2021)

Table 2.1: Thematic Synthesis of AI–HRM Literature

2.2.1 AI in Recruitment

Recruitment represents the most extensively transformed HR function under AI adoption, due to its repetitive, data-intensive, and time-sensitive nature (Tambe et al., 2019; Dadaboyev et al., 2025). Traditionally, recruitment relied heavily on subjective human judgement, which often led to inconsistencies, delays, and bias. AI reshapes this landscape through tools such as automated CV screening, natural language processing (NLP) applications, predictive candidate scoring, and AI-enabled chatbots (Alshahrani et al., 2025). Budhwar et al. (2022) note that these tools streamline early-

stage hiring by reducing workload and accelerating decision-making, enabling HR teams to handle larger applicant pools with greater efficiency. This efficiency-driven viewpoint is supported by Malik et al. (2022), who argue that organizations adopting AI in recruitment can significantly improve the accuracy and objectivity of candidate shortlisting.

Despite these advantages, scholars caution that AI-driven recruitment introduces substantial risks related to fairness and algorithmic bias. Bandara et al. (2025) argue that AI systems often reflect biases present in the training data, potentially perpetuating discriminatory hiring practices. This point is reinforced by Gollan et al. (2021), who emphasize that candidates' perceptions of fairness strongly influence their acceptance of AI-based selection systems. Mirowska and Mesnet (2022) further note that applicants tend to prefer human evaluators because they believe humans can understand context, emotion, and nuance better than algorithms. The literature therefore presents a tension between AI's capacity to reduce human bias and its potential to embed systemic bias—an issue that complicates claims of AI-driven objectivity.

Transparency is another major concern in AI-enabled recruitment. Scholars such as Rahman (2021) and Anthony (2021) highlight the opacity of algorithmic decision-making, which often makes it difficult for organisations to explain why candidates are rejected or shortlisted. This lack of clarity undermines trust and accountability, increasing fears of “black box” decision systems. Kellogg et al. (2020) expand this discussion by arguing that AI introduces new forms of organisational control, where algorithmic monitoring and evaluation reduce human agency. These concerns suggest that AI's value in recruitment is contingent on responsible implementation and transparent system design.

Alongside ethical risks, candidate experience is a significant theme in the literature. Li and Greer (2023) argue that AI-driven chatbots enhance engagement by providing instant responses to queries, thereby reducing frustration during the recruitment process. Malik et al. (2022) similarly suggest that automated communication improves consistency and accessibility. However, Escobar-Rodríguez and Romero-Alonso (2021) caution that over-automation can create impersonal interactions, weakening the relational aspect of recruitment and diminishing employer branding. This highlights

the need for a balanced approach that integrates automation without sacrificing human connection.

On a strategic level, AI also contributes to predictive workforce planning. Gill et al. (2023) argue that AI-enabled analytics assist organizations in anticipating future skills gaps and aligning recruitment strategies accordingly. Căvescu and Popescu (2025) extend this claim by showing that predictive analytics not only support hiring decisions but also help identify candidates more likely to remain with the organization. However, Nawaz et al. (2024) highlight that the effectiveness of such tools depends on organizational readiness, technological infrastructure, and employee acceptance, suggesting that AI's strategic value is not universal.

Comprehensive reviews also show that recruitment dominates AI–HRM research. Rana and Kumar (2025) note that scholars focus heavily on recruitment because it offers measurable outcomes and is more adaptable to automation. However, they also argue that research remains fragmented and lacking empirical depth, particularly regarding long-term ethical implications. Cornacchia et al. (2023) similarly call for stronger frameworks to guide responsible AI use in recruitment. Together, these insights indicate that while AI significantly enhances recruitment efficiency and strategy, its ethical challenges require careful governance.

2.2.2 AI in Training and Development

Training and development have long been central to organisational competitiveness, and AI has become increasingly important in reshaping how employee learning is designed, delivered, and evaluated. Traditional HR-led training programmes often relied on one-size-fits-all approaches that failed to account for individual differences in learning pace, prior knowledge, or career trajectories. AI challenges these limitations by enabling personalised, adaptive learning systems that adjust content based on real-time performance data (Madhumithaa et al., 2025). This shift reflects a broader movement towards leveraging data-driven insights to enhance the strategic value of human capital development. Madhumithaa et al. (2025) argue that such systems significantly increase engagement and learning effectiveness, as employees receive content tailored to their preferences and competencies.

The introduction of AI-driven learning analytics and intelligent tutoring systems also reflects an increased organizational emphasis on continuous learning. Dima et al. (2024) highlight how AI-powered learning management systems (LMS) use behavioral data to identify skill gaps, track learner progress, and recommend targeted modules, thereby improving the alignment between organizational needs and employee development. Li et al. (2023), in a sectoral study within healthcare, further demonstrate that AI-enhanced training improves employee satisfaction and task competency, supporting the notion that AI contributes positively to professional growth and service quality. These findings collectively suggest that AI strengthens both individual and organizational learning outcomes.

However, despite these advantages, the literature identifies several challenges that complicate the integration of AI into training and development. Nawaz et al. (2024) argue that effective AI adoption requires significant technological infrastructure and digital readiness, which many organizations—particularly those in developing regions—struggle to achieve. Furthermore, reliance on AI-driven personalization may disadvantage employees with low digital literacy or limited access to technology, creating new forms of exclusion within the workplace. Soulami et al. (2024) reinforce this concern by showing that AI-based systems may contribute to workplace stress, as employees feel monitored or evaluated through constant data collection. These tensions emphasize that while AI enhances training efficiency, it also risks deepening inequalities if not managed carefully.

A further concern arises around privacy and data protection. AI-enabled training systems collect detailed behavioral and performance data, raising ethical questions about data use, consent, and transparency. Citrin and Davison (2022) argue that AI contributes to heightened workplace surveillance, particularly when learning systems monitor micro-behaviors or track engagement patterns. This aligns with Banking and Formosa's (2023) broader argument that AI challenges the meaningfulness of work through intrusive monitoring mechanisms. Such concerns are important because, while AI enables personalized development, it simultaneously increases the need for robust ethical governance to maintain trust and protect employee rights.

The long-term effectiveness of AI-driven training also remains a developing area within academic research. Chowdhury et al. (2024) observe that, although AI enhances

training delivery and analysis, empirical studies rarely evaluate sustained performance outcomes or transfer of learning into real practice. Similarly, França et al. (2023) point out that AI is underutilized in talent identification and potential assessment, despite its capacity to analyze patterns in performance and learning. Their findings imply that organizations have yet to fully exploit AI's potential to support broader talent development strategies.

Overall, the literature portrays AI in training and development as a transformative but complex domain. Its benefits—personalisation, efficiency, and strategic alignment—are substantial, but these come with ethical risks, inclusion challenges, and implementation barriers. More importantly, the integration of AI into training directly connects with performance management systems, as the data generated from learning analytics increasingly shapes how employee performance is assessed.

2.2.3 AI in Performance Management

AI's role in performance management is widely discussed as one of the most strategically disruptive transformations within HRM. Conventional performance appraisal processes have been criticized for subjectivity, infrequent feedback, and limited linkage to real-time performance indicators. AI addresses these limitations by enabling continuous monitoring, automated feedback, and data-driven evaluations that aim to increase objectivity and accuracy (Venugopal et al., 2024; Gill et al., 2023). These capabilities reflect a shift toward performance systems that focus on predictive analytics rather than retrospective judgement, allowing organizations to anticipate performance issues and intervene proactively. Selvamohana et al. (2025) argue that AI-driven performance tools contribute to enhanced workforce productivity by providing ongoing, personalized insights rather than relying on annual reviews.

While many scholars highlight AI's potential to strengthen HRM strategy, others raise critical concerns about employee perceptions and ethical implications. Cai et al. (2024) find that employees often experience discomfort with AI-based monitoring, perceiving it as intrusive and overly mechanistic. This discomfort is tied to broader trust issues identified by Glikson and Woolley (2020), who argue that trust in AI is strongly influenced by transparency and perceived fairness. Budhwar et al. (2022) add that employees may resist performance systems that rely heavily on algorithms, especially

when they lack clarity about how data is interpreted or how decisions are generated. These insights highlight that technological sophistication alone does not guarantee acceptance; employee trust remains a central mediating factor.

Algorithmic bias is another major theme in discussions of AI-enabled performance systems. Bandara et al. (2025) caution that biased datasets can result in inequitable evaluations, particularly for underrepresented groups. Their concern echoes the findings of Bar-Gil et al. (2023), who argue that algorithmic opacity prevents employees from challenging unfair decisions, thereby weakening procedural justice. Anthony (2021) adds that AI can 'black box' decision-making processes, making it unclear how performance evaluations are derived and undermining the legitimacy of managerial authority. These critiques show that AI may inadvertently intensify inequalities and diminish perceived fairness if not designed and governed responsibly.

Beyond fairness concerns, scholars focus on the psychological and organizational implications of AI-based performance monitoring. Rahman (2021) describes AI-enabled evaluation systems as an "invisible cage," where constant assessment pressures employees to behave in ways that maximize algorithmic favorability, often at the expense of creativity or well-being. This argument aligns with Kellogg et al. (2020), who describe algorithmic control systems as reshaping workplace power dynamics by prioritizing data measurement over human judgement. Soulami et al. (2024) further note that AI-driven surveillance can contribute to emotional exhaustion, particularly among employees who perceive constant tracking as a threat to autonomy.

Despite these significant risks, the literature also recognizes AI's potential to support more strategic and developmental approaches to performance management. Li et al. (2023) find that AI-driven analytics can help identify trends in employee output, enabling managers to provide targeted support. Strohmeier and Piazza (2015) also highlight how AI techniques support multi-dimensional performance insights that go beyond traditional appraisal metrics. Prikshat et al. (2023) suggest that integrating AI with HR analytics creates opportunities for more future-oriented performance strategies, particularly when organizations seek to align performance indicators with long-term objectives. Such perspectives reinforce the idea that AI's value depends not on full automation but on thoughtful integration with human oversight.

Taken together, the literature demonstrates that AI significantly enhances data-driven performance assessment but simultaneously raises profound ethical, psychological, and organizational challenges. The next section will explore how these themes extend into employee retention and engagement, demonstrating the interconnectedness of AI's impact across HR functions.

2.2.4 AI in Employee Retention and Engagement

Employee retention and engagement have become critical organizational priorities, especially as global talent competition intensifies and workforce expectations evolve. AI technologies are increasingly positioned as tools that can help organizations understand employee sentiments, predict attrition, and enhance engagement strategies. Căvescu and Popescu (2025) highlight that AI-enabled predictive analytics can identify patterns associated with turnover intentions, allowing HR managers to intervene proactively with personalized strategies such as tailored development opportunities or internal mobility pathways. This early detection capability positions AI as a strategic asset for maintaining workforce stability.

Alongside predictive retention analytics, AI-driven communication systems have emerged as tools for supporting continuous employee engagement. Li and Greer (2023) find that chatbots and conversational agents facilitate timely responses to employee inquiries, improving perceived support and organizational responsiveness. Selvamohana et al. (2025) build on this perspective by arguing that AI-driven HR systems foster more frequent feedback loops, encouraging a sense of involvement and collaboration between employees and management. This continuous communication model shifts HRM from periodic engagement initiatives to real-time support structures powered by AI.

Despite these benefits, scholars caution that AI systems may inadvertently weaken the human-centric aspects of engagement. Escobar-Rodríguez and Romero-Alonso (2021) argue that excessive automation risks depersonalizing interactions, undermining the empathy and relational depth traditionally associated with HR roles. Soulami et al. (2024) similarly warn that AI-driven monitoring may contribute to anxiety and emotional strain, especially when employees feel surveilled or judged through algorithmic metrics. These findings highlight a tension between efficiency and human

connection, suggesting that AI must be carefully integrated to avoid reducing engagement to a transactional process.

Ethical considerations are equally important in AI-driven engagement systems. Citrin and Davison (2022) note that retention analytics often rely on sensitive behavioural and emotional data, raising concerns about privacy and consent. Their findings align with Bankins and Formosa’s (2023) broader argument that AI may erode meaningful work if used improperly, as employees may feel reduced to data points within predictive models. Such concerns emphasize that while AI can strengthen engagement, its effectiveness depends heavily on ethical governance, transparency, and employee trust.

Another emerging theme in the literature concerns AI’s ability to support employee well-being. Chowdhury et al. (2024) highlight that AI systems can detect burnout indicators by analyzing communication patterns, workload distributions, and behavioral data. These insights allow organizations to provide timely support to employees, thereby contributing to healthier work environments. However, Rahman (2021) warns that such monitoring may amplify feelings of constraint and surveillance, particularly when employees perceive the monitoring as controlling rather than supportive. This duality reinforces the argument that AI’s role in engagement is inherently complex, presenting both opportunities for improved well-being and risks of psychological harm.

Overall, AI’s contribution to employee retention and engagement is characterized by promise and caution. While predictive analytics, chatbots, and sentiment analysis tools offer powerful insights into workforce behavior, concerns regarding privacy, surveillance, depersonalization, and fairness require responsible implementation. These themes align closely with the broader discourse across other HR functions, reinforcing the need for a comprehensive conceptual framework to guide AI–HRM integration.

Authors	Position / Argument	Opposing / Contrasting Authors	Contradicting View

Glikson & Woolley (2020)	Trust in AI depends on transparency and understanding	Anthony (2021)	Argues AI is inherently opaque, making transparency unrealistic
Soulami et al. (2024)	AI can increase workplace insight but adds stress	Selvamohana et al. (2025)	AI improves engagement when used for real-time support
Bandara et al. (2025)	AI cannot avoid bias due to flawed datasets	Malik et al. (2023)	Strategic AI–HRM frameworks can reduce human bias
Rahman (2021)	AI monitoring creates stress (“invisible cage”)	Li & Greer (2023)	AI chatbots can improve employee support and well-being
Budhwar et al. (2022)	AI enhances HR strategic value	Escobar-Rodríguez & Romero-Alonso (2021)	Excess automation weakens relational HR roles

Table 2.2: Comparison of Author Perspectives (Agreement vs Contradiction)

2.3 Conceptual Framework: AI–HRM Integration Model

The review of literature across recruitment, training, performance management, and engagement highlights the need for an integrative model that considers both the technological capabilities of AI and the human-centered challenges associated with its use. Building on insights from Kaushal et al. (2021), Budhwar et al. (2022), and Rana and Kumar (2025), the proposed AI–HRM Integration Model synthesizes four core dimensions: technological enablement, strategic alignment, ethical governance, and human–AI collaboration.

The first dimension, technological enablement, reflects the operational role of AI in automating administrative tasks, optimizing decisions, and generating predictive insights. As evidenced across multiple studies, AI’s technical capabilities support

improvements in recruitment efficiency (Tambe et al., 2019), personalized training (Madhumithaa et al., 2025), continuous performance monitoring (Venugopal et al., 2024), and early attrition detection (Căvescu & Popescu, 2025). This dimension recognises that AI's value is rooted in its ability to process data at scales and speeds beyond human capacity.

The second dimension concerns strategic alignment. Hillebrand et al. (2025) argue that AI produces the greatest organisational value when aligned with long-term HRM strategies rather than adopted for operational convenience. This view is supported by Malik et al. (2022), who propose that AI-enabled HRM requires integration with broader organisational objectives such as workforce planning, skill development, and productivity enhancement. Strategic alignment reinforces that AI is not merely a tool but an organisational capability that must co-evolve with HR's strategic priorities.

Ethical governance forms the third dimension and addresses the concerns raised throughout the literature regarding fairness, transparency, privacy, and accountability. The 3T Framework introduced by Chalutz Ben Gal and Tursunbayeva (2022) provides a foundation for assessing AI readiness along dimensions of Talent, Trust, and Technology. Scholars such as Bandara et al. (2025) and Cornacchia et al. (2023) emphasize that without ethical safeguards, AI can reproduce bias or compromise autonomy. This dimension therefore stresses the need for governance structures that ensure responsible data use, transparent algorithms, and inclusive design.

The fourth and final dimension highlights human–AI collaboration. Fenwick et al. (2024) and Raisch and Fomina (2024) argue that AI should augment rather than replace human expertise, enabling new forms of hybrid problem-solving. This involves recognising the complementary strengths of humans—contextual understanding, empathy, ethical reasoning—and AI—consistency, scalability, and analytical precision. Glikson and Woolley (2020) further reinforce that trust in AI is contingent on clear communication and human oversight. Consequently, this dimension positions HR professionals as mediators who balance technological innovation with human values.

Collectively, these four dimensions provide a comprehensive lens for understanding how organizations can integrate AI into HRM responsibly and effectively. They

emphasize that successful AI adoption requires not only technological investment but also strategic vision, ethical regulation, and human-centered leadership.

This framework was developed based on patterns identified through the systematic analysis and thematic synthesis of the reviewed studies

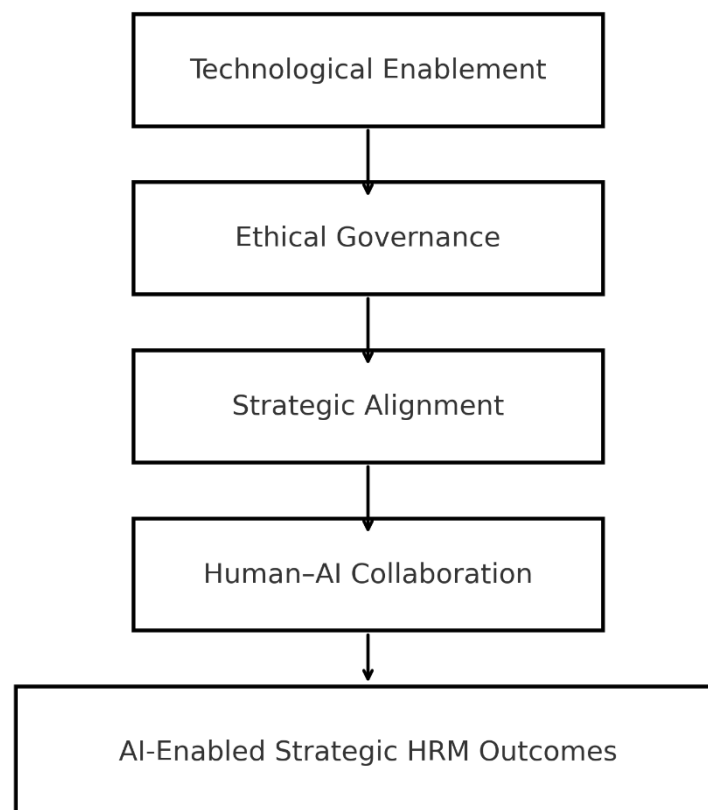


Figure 1: Suggested Framework

2.4 Conclusion of Chapter

The literature reviewed in this chapter demonstrates that AI is reshaping HRM across recruitment, training, performance management, and retention in profound and interconnected ways. Across all domains, AI enhances efficiency, personalization, and predictive capability, supporting HRM's shift toward strategic, data-driven decision-making. However, these benefits are counterbalanced by significant challenges related to algorithmic bias, transparency, privacy, surveillance, and employee trust. The conflicting perspectives among scholars emphasize that AI's value cannot be

understood solely through technological outcomes; rather, it must be evaluated through its ethical, psychological, and organizational implications.

The chapter also identifies recurring research gaps, including the need for more empirical evidence, longitudinal studies, and cross-sector analysis. While existing frameworks such as the AI capability model (Chowdhury et al., 2023) and the 3T Framework (Chalutz Ben Gal & Tursunbayeva, 2022) provide valuable foundations, they often lack empirical validation across diverse contexts. The conceptual framework developed in this chapter addresses these limitations by offering an integrated perspective that moves beyond function-specific analysis to consider AI–HRM integration holistically.

Overall, the chapter establishes that the future of HRM lies not in the full automation of people processes but in strategic, ethical, and collaborative human–AI partnerships. This forms the foundation for the next chapter, which outlines the methodological approach used to investigate these themes in greater depth.

HR Function	Degree of AI Adoption (Based on Literature Volume)	Example Uses	Key References
Recruitment	Very High	Automated screening, chatbots, predictive scoring	Tambe et al. (2019); Dadaboyev et al. (2025)
Training & Development	High	Adaptive LMS, personalised learning	Dima et al. (2024); Li et al. (2023)
Performance Management	High	Real-time monitoring, predictive analytics	Gill et al. (2023); Selvamohana et al. (2025)

Retention & Engagement	Moderate	Attrition prediction, sentiment analysis	Căvescu & Popescu (2025)
HR Analytics	Very High	Workforce planning, modelling, risk prediction	Gill et al. (2023); Prikshat et al. (2023)
Ethical/Responsible AI	Growing	Bias detection, governance mechanisms	Bandara et al. (2025); Cornacchia et al. (2023)

Table 2.3: Trend of AI Applications in HRM

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

This chapter explains the methodological framework used to conduct this dissertation. Unlike primary research designs that rely on interviews, surveys, or experiments, this study adopts a **Systematic Literature Review (SLR)** approach. A systematic review is a structured and transparent method of identifying, evaluating, and synthesizing existing academic research to answer specific research questions. Given the rapid expansion of Artificial Intelligence (AI) in Human Resource Management (HRM), a systematic approach is appropriate to ensure that the findings are grounded in high-quality, peer-reviewed evidence.

Chapter 2 identified key debates around AI adoption in HRM, including issues of recruitment automation, algorithmic bias, trust, transparency, workforce analytics, and ethical governance (Tambe et al., 2019; Budhwar et al., 2022; Raisch & Krakowski, 2021). However, while the literature review mapped these themes conceptually, this chapter focuses on **how** the literature was systematically collected, screened, analyzed, and synthesized. The purpose of this chapter is to demonstrate that the research process was rigorous, transparent, replicable, and free from personal bias.

The methodological framework follows established guidelines for systematic reviews, particularly transparency, replicability, and structured screening (Saunders et al., 2019; Tranfield et al., 2003). The systematic literature review allows for a comprehensive understanding of how AI is transforming HRM while ensuring that only high-quality academic evidence is included. This approach is particularly effective for emerging research fields, where findings may be fragmented across disciplines and journals.

A Systematic Literature Review (SLR) was selected because it allows for a structured, transparent, and replicable synthesis of existing research, which is particularly suitable for emerging and rapidly evolving fields such as Artificial Intelligence in Human Resource Management. Unlike primary research methods, the SLR minimises researcher bias and enables the consolidation of fragmented evidence into coherent insights.

3.2 Research Philosophy

The research philosophy underpinning this study is **pragmatism**. Pragmatism focuses on practical outcomes and problem-solving rather than purely subjective or purely objective positions. This philosophical stance is appropriate because the study does not seek to explore individual lived experiences (which would suit interpretivism) or test strict hypotheses (which would align with positivism). Instead, the study aims to consolidate existing academic knowledge and develop practical insights that can inform HR practice and organizational strategy.

The pragmatist perspective aligns well with AI–HRM research, which often focuses on balancing technological efficiency with human and ethical considerations (Raisch & Krakowski, 2021; Malik et al., 2023). Scholars argue that AI in HRM should not be approached as a purely technical issue, but as an organizational challenge that requires balanced judgement, human oversight, and strategic alignment (Chowdhury et al., 2023). Pragmatism supports this balanced view by allowing the researcher to draw on multiple theoretical perspectives depending on what best answers the research questions.

Furthermore, pragmatism is widely recognized as suitable for systematic reviews because such reviews are designed to synthesize evidence for practical application (Saunders et al., 2019). This philosophy allows the researcher to focus on “what works” in real organizational settings while critically evaluating claims made in existing studies. Therefore, pragmatism provides an appropriate philosophical foundation for this dissertation.

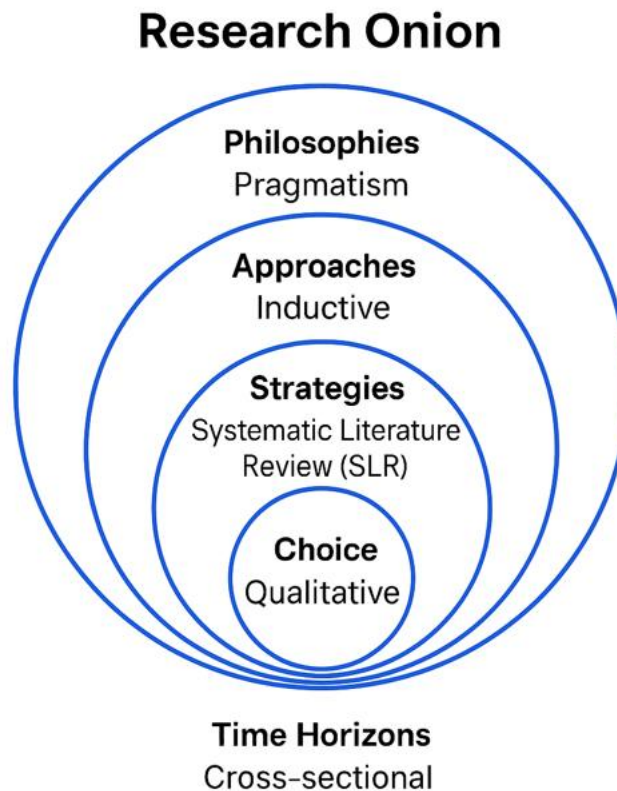


Figure 3.1 Research Onion Adopted from Saunders et al. (2019)

As illustrated in Figure 1, this study adopts a pragmatic research philosophy, an inductive research approach, and a qualitative research choice. The research strategy is a Systematic Literature Review (SLR), supported by a cross-sectional time horizon. This structure reflects the study's focus on synthesising existing knowledge rather than generating primary data.

3.3 Research Approach

This study follows an **inductive research approach**. Induction involves developing broader themes and conceptual understanding from specific observations found within the literature. This is appropriate because the field of AI in HRM is still developing, and there is no single, unified theory that fully explains how AI transforms HR practices (Prikshtat et al., 2023; Pan & Froese, 2023).

Rather than testing predefined hypotheses, the inductive approach allows patterns, themes, and relationships to emerge from the reviewed studies. For example, Chapter 2 highlighted recurring concepts such as algorithmic bias, employee trust, strategic value creation, automation versus augmentation, and ethical governance. In this

chapter, these themes are systematically traced through the literature using a structured method to ensure consistency and reliability.

An inductive approach also enables flexibility. As highlighted by Budhwar et al. (2022), AI–HRM research spans multiple disciplines, including management, psychology, ethics, and information systems. Therefore, an inductive approach allows the study to integrate diverse academic perspectives rather than restricting the analysis to a single theoretical framework. This strengthens the explanatory power of the research and ensures that the findings are grounded in evidence rather than assumption.

3.4 Systematic Literature Review Design

The research design is based on a **Systematic Literature Review (SLR)** framework. An SLR is distinguished from a traditional narrative literature review by its structured, transparent, and replicable process (Tranfield et al., 2003). The aim is to minimise researcher bias and ensure that the review reflects the true state of academic knowledge on the topic.

The design of this systematic review follows three core stages:

1. **Planning the Review**
2. **Conducting the Review**
3. **Reporting and Synthesizing the Findings**

During the **planning stage**, clear research objectives and questions were defined. These were aligned with Chapter 1 and Chapter 2, which focus on understanding the strategic, ethical, and operational implications of AI in HRM. The research questions were designed to explore how AI influences recruitment, training, performance management, decision-making, and employee experience.

The **conducting stage** involved systematically searching academic databases, applying inclusion and exclusion criteria, and screening studies for relevance and quality. Only peer-reviewed academic articles were considered to ensure reliability. Grey literature such as blogs, opinion pieces, and non-academic websites were excluded to maintain academic rigor.

The **reporting stage** involves synthesizing the findings into themes and frameworks, which are later presented in Chapter 4. This stage focuses on drawing connections between studies, identifying contradictions, and highlighting research gaps. This design mirrors the structured and critical approach used by AI–HRM scholars such as Cornacchia et al. (2023) and Soulami et al. (2024), who emphasize the importance of systematic evidence aggregation.

3.5 Search Strategy

A systematic and transparent search strategy is essential to ensure that the literature review is comprehensive, unbiased, and replicable. This study used a structured search process to identify relevant academic literature on Artificial Intelligence (AI) in Human Resource Management (HRM). The search strategy was designed to align directly with the themes developed in Chapter 2, including recruitment automation, algorithmic bias, trust in AI, strategic HRM, ethical concerns, and workforce analytics (Tambe et al., 2019; Budhwar et al., 2022; Raisch & Krakowski, 2021).

The primary academic databases used were:

- **Scopus**
- **Web of Science**
- **Google Scholar**
- **ScienceDirect**
- **Emerald Insight**

These databases were selected because they offer broad coverage of peer-reviewed journals in management, information systems, psychology, and business ethics. These subject areas are highly relevant to AI–HRM research (Pan & Froese, 2023).

A combination of keywords and Boolean operators was used to ensure precision and breadth. The main search terms included:

- “Artificial Intelligence” OR “AI”
- “Human Resource Management” OR “HRM” OR “HR”
- “Recruitment” OR “Talent Management”

- “Algorithmic Bias” OR “Fairness”
- “HR Analytics” OR “Predictive Analytics”
- “Chatbots” OR “Automation”

An example of a Boolean search string used was:

("Artificial Intelligence" OR AI) AND ("Human Resource Management" OR HRM) AND (Recruitment OR "HR Analytics" OR Bias OR Ethics)

This structured search ensured that the findings were focused, relevant, and consistent with the research objectives. It also allowed the researcher to balance breadth and depth by capturing both broad thematic studies and highly focused empirical investigations.

Concept	Keywords Used
Artificial Intelligence	“Artificial Intelligence”, “AI”, “Machine Learning”
Human Resources	“HRM”, “HR”, “Human Resource Management”
HR Functions	“Recruitment”, “Training”, “Performance”, “Retention”
Ethics & Risk	“Bias”, “Fairness”, “Privacy”, “Transparency”

Table 3.1 : Search Strategy and keywords

3.6 Inclusion and Exclusion Criteria

To maintain the quality and relevance of the review, clear inclusion and exclusion criteria were developed before screening began. This is a standard practice in systematic reviews and helps reduce the risk of researcher bias (Tranfield et al., 2003).

Inclusion Criteria

Studies were included in the review if they met the following conditions:

- Published in **peer-reviewed academic journals**

- Written in **English language**
- Published between **2000 and 2025** to AI development
- Focused explicitly on **AI applications in HRM or HR-related functions**
- Presented empirical findings, systematic reviews, or strong conceptual frameworks

Exclusion Criteria

Studies were excluded if they:

- Were not peer-reviewed (e.g., blogs, opinion articles, commercial reports)
- Focused on general AI without HR relevance
- Discussed automation without human or organizational implications
- Were book reviews, opinion pieces, or editorials without academic rigor

These criteria ensured that only high-quality and relevant academic evidence formed the foundation of this study. This is particularly important because AI in HRM is a rapidly expanding field with varying levels of academic quality (Cornacchia et al., 2023; Ekuma, 2024).

3.7 Screening and Selection Process

The screening process followed a structured, multi-stage approach similar to the logic used in the **PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses)** framework.

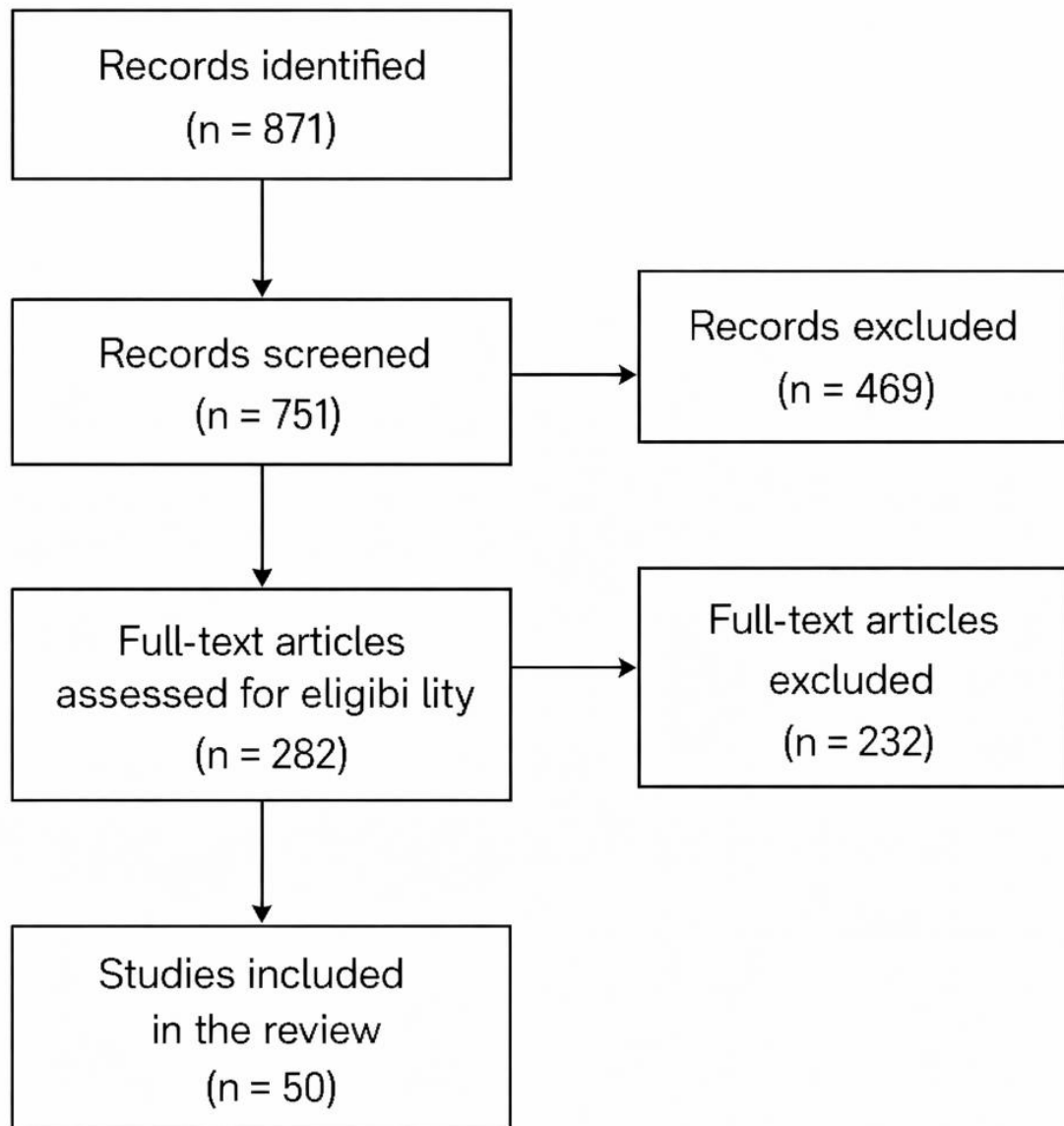


Figure 3.2: PRISMA Flow Diagram of Study Selection Process

Although PRISMA is commonly used in medical research, its structured logic is increasingly applied in management and organizational studies to improve transparency (Saunders et al., 2019).

Stage 1: Identification

All records retrieved from database searches were exported to a reference management system (e.g., Mendeley or Zotero). Duplicate articles were removed to ensure that each study was screened only once.

Stage 2: Title and Abstract Screening

The titles and abstracts of the remaining studies were screened against the inclusion and exclusion criteria. At this stage, studies that clearly did not focus on AI in HRM were excluded. This helped reduce the dataset to only relevant literature.

Stage 3: Full-Text Review

The full text of the remaining studies was carefully assessed. During this stage, the researcher evaluated the relevance, methodological quality, and theoretical contribution of each article. Studies that lacked sufficient academic rigor or relevance were excluded.

Stage 4: Final Selection

The final set of studies formed the core dataset for thematic synthesis. These studies provided the evidence base used for the analysis in Chapter 4. This structured screening process ensured transparency and reproducibility, which are key strengths of systematic review methodology.

This process is consistent with best practices in management research and aligns with review methods used by AI–HRM scholars such as Souлами et al. (2024) and Prikshat et al. (2023), who emphasize systematic transparency in literature synthesis.

3.8 Data Extraction Process

Data extraction is a critical stage in a Systematic Literature Review because it ensures that relevant information from each selected study is collected consistently and accurately. After the screening process, the final set of articles was analyzed using a structured data extraction form. This form was designed to ensure consistency across studies and alignment with the research objectives of the dissertation.

The data extraction form captured several key elements from each study, including:

- Author(s) and year of publication
- Journal and geographical context of the study
- Research objectives
- HR function examined (e.g., recruitment, training, performance management)

- Type of AI application used (e.g., chatbots, predictive analytics, automated screening)
- Key findings and arguments
- Ethical issues discussed (e.g., bias, fairness, privacy, transparency)

This structured approach ensured that all relevant dimensions discussed in Chapter 2—such as trust (Glikson & Woolley, 2020), algorithmic bias (Bandara et al., 2025), and strategic HRM alignment (Malik et al., 2023)—were systematically traced across the selected studies. The use of a consistent extraction framework reduced the risk of selective attention and improved the transparency of the review process (Tranfield et al., 2003).

Author	Year	HR Function	AI Application	Key Findings
Tambe et al.	2019	Recruitment	AI screening	Improves efficiency, risk of bias
Budhwar et al.	2022	Strategic HRM	AI frameworks	Requires ethical governance

Table 3.2 Sample Data Extraction Template for Systematic Literature Review

3.9 Quality Appraisal of Studies

Quality appraisal is essential in a systematic literature review to ensure that only robust and credible studies inform the final synthesis. Not all academic articles offer the same level of methodological rigor; therefore, it is important to critically evaluate the quality of each study before including it in the final review.

This study used a simplified quality assessment framework adapted from Saunders et al. (2019), focusing on several core criteria:

- Clarity of research aims
- Appropriateness of research design

- Transparency of methods
- Strength of analysis
- Relevance to AI in HRM

Each selected article was assessed against these criteria and categorized as **high**, **medium**, or **low** quality. Studies assessed as low quality were excluded from the final dataset to maintain the integrity of the review. This approach is consistent with recommendations in systematic review methodology and ensures that the final findings are based on trustworthy evidence.

The importance of quality appraisal is highlighted by AI–HRM scholars who note that weak empirical studies can produce misleading conclusions about AI effectiveness, fairness, or risk (Cornacchia et al., 2023; Ekuma, 2024). Therefore, by filtering studies through quality criteria, the review increases reliability and academic credibility.

3.10 Data Synthesis Strategy

The thematic synthesis revealed that the core pattern across the selected studies centres on the **tension between the benefits and challenges of AI adoption in HRM**. Across recruitment, training, performance management and retention, two dominant themes consistently emerged:

(1) **Efficiency gains** produced by AI systems

(2) **Fairness and ethical risks** that accompany algorithmic decision-making.

1. Efficiency and Accuracy Improvements

A major benefit identified across the literature is the ability of AI to improve speed, accuracy, and consistency in HR processes. Studies highlight that AI enhances recruitment screening efficiency (Tambe et al., 2019), enables personalized training pathways (Li et al., 2023), supports continuous and data-driven performance evaluations (Venugopal et al., 2024), and strengthens retention forecasting (Căvescu & Popescu, 2025). These operational improvements form a central theme showing that AI allows HR departments to handle larger workloads, reduce human error, and make more informed strategic decisions.

2. Bias, Fairness, and Ethical Challenges

Alongside its benefits, the literature repeatedly emphasizes risks relating to algorithmic bias, lack of transparency, data privacy, and employee trust. Several studies argue that AI systems can unintentionally replicate or amplify biases present in training datasets (Bandara et al., 2025). Others highlight concerns about opaque “black-box” decision-making, which reduces employees’ sense of fairness and accountability (Anthony, 2021). Privacy and surveillance concerns also appear frequently, particularly in performance and engagement systems that involve constant data monitoring (Citrin & Davison, 2022).

3. Employee Trust and Acceptance

Another recurring issue across the literature is how employees perceive AI-based HR processes. Findings show that trust and acceptance are influenced by transparency, explainability, and perceived fairness (Glikson & Woolley, 2020). When employees cannot understand how AI makes decisions, their confidence in HR procedures declines, affecting engagement and performance.

4. Human Oversight as a Moderating Factor

The synthesis shows that most studies emphasize the need for maintaining human judgement alongside AI tools. Human oversight is viewed as essential for mitigating bias, improving fairness, and ensuring contextual interpretation of algorithmic outcomes.

Together, these patterns demonstrate that the integration of AI in HRM is shaped by a **balance between efficiency-enhancing benefits and fairness-related challenges**. This theme directly supports the research objectives and responds to the research questions by showing how AI transforms HR functions while simultaneously introducing ethical, psychological, and organizational concerns that HR leaders must address.

3.11 Chapter Summary

This chapter explained the systematic and structured methodology used to conduct the dissertation. Unlike primary research methods, the study utilised a **Systematic Literature Review** to ensure that findings were grounded in high-quality academic research.

The chapter outlined the **pragmatist research philosophy** and **inductive research approach**, which allowed for a flexible yet rigorous exploration of an emerging field. It also described the **search strategy, inclusion and exclusion criteria**, and **screening process**, ensuring transparency and replicability.

The chapter further detailed the **data extraction, quality appraisal**, and **thematic synthesis** processes, which together ensured that the review was systematic, credible, and aligned with the themes developed in Chapter 2. By using a structured, transparent, and ethically responsible methodology, this study provides a strong foundation for the findings presented in Chapter 4.

The next chapter will present and analyse the key themes derived from the selected literature.

CHAPTER 4 – FINDINGS, ANALYSIS AND DISCUSSION

4.1 Introduction

This chapter presents the findings derived from the Systematic Literature Review (SLR), conducted in line with the methodological procedures outlined in Chapter 3. The purpose of the chapter is to synthesize empirical and conceptual evidence concerning the influence of Artificial Intelligence (AI) on Human Resource Management (HRM), while addressing the research aim and responding directly to the research objectives and research questions. In accordance with SLR guidelines, the findings are drawn exclusively from peer-reviewed studies selected through the screening criteria, ensuring that the analysis reflects the current state of academic knowledge without the introduction of researcher assumptions or unsupported interpretations. The themes presented in this chapter represent recurring patterns identified across the literature related to AI's impact on recruitment, training, performance management, and employee retention. These findings also reveal consistent tensions between efficiency-enhancing benefits and fairness-related risks, which collectively form the core of the academic debate on AI-driven HRM.

4.2 Presentation of Findings

The findings show that one of the most prominent patterns across the literature is the consistent view that AI significantly enhances efficiency and accuracy in HR processes. Several studies report that organisations adopting AI-driven recruitment tools benefit from faster application screening, improved matching between candidates and job requirements, and reduced administrative workload for HR professionals. Tambe et al. (2019) explain that AI-based screening allows firms to process large applicant volumes with increased consistency compared to traditional methods. This claim is strengthened by Budhwar et al. (2022), who argue that AI-driven recruitment systems reduce manual intervention and enable HR units to focus on more strategic activities. Dadaboyev et al. (2025) further reinforce the efficiency narrative by noting that AI automates repetitive tasks in recruitment and provides predictive scoring mechanisms that support more informed selection decisions. Collectively, these studies indicate that AI's operational benefits are most visible in

recruitment, where time-saving and accuracy improvements appear frequently across the literature.

Similar efficiency gains are documented in training and development. AI-enabled learning management systems increasingly provide personalized and adaptive learning experiences based on employee behavior and performance data. Dima et al. (2024) find that AI contributes to more targeted learning pathways by identifying skill gaps and recommending appropriate training modules. Li et al. (2023), studying AI adoption in healthcare training, conclude that personalized learning not only enhances the learning experience but also increases competence and employee satisfaction. These findings show that AI-driven personalization is perceived as superior to traditional training approaches, particularly in large organizations where standardized programs may lack relevance for individual learners.

The literature also highlights significant benefits in performance management, where AI enables continuous monitoring and more objective assessments. Selvamohana et al. (2025) note that AI-driven performance systems provide real-time feedback, supporting timely managerial decisions and facilitating early performance interventions. Similarly, Gill et al. (2023) emphasize that predictive analytics allow organizations to anticipate performance trends and align talent management strategies accordingly. This positions AI as a tool that strengthens the link between performance data and organizational outcomes. Across these studies, a common argument emerges: AI's analytical capabilities enhance HRM's strategic potential by transforming how performance information is generated, interpreted, and utilised.

However, despite these benefits, the literature reveals persistent challenges centered on algorithmic bias, fairness, transparency, and ethical implications. A significant number of studies caution that AI systems often reproduce biases embedded in their training datasets. Bandara et al. (2025) argue that biased algorithms can generate unfair outcomes in hiring and performance evaluations, especially when organizations lack adequate oversight mechanisms. This aligns with the findings of Gollan et al. (2021), who emphasize that applicants perceive AI-based decisions as fair only when systems demonstrate clear and transparent reasoning. When transparency is lacking, trust deteriorates, and bias concerns become more pronounced. Anthony (2021) and Rahman (2021) describe algorithmic opacity as a source of "black-box" decision-

making, which prevents employees from understanding how evaluations are generated. This perceived lack of explainability raises legitimacy concerns and contributes to employee discomfort, particularly in monitored environments.

Ethical risks extend beyond bias. Several studies highlight privacy and surveillance concerns, especially in training and performance management contexts. Citrin and Davison (2022) caution that AI-driven monitoring systems may collect sensitive behavioral data, raising concerns about consent, data protection, and intrusive oversight. Escobar-Rodríguez and Romero-Alonso (2021) similarly argue that excessive automation may depersonalize HR interactions, leading employees to feel reduced to data points rather than valued contributors. These insights suggest that AI's ethical implications are not peripheral concerns but central issues that shape employee perceptions and organizational credibility.

The literature also identifies a strong connection between fairness concerns and employee trust. Glikson and Woolley (2020) note that trust in AI systems depends largely on transparency, perceived competence, and the extent to which employees feel that decisions are explained. Cai et al. (2024) provide further evidence by showing that employees frequently perceive AI-driven evaluations as less fair than human judgment, contributing to resistance and negative attitudes. Mirowska and Mesnet (2022) find that job applicants tend to prefer human interviewers, believing that humans are better able to interpret context, emotion, and nuance. These studies illustrate that employee acceptance of AI is not determined solely by accuracy or efficiency; rather, it is strongly shaped by psychological and relational factors such as trust, perceived fairness, and comfort.

Employee experience also appears influenced by the degree of automation used in HR systems. Malik et al. (2022) note that AI can enhance consistency and fairness when implemented carefully, while Li and Greer (2023) highlight the positive role of chatbots in supporting communication and improving employee engagement. However, these benefits rely on thoughtful integration; otherwise, employees may perceive AI interactions as impersonal or overly mechanistic, limiting the perceived value of technological enhancements.

Overall, the findings reveal a consistent pattern: while AI introduces substantial efficiency-enhancing capabilities across HR functions, its adoption simultaneously

raises concerns about fairness, bias, transparency, privacy, and trust. These dualities form the foundation of the themes explored in this chapter and directly relate to the research objectives and research questions guiding the study.

The literature further reveals that AI adoption in HRM is strongly influenced by organizational readiness and the strategic alignment between technological capabilities and HR goals. Several studies argue that AI delivers its full value only when embedded within broader HR strategies rather than implemented as isolated technological tools. Malik et al. (2022) emphasize that strategic HRM approaches are essential for ensuring that AI supports long-term workforce planning, enhances individualized employee experiences, and contributes to organizational effectiveness. Their findings suggest that organizations must integrate AI into their HR frameworks in ways that reinforce rather than disrupt existing strategic priorities.

Chowdhury et al. (2023) similarly argue that AI capability frameworks provide organizations with a structured means of assessing technological maturity, workforce readiness, and managerial understanding before implementing AI-driven HR initiatives. Their research indicates that AI integration is not merely a technical process but one requiring organizational learning and alignment across multiple stakeholders. This view echoes Nawaz et al. (2024), who find that successful AI adoption is contingent on supportive infrastructure, technological literacy, and positive organizational culture. Without these enabling conditions, AI systems may underperform or face resistance from both managers and employees.

The literature also highlights the importance of considering multi-level influences in AI adoption, ranging from individual employee attitudes to institutional and cultural factors. Prikshat et al. (2023) emphasize that AI-augmented HRM must account for interactions between individuals, teams, and organizational structures. They argue that AI's impact is shaped not only by system design but also by social and organizational dynamics that influence how HR technologies are used and evaluated. Complementing this perspective, Soulami et al. (2024) report that organizational responses to AI adoption vary significantly depending on employee perceptions, managerial communication, and the extent to which AI is positioned as a supportive rather than controlling tool.

Collectively, these studies demonstrate that organizational readiness and strategic coherence play a central role in shaping the outcomes of AI adoption. When organizations align AI initiatives with HR strategies, provide transparent communication, and develop internal capability, AI is more likely to generate positive outcomes. Conversely, a lack of readiness can amplify risks related to bias, mistrust, and ethical concerns.

Benefits of AI in HRM	Risks / Challenges of AI in HRM
Increased efficiency and reduced workload	Algorithmic bias and unfair outcomes
Improved accuracy in recruitment decisions	Privacy and data surveillance concerns
Personalized employee learning pathways	Depersonalization of HR interactions
Continuous performance monitoring	Psychological strain and autonomy issues
Predictive analytics for retention	Lack of transparency ("black box" systems)
Enhanced communication via chatbots	Reduced trust if poorly managed

Table 4.1: Benefits vs Risks of AI in HRM

4.3 Analysis of Results

The findings across the reviewed studies reveal several overarching patterns that directly address the research objectives and research questions. First, the evidence clearly demonstrates that AI is transforming core HR functions by enhancing efficiency, precision, and decision-making quality. Recruitment, training, performance management, and retention all show measurable improvements when AI tools are applied appropriately. This supports the first research objective, which sought to identify HR functions most impacted by AI. The literature consistently positions

recruitment and performance management as the most technologically advanced domains, while training and retention show growing but comparatively moderate integration.

However, a deeper analysis reveals that efficiency alone does not determine the effectiveness of AI in HRM. The benefits identified across the studies are counterbalanced by persistent ethical, psychological, and organizational challenges. Bias, fairness, transparency, and trust emerge as recurring concerns across multiple studies, underscoring the limitations of algorithmic decision-making. This directly addresses the second and fourth research objectives, which focus on evaluating benefits and challenges as well as examining ethical implications.

Moreover, the findings indicate that employee perceptions play a crucial role in mediating the success of AI adoption. While AI offers efficiency advantages, employees and applicants often express discomfort or skepticism when decisions are automated, opaque, or appear unfair. This insight aligns strongly with the third research question regarding perceived benefits and the fourth research question concerning ethical and trust-related concerns. Studies such as Glikson and Woolley (2020), Mirowska and Mesnet (2022), and Cai et al. (2024) demonstrate that human reactions to AI systems can either reinforce or undermine their effectiveness, depending on how transparent and fair the systems appear.

Another key analytical insight relates to the importance of strategic alignment. The findings show that organizations must integrate AI cautiously, ensuring that technological adoption supports rather than disrupts existing HR strategies. Malik et al. (2022) and Chowdhury et al. (2023) emphasize the need for governance mechanisms, ethical oversight, and workforce readiness, indicating that strategic alignment is a prerequisite for maximizing AI's value. This links directly to the research objective examining how HR strategies influence AI implementation.

Finally, the analysis reveals a pattern of duality: AI presents significant opportunities for improving HRM, yet also introduces risks that require careful management. This dual nature forms the foundation of the discussion that follows.

4.4 Discussion of Results

The findings of the systematic literature review indicate that AI is exerting a profound influence on HRM, shaping both operational processes and strategic decision-making. In alignment with the research aim, the results demonstrate that AI contributes to the transformation of HR functions in ways that enhance efficiency, accuracy, and analytical capability. This is consistent with earlier literature, such as Tambe et al. (2019) and Budhwar et al. (2022), which highlight the potential of AI to replace repetitive administrative tasks and improve decision-making quality.

The findings also support the argument made by Raisch and Krakowski (2021) regarding the automation–augmentation paradox. Across the reviewed studies, AI is shown not merely as a substitute for human labour, but as a tool that enhances human capabilities when used appropriately. For instance, AI-supported recruitment reduces workload while still requiring human oversight to ensure fairness and contextual interpretation. Similarly, AI-driven performance management offers continuous insights, but managers remain essential for interpreting and acting upon these insights.

At the same time, the findings reinforce the concerns raised by authors such as Bandara et al. (2025) and Anthony (2021), who argue that AI's opacity and reliance on historical data can reproduce existing inequalities. The SLR confirms that bias remains one of the most critical issues associated with AI in HRM, affecting recruitment, performance appraisal, and career progression. The consistency of this concern across studies indicates that fairness is not an isolated issue but a systemic challenge requiring strong governance frameworks.

The results also highlight the importance of employee trust, a factor emphasized in prior literature by Glikson and Woolley (2020). The SLR shows that employee acceptance of AI is not automatically granted; rather, it depends on transparency, communication, and perceived legitimacy of AI-driven decisions. This finding corresponds with the concerns reported by Cai et al. (2024) and Mirowska and Mesnet (2022), who find that employees remain cautious about AI-based evaluations. Such insights suggest that employee trust should be considered a core dimension of AI implementation strategies.

Strategic alignment emerges as a second major theme in the discussion. Studies by Malik et al. (2022) and Chowdhury et al. (2023) indicate that AI adoption is most successful when integrated within a coherent HR strategy supported by organizational readiness and ethical governance. This aligns with the claims raised in conceptual frameworks discussed in Chapter 2, such as the need for hybrid intelligence and responsible AI models. The findings therefore support the idea that successful AI–HRM integration requires more than technological adoption—it demands strategic coherence, capability development, and ethical safeguards.

In summary, the discussion reveals that AI presents substantial opportunities for transforming HRM, but its effectiveness depends on balancing efficiency-enhancing benefits with fairness, transparency, and trust. These insights respond directly to all research questions and objectives, providing a comprehensive understanding of AI's dual impact on HRM.

CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter concludes the study by summarizing the findings of the systematic literature review, presenting critical conclusions in relation to the research questions, and outlining recommendations for practice and future research. The study explored the transformative effects of Artificial Intelligence (AI) on Human Resource Management (HRM), concentrating on how AI reshapes recruitment, training, performance management, and retention processes. By synthesizing evidence from peer-reviewed publications, the research identified both benefits and challenges associated with AI adoption in HR contexts. The chapter therefore builds on the thematic discussion in Chapter 4 by offering a holistic interpretation of the literature, highlighting strategic issues and ethical tensions that accompany AI-enabled HRM, and considering the conditions under which AI can support sustainable and responsible HR practices.

5.2 Summary of Main Findings

The findings of the review reveal that AI is exerting a significant and multifaceted influence on HRM. Across HR functions, the benefits of AI are predominantly associated with **efficiency, accuracy, and enhanced decision-making**. AI-enabled recruitment systems streamline applicant screening, reduce administrative burdens, and enable organizations to assess larger candidate pools more systematically. These systems provide a scalable means of matching candidates to role specifications using predictive analytics, resulting in more consistent selection processes. Likewise, AI-supported training tools enable personalized learning pathways that respond to employee needs, supporting continuous development and improving skill acquisition. In performance management, AI offers real-time feedback systems and advanced analytics that help organizations understand capability gaps, anticipate trends, and guide managerial intervention. Employee retention benefits emerge through predictive models that help HR teams identify turnover risks, facilitating proactive engagement strategies.

However, despite clear benefits, the literature reveals **persistent and systemic ethical challenges**. Chief among these are algorithmic bias, lack of decision transparency, and privacy concerns. Algorithms often replicate biases embedded in

historical datasets, making AI likely to reproduce systemic inequalities if not adequately governed. The absence of transparency—where AI systems operate as “black boxes”—erodes perceived fairness because employees and applicants cannot easily understand how decisions are made. Data-driven performance monitoring also creates concerns about surveillance, consent, and the ethical use of behavioral data. These issues are directly associated with diminished trust, skepticism, and reduced acceptance of AI among employees and candidates.

A further critical insight relates to **employee trust and perception**, which the literature identifies as a moderating factor in AI implementation. Although AI offers improved consistency, employees often question the legitimacy of machine-based judgement. Concerns arise particularly where AI makes evaluative or predictive assessments about human performance. Trust is shown to depend on transparency, communication, perceived explainability, and continued human oversight. Employees demonstrate higher acceptance when AI supports—rather than replaces—human decision-making.

Finally, organizational readiness and strategic alignment emerge as central determinants of successful AI-enabled HR transformation. AI is unlikely to produce meaningful value if organizations lack the infrastructure, capability, ethical governance, or strategic vision needed to integrate it effectively. The literature emphasizes that AI must be aligned with HR objectives, supported by training, regulated through clear policies, and implemented through collaborative change management. In short, AI’s transformative potential is contingent on both technological and organizational maturity.

5.3 Conclusions Linked to Research Questions

To present clear answers to the research questions, Table 1 summarizes the conclusions derived from the systematic literature review and thematic synthesis conducted in this study.

Table 1: Conclusions Mapped to the Research Questions

Research Question	Conclusion Derived from Literature
RQ1: How is AI transforming HRM processes in recruitment, training,	AI transforms HRM by increasing efficiency, accuracy, and scalability in

performance management, and retention?	decision-making. Recruitment demonstrates the highest level of transformation through automated CV screening, chatbot-enabled candidate communication, and predictive scoring systems that process large applicant volumes with greater consistency. Training becomes increasingly personalised through adaptive learning management systems that respond to individual employee performance data and learning preferences. Performance assessment shifts from periodic reviews to continuous, data-driven monitoring supported by real-time analytics and automated feedback mechanisms. Retention strategies benefit from predictive analytics that identify attrition risks and enable proactive intervention. However, the literature reveals significant variation in transformation levels: recruitment and performance management show the most advanced AI adoption, while training demonstrates moderate integration, and retention applications remain emerging. Transformation also varies substantially by sector, with technology, finance, and healthcare industries leading adoption, while traditional sectors show slower integration due to infrastructure and readiness constraints.
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RQ2: What are the benefits of using AI in HRM?	The primary benefits of AI adoption in HRM include: operational efficiency through automation of repetitive tasks, enhanced analytical capability enabling data-driven decision-making, reduced administrative burden freeing HR professionals for strategic activities, personalised learning pathways that improve employee development outcomes, and improved strategic workforce planning through predictive insights. Collectively, these benefits elevate HR from a primarily transactional, administrative function to a strategic partner in organisational performance and competitive advantage. However, the literature emphasises that these benefits are contingent on proper implementation aligned with the four dimensions identified in the conceptual framework developed in this study: technological enablement (infrastructure and capability), strategic alignment (coherence with organisational objectives), ethical governance (bias mitigation and transparency), and human-AI collaboration (hybrid intelligence rather than full automation). When these dimensions are absent or weak, anticipated benefits fail to materialise, and implementation may generate new challenges.
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RQ3: What ethical challenges arise from AI implementation in HRM And How does employee perception influence the adoption of AI in HRM?

Ethical and human challenges are central to AI adoption in HRM and significantly shape organizational outcomes. The literature highlights algorithmic bias as a key risk, arising from biased training data and system design that can reproduce or amplify historical inequalities in recruitment, promotion, and performance evaluation. These risks are exacerbated by the opacity of “black box” algorithms, which undermine transparency, procedural justice, and accountability, alongside privacy concerns linked to extensive data collection, monitoring, and workplace surveillance. Additionally, the growing depersonalization of HR interactions weakens the relational and empathetic foundations of people management. Crucially, the literature identifies a paradox whereby AI may reduce individual human bias through standardization while simultaneously introducing new forms of bias embedded within technological systems. As a result, fairness is not automatically improved but redistributed, necessitating robust governance, transparency, bias auditing, and sustained human oversight. Employee perceptions play a decisive role in determining the success of AI implementation in HRM. Trust, perceived fairness, and explainability consistently

	influence acceptance, with transparent systems operating under human supervision generating greater trust than opaque or surveillance-oriented applications. Persistent preferences for human decision-makers reflect beliefs that humans better account for contextual and emotional nuances. Consequently, employee acceptance—rather than technical sophistication alone—emerges as the critical determinant of successful implementation. Organizations must therefore prioritize transparent communication, AI literacy, change management, and mechanisms for employee feedback and contestation. Without addressing these human and ethical dimensions, even advanced AI systems are unlikely to deliver sustainable organizational value.
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Table 5.1: Conclusions Mapped to the Research Questions

Synthesis Addressing Research Objective 3:

While the four research questions systematically address the transformational impact (RQ1), benefits (RQ2), ethical challenges (RQ3), and human factors of AI in HRM, the synthesis of findings reveals an overarching conclusion that directly addresses Research Objective 3 concerning how HR strategies influence AI implementation success. The literature demonstrates that AI's transformational potential is mediated by organizational readiness, strategic alignment, and ethical governance—the key dimensions captured in the AI-HRM Integration Framework developed in Chapter 2.

Specifically, successful implementation requires: strategic coherence between AI capabilities and HR objectives, organizational infrastructure and capability

development, robust ethical governance frameworks, and effective change management that prioritizes employee engagement and trust-building. Studies consistently show that organizations achieve sustainable AI-HRM transformation only when technological adoption is embedded within comprehensive strategic initiatives rather than treated as isolated technical upgrades. This finding reinforces that AI effectiveness in HRM depends not on algorithmic sophistication alone but on the strategic, ethical, and human-centered contexts within which AI systems are designed, deployed, and governed.

Narrative Conclusions

The findings clearly demonstrate that AI enhances HR processes most significantly when performing analytical, repetitive, or data-intensive tasks that benefit from consistency and scale. Recruitment and performance management emerge as the most advanced domains in terms of AI adoption, reflecting both the availability of structured data and the measurable efficiency gains these functions offer. Training and development shows moderate but growing adoption, with AI-enabled personalization representing a significant value proposition. Employee retention benefits from predictive analytics capabilities, though implementation remains emerging compared to recruitment applications.

In terms of benefits, the literature confirms that AI substantially increases HR's strategic importance by enabling data-informed workforce planning, improving talent development through personalization, facilitating predictive decision-making, and freeing HR professionals from administrative burdens to focus on strategic activities. These operational and strategic advantages position AI as a potentially transformative force in HRM.

However, the findings equally highlight that AI introduces profound ethical and relational tensions that fundamentally redefine HR responsibilities and challenge traditional assumptions about people management. Where HR has historically operated as a human-centered practice emphasizing empathy, contextual judgment, and interpersonal relationships, AI shifts decision-making authority toward algorithmic systems. The literature reveals a central paradox: AI can enhance fairness through consistency and reduction of individual bias, yet simultaneously risks undermining

fairness through algorithmic bias, lack of transparency, and depersonalization of human interactions. This paradox means that AI does not automatically improve HR effectiveness; rather, its impact depends critically on implementation quality, governance strength, and attention to human factors.

Employee acceptance emerges as a crucial mediating variable linking technological capability to organizational value. Without trust—built through transparency, explainability, and visible human oversight—AI's technical advantages fail to translate into practical improvements. Employees who perceive AI systems as opaque, intrusive, or unfair respond with resistance that undermines implementation success regardless of algorithmic accuracy.

Furthermore, the synthesis reveals that **organizational readiness and strategic alignment** are prerequisite conditions for realizing AI's potential benefits. Technology alone does not drive transformation; rather, transformation emerges from the interaction between technological capability, strategic vision, ethical governance, organizational culture, and human acceptance. Organizations that approach AI implementation as a purely technical upgrade consistently experience disappointing outcomes, while those embedding AI within comprehensive strategic initiatives supported by robust governance and change management achieve sustainable transformation.

In conclusion, the systematic review demonstrates that **AI does not improve HRM through technology alone but through a combination of data capability, ethical governance, organizational readiness, strategic coherence, and sustained human involvement**. These insights reflect a balanced view acknowledging both the substantial opportunities and significant risks that characterize AI's dual impact on HRM. The four-dimensional AI-HRM Integration Framework developed in this study—encompassing technological enablement, strategic alignment, ethical governance, and human-AI collaboration—provides a holistic lens for understanding and guiding responsible AI adoption in HR contexts.

5.4 Recommendations

Based on the systematic review findings, this section presents evidence-based recommendations for practitioners, policymakers, and organisational leaders seeking to integrate AI into HRM responsibly and effectively. These recommendations are

structured according to priority levels and align with the four-dimensional AI-HRM Integration Framework developed in this study.

5.4.1 Critical Priority Recommendations

Establish Robust Ethical Governance Frameworks

Organizations must implement comprehensive governance structures to oversee AI deployment in HRM. The literature consistently demonstrates that algorithmic bias represents one of the most significant risks in AI-enabled HR systems (Bandara et al., 2025; Cornacchia et al., 2023). Governance frameworks should include regular bias audits, fairness testing protocols, and clear accountability mechanisms. As Budhwar et al. (2022) emphasize, ethical governance is not optional but foundational to responsible AI adoption. Organizations should establish ethics committees comprising HR professionals, data scientists, legal experts, and employee representatives to review AI systems before deployment and conduct ongoing evaluations.

****Implementation Timeline:**** Immediate (0-3 months)

****Responsible Parties:**** Senior HR Leadership, Legal/Compliance Teams, IT Departments

Ensure Human Oversight in Critical Decision-Making

AI should augment rather than replace human judgment in consequential HR decisions. The literature reveals that employee trust deteriorates when algorithmic systems operate without visible human involvement (Glikson & Woolley, 2020; Cai et al., 2024). Following the hybrid intelligence model proposed by Raisch and Fomina (2024), organizations should design "human-in-the-loop" systems where AI provides recommendations while humans retain final decision authority, particularly in recruitment, promotion, and performance evaluation contexts. This approach balances AI's analytical capabilities with human contextual understanding and ethical reasoning (Fenwick et al., 2024).

****Implementation Timeline:**** Immediate (0-3 months)

****Responsible Parties:**** HR Directors, Recruitment Managers, Performance Management Teams

Priorities Transparency and Explainability

Organizations must ensure that AI-driven HR decisions are transparent and explainable to all stakeholders. The "black box" nature of many algorithms undermines procedural justice and employee trust (Anthony, 2021; Rahman, 2021). HR departments should adopt explainable AI (XAI) technologies that provide clear reasoning for automated recommendations. As Gollan et al. (2021) demonstrate, perceived fairness increases significantly when employees understand how AI systems evaluate them. Transparency requirements should extend to data collection practices, algorithmic logic, and decision-making processes, supported by accessible documentation and communication strategies.

****Implementation Timeline:**** Short-term (3-6 months)

****Responsible Parties:**** HR Technology Teams, Communications Departments, IT Governance

5.4.2 High Priority Recommendations

Develop Organizational AI Capability and Digital Readiness

Successful AI-HRM integration requires comprehensive capability development across the organization. As Nawaz et al. (2024) emphasise, technological infrastructure alone is insufficient without corresponding workforce readiness and managerial understanding. Organizations should invest in training programmes that enhance AI literacy among HR professionals, equipping them to interpret algorithmic outputs, identify potential biases, and manage human-AI collaboration effectively. The AI capability framework proposed by Chowdhury et al. (2023) provides a structured approach to assessing and developing organizational readiness across technical, human, and strategic dimensions.

****Implementation Timeline:**** Medium-term (6-12 months)

****Responsible Parties:**** Learning & Development Teams, HR Strategy Units, Change Management

Implement Strategic Alignment Mechanisms

AI adoption must align with broader HR and organisational strategies rather than being pursued as isolated technological upgrades. Malik et al. (2022) argue that AI delivers maximum value when embedded within strategic HRM frameworks that support long-term workforce planning, talent development, and organisational effectiveness. Organisations should conduct strategic reviews to identify how AI capabilities can address specific HR challenges, support business objectives, and enhance employee experiences. This requires cross-functional collaboration between HR, IT, and business units to ensure coherent integration.

****Implementation Timeline:**** Medium-term (6-12 months)

****Responsible Parties:**** Senior Leadership, HR Strategy, Business Unit Leaders

Strengthen Data Privacy and Employee Consent Practices

The extensive data collection required for AI systems raises significant privacy concerns, particularly in performance monitoring and behavioural analytics contexts (Citrin & Davison, 2022; Bankins & Formosa, 2023). Organisations must strengthen data governance policies, ensuring compliance with regulations such as GDPR while maintaining ethical standards that exceed minimum legal requirements. This includes obtaining informed consent for data collection, clearly communicating data usage boundaries, providing employees with data access rights, and implementing robust data security measures. As Soulami et al. (2024) note, transparent data practices are essential for maintaining employee trust and reducing surveillance-related anxiety.

****Implementation Timeline:**** Short-term (3-6 months)

****Responsible Parties:**** Data Protection Officers, Legal Teams, HR Operations

5.4.3 Important Priority Recommendations

Enhance Employee Engagement and Change Management

Because employee perceptions strongly mediate AI adoption success, organisations must prioritise comprehensive change management strategies (Mirowska & Mesnet, 2022). This includes transparent communication about AI capabilities and limitations, creation of feedback channels for employee concerns, involvement of employee

representatives in AI implementation planning, and provision of support resources to address anxiety or resistance. As Glikson and Woolley (2020) demonstrate, trust building requires ongoing dialogue rather than one-time communications. Organisations should establish regular forums where employees can voice concerns, ask questions, and participate in shaping AI deployment approaches.

****Implementation Timeline:**** Ongoing (initiated within 3 months)

****Responsible Parties:**** Change Management Teams, Employee Relations, HR Communications

Adopt Sector-Specific Implementation Approaches

The literature reveals significant variation in AI-HRM adoption patterns across industries (Alshahrani et al., 2025; Li et al., 2023). Rather than implementing generic AI solutions, organisations should adopt sector-specific approaches that account for industry characteristics, regulatory environments, workforce demographics, and cultural contexts. Healthcare organisations, for example, face distinct privacy regulations and professional autonomy concerns compared to technology sector firms. As Prikshat et al. (2023) suggest, successful AI-augmented HRM requires multi-level consideration of individual, team, organisational, and institutional factors specific to each context.

****Implementation Timeline:**** Medium-term (6-12 months)

****Responsible Parties:**** Industry Associations, HR Strategy Units, Sector Specialists

Establish Continuous Monitoring and Evaluation Systems

AI systems require ongoing monitoring to detect bias drift, performance degradation, and unintended consequences (Bandara et al., 2025). Organisations should implement continuous evaluation mechanisms that track key metrics including algorithmic fairness across demographic groups, employee trust and satisfaction scores, system accuracy and reliability, and alignment with HR objectives. The 3T Framework proposed by Chalutz Ben Gal and Tursunbayeva (2022), focusing on Talent, Trust, and Technology dimensions, provides a structured approach to ongoing

assessment. Regular evaluation enables organisations to identify problems early and make necessary adjustments before significant harm occurs.

****Implementation Timeline:**** Ongoing (initiated within 6 months)

****Responsible Parties:**** HR Analytics Teams, Quality Assurance, Ethics Committees

5.4.4 Recommendations for Policymakers and Academic Institutions

Develop Industry Standards and Regulatory Frameworks

Policymakers should establish clear regulatory frameworks governing AI use in employment contexts, addressing algorithmic transparency requirements, bias prevention standards, data protection specifications, and employee rights to contest automated decisions. As Ncube et al. (2025) observe, technological development has outpaced regulatory adaptation, creating governance gaps. Industry associations should collaborate to develop ethical AI standards and certification programmes that provide organisations with clear implementation guidance while protecting worker rights.

Advance Research-Practice Partnerships

Academic institutions should strengthen partnerships with organisations to conduct empirical research on AI-HRM implementation outcomes. The literature review identified significant gaps in longitudinal, cross-sector, and outcome-focused studies (Rana & Kumar, 2025; Pan & Froese, 2023). Research-practice collaborations can generate evidence-based insights that inform both theoretical development and practical application, while helping organisations evaluate their AI initiatives rigorously.

5.4.5 Summary of Recommendations

The recommendations presented above reflect a balanced approach to AI-HRM integration that acknowledges both technological opportunities and human-centred imperatives. Successful implementation requires simultaneous attention to ethical governance, strategic alignment, capability development, and employee engagement. Organisations that adopt piecemeal approaches focusing solely on technological deployment while neglecting governance, transparency, or change management are likely to experience disappointing outcomes and potential ethical failures. As Raisch and Krakowski (2021) argue, AI's value in HRM emerges not from automation alone

but from thoughtful integration that preserves human dignity, fairness, and organisational legitimacy.

5.5 Limitations of the Study

While this systematic literature review followed rigorous methodological procedures aligned with established SLR protocols (Tranfield et al., 2003; Saunders et al., 2019), several limitations inherent to the research design and literature base must be acknowledged. These limitations provide important context for interpreting findings and identify boundaries within which conclusions should be understood.

5.5.1 Methodological Limitations Reliance on Published Literature

As a systematic literature review, this study necessarily depends on published academic research, which introduces several constraints. Publication bias may skew the evidence base toward studies reporting positive or significant findings, potentially underrepresenting implementation failures or null results (Bryman, 2016). Additionally, the peer review and publication process creates temporal lags, meaning the most recent AI developments may not yet be reflected in academic literature. Given the rapid evolution of AI technologies, particularly generative AI systems such as ChatGPT discussed by Budhwar et al. (2023) and Dwivedi et al. (2023), the dissertation may not capture the most current technological capabilities or organisational practices.

Search Strategy Constraints

Despite employing comprehensive search strategies across multiple databases (Scopus, Web of Science, Google Scholar, ScienceDirect, Emerald Insight), some relevant studies may have been inadvertently excluded due to keyword limitations, language restrictions (English-only), or database coverage gaps. Grey literature, industry reports, and practitioner publications were deliberately excluded to maintain academic rigour, but these sources often contain valuable insights about real-world implementation experiences that complement academic research (Silverman, 2017).

Quality and Depth of Primary Studies

The review identified considerable variation in methodological quality and empirical depth across included studies. As noted by Cornacchia et al. (2023) and Ekuma

(2023), much AI-HRM research remains conceptual, exploratory, or based on limited samples, restricting the strength of conclusions that can be drawn. The predominance of cross-sectional studies limits understanding of longitudinal effects, while the scarcity of large-scale empirical investigations constrains generalisability. These limitations in the primary literature necessarily constrain the robustness of the systematic review's synthesis.

5.5.2 Contextual and Scope Limitations

Geographical and Cultural Constraints

The reviewed literature demonstrates geographical concentration in Western contexts, particularly North America and Europe, with comparatively limited representation of research from developing economies, Asia-Pacific regions, and Africa (Alshahrani et al., 2025). This geographical imbalance limits the study's ability to draw universal conclusions about AI-HRM integration, as cultural values, regulatory environments, technological infrastructure, and labour market conditions vary substantially across regions (Budhwar et al., 2022). The applicability of findings to non-Western organisational contexts therefore requires careful consideration.

Sectoral Variation

While the review identified sectoral differences in AI adoption patterns, with technology, finance, and healthcare sectors demonstrating more advanced integration (Li et al., 2023; Dadaboyev et al., 2025), many studies do not specify industry contexts clearly or focus on specific sectors, limiting comparative insights. Traditional industries such as manufacturing, hospitality, and retail are underrepresented in the literature, constraining understanding of how AI-HRM integration manifests across the full spectrum of organisational contexts.

Organisational Size and Resource Constraints

The literature predominantly focuses on medium to large organisations with substantial technological resources and dedicated HR functions. Small and medium-sized enterprises (SMEs), which constitute the majority of employers globally, are underrepresented in AI-HRM research. Implementation challenges, resource constraints, and adoption patterns likely differ significantly for SMEs compared to large corporations, yet these differences receive limited scholarly attention.

5.5.3 Thematic and Coverage Limitations

Focus on Specific HR Functions

While the study comprehensively examined AI's impact on recruitment, training, performance management, and retention, other HR functions received less attention due to literature availability. Areas such as compensation management, employee relations, workforce planning, and HR administration represent emerging AI application domains that require more extensive research before systematic synthesis becomes possible (Grasiaswaty, 2025).

Limited Longitudinal Perspective

The absence of extensive longitudinal research in the literature base prevents this study from drawing strong conclusions about the long-term effects of AI-HRM integration. Questions regarding sustained performance outcomes, evolution of employee attitudes over time, cumulative effects of algorithmic decision-making on career trajectories, and long-term organisational consequences remain inadequately addressed in existing research (Chowdhury et al., 2024).

Insufficient Attention to Implementation Processes

While the literature identifies benefits, challenges, and outcomes associated with AI-HRM, research examining implementation processes, change management strategies, and organisational learning remains limited. Understanding how organisations successfully navigate AI adoption, overcome resistance, and develop capabilities would provide valuable practical insights but constitutes an underdeveloped research area (Nawaz et al., 2024).

5.5.4 Researcher Positionality and Interpretive Limitations

Interpretive Nature of Thematic Synthesis

Despite employing systematic procedures, thematic synthesis necessarily involves interpretive judgments in identifying patterns, categorising findings, and constructing conceptual frameworks. While the study maintained transparency and replicability through structured data extraction and analysis protocols (Chapter 3), alternative researchers might emphasise different themes or construct alternative frameworks from the same literature base (Braun & Clarke, 2006).

Pragmatic Philosophical Stance

The pragmatic research philosophy adopted (Section 3.2) prioritises practical problem-solving and balanced perspectives, which brings strengths in synthesising diverse evidence but may underemphasise deeper epistemological debates about the nature of knowledge, truth, and reality in AI-HRM contexts. Alternative philosophical approaches such as critical theory might highlight power dynamics, structural inequalities, or emancipatory concerns more prominently (Creswell, 2014).

5.5.5 Technological Evolution and Time Sensitivity

Perhaps the most significant limitation concerns the rapid pace of AI technological development. The knowledge cutoff inherent in any research project means that emerging technologies, new algorithmic approaches, and evolving organisational practices may not be captured. Generative AI, large language models, and advanced natural language processing capabilities are transforming HRM rapidly, yet academic research examining these developments remains nascent (Budhwar et al., 2023). Consequently, some findings may require updating as both technology and organisational practice evolve.

5.5.6 Implications of Limitations

These limitations should not be interpreted as diminishing the value or validity of the research but rather as defining its boundaries and appropriate interpretation. The systematic approach employed ensures that conclusions are grounded in the best available academic evidence while acknowledging that evidence has inherent constraints. The limitations identified also generate important directions for future research, discussed in Section 5.6, which can address these gaps and extend understanding of AI's role in HRM.

Despite these limitations, the study makes valuable contributions by providing comprehensive synthesis of existing knowledge, identifying recurring themes and tensions, developing an integrative conceptual framework, and offering evidence-based recommendations for practice. The findings provide a robust foundation for understanding AI's transformative but complex influence on HRM while recognising that continued research and practical experimentation will refine and extend these insights.

5.6 Recommendations for Future Research

The reviewed studies consistently highlight gaps that require further scholarly investigation. Future research should prioritise empirical studies examining real-world AI implementation outcomes, including large-scale field experiments and longitudinal studies assessing long-term effects on employee retention and performance. Ethical implications require further examination, particularly concerning bias mitigation, fairness auditing, and privacy regulation. Cross-cultural studies are needed to explore how regulatory, cultural, and organisational contexts influence employee attitudes toward AI. Research should also explore hybrid intelligence models in HR, examining how human expertise and AI can complement each other to foster ethical and strategic HR practices.

Final Reflection

AI presents a transformative opportunity for HRM, yet its value depends not on automation alone but on the ability of organisations to balance efficiency with fairness, and technology with humanity. As the literature indicates, strategic alignment, transparency, ethical governance, and human oversight are not optional supplements to AI adoption—they are the determinants of whether AI strengthens or undermines the legitimacy of HR practices. AI may change HR functions, but it does not replace the human responsibility to ensure justice, dignity, and accountability within the workplace.

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