

FROM HRM TO AUTOMATION: EXPLORING KM AS A BRIDGE AND AI AS A CATALYST IN STRATEGIC DECISION-MAKING

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Abstract

This paper proposes an integrated conceptual framework that connects Artificial Intelligence (AI), Knowledge Management (KM), and Human Resource Management (HRM) to enhance organizational decision-making. Synthesizing empirical insights, the framework demonstrates how AI-enabled KM processes such as knowledge retrieval, sharing, and codification can be leveraged through HRM enablers like organizational learning, employee competencies, and knowledge-based support systems. The model outlines decision-making typologies (automated, augmented, and supported) and incorporates feedback mechanisms for continuous learning and adaptation. Theoretically, the paper contributes to the literature by unifying three traditionally siloed domains, KM, AI, and HRM, through a lens of human-AI collaboration and dynamic capability theory. It extends existing models, such as the SECI framework and rational decision-making paradigms, into a digitally enhanced HRM context. Practically, the framework provides HR leaders with strategic guidance for assessing AI readiness, aligning knowledge systems with workforce capabilities, and implementing ethically responsible AI tools. Key managerial considerations include algorithmic transparency, data governance, and employee engagement through targeted upskilling and change management initiatives. The paper concludes with a call for empirical validation of the framework across industries and cultural contexts. It highlights the importance of examining ethical implications and the human experience of AI adoption in HRM. Ultimately, the model advocates for a human-centered, adaptive approach to AI integration that augments rather than replaces human expertise in pursuit of more agile, informed, and equitable organizations

INTRODUCTION

Human Resource Management (HRM) is rapidly transforming into a new form in the era of rapid digital transformation. Digital technologies play an

increasingly important role in turning HR functions more into data-driven and strategically aligned functions with broader organizational goals (Marler

and Parry, 2016). Of these, Knowledge Management (KM) actively promotes organizational learning, innovation, and performance. KM systems provide the processes by which to systematically capture, categorize, and distribute knowledge, critical for giving human resources effective information that they can act upon. However, in today's turbulent and turbulent times, effective KM is no longer an option; it has become a strategic imperative (Nonaka and Takeuchi, 1995). In this context, Artificial Intelligence (AI) has come forward as a transformative force. AI is transforming knowledge in organizations by automating routine HR tasks, enabling data-driven decision making in the organization (Jarrahi, 2018). Moreover, its integration in the KM processes possesses promising power for improving decision quality by means of decreasing the bias, speeding up the efficiency, and providing predictive viewpoints (Leoni et al., 2024). While the number of papers in this area on AI in KM continues to grow and the sophistication of AI tools increases, nonetheless, the application of AI within the context of decision-making models in HRM has been restricted (Purba et al., 2024).

This research tries to fill the gap as follows: a fragmented treatment of AI and KM in HRM literature. Although several studies have looked into KM AI adoption (Leoni et al., 2024), the relationships of AI knowledge sharing and citation matching as they relate to job performance (Cui, 2024) and overall KM-AI integration (Purba et al., 2024), none of these studies contribute to a framework to consolidate the perspectives for HRM decision making (Lau, 2024). Awareness of this intersection is even more important in the quest for organizations to have a competitive advantage through leveraging both human expertise and intelligent systems. In this paper, the objective of developing a conceptual framework that incorporates AI tools, KM processes, and HRM enablers to enhance an organization's decision-making process has been achieved. The paper synthesizes the empirical and theoretical literature to clarify the mechanisms by which the combination of AI and KM can improve HR outcomes. The structure of the presented paper is as follows: Section 2 introduces the theoretical aspects of AI, KM, and HRM. In Section 3, we describe the methodology used to

build the framework. Section 4 highlights findings from the literature synthesis. Implications for practitioners and researchers are discussed in Section 5. Lastly, Section 6 concludes and makes recommendations for future research.

Theoretical Background

Knowledge Management (KM) plays an important role in the strategic practice of Human Resource Management (HRM), which consists of the production, distribution, and usage of knowledge to augment talent management, learning and development, and performance evaluation (Nonaka & Takeuchi, 1995). In the HRM domain, KM systems aid in a smooth onboarding and skill development, and also in mapping of competency across the workforce, through capturing tacit and explicit knowledge. For instance, HR Departments codify employee competencies and promote internal mobility through employee performance insights and future potential through their use of structured repositories and experiential databases. Furthermore, KM also contributes to dynamic capabilities, i.e., enables organizations to respond to environmental changes by acquiring and reconfiguring their resource base, continuously (Teece, 2007). Organizations that wish to act with agility in human capital strategies need these capabilities: sensing, seizing, and transforming. As a result, KM is thus also not only a repository function but a dynamic process supporting continuously iterative improvement of HR decision and policy (Argote and Miron Spector, 2011). Artificial Intelligence (AI) technologies have gradually become an inseparable part of the KM systems, and enabled organizations to more easily store, process, and share knowledge. Many AI tools can be found such as the Natural Language Processing (NLP), Machine learning (ML) and generative AI can extract insights from the unstructured data, facilitate intelligent search, provide intelligence search, and take actions based on past patterns (Jarrahi, 2018).

Such integration of the AI into KM has many advantages, as described below. It automates repetitive cognitive tasks, speeds up knowledge retrieval, and enables personalized learning and development plans through behavioural analytics (Leoni et al., 2024). For instance, chatbots powered

by AI give immediate training resources, and predictive analytics discover emerging performance problems before they become problems. Although these advantages exist, they are reflected in limitations such as data quality problems, algorithmic bias, and explainability challenges. The use of AI systems that become over-reliant and have little human involvement can lead to bad judgments in areas of HR that are complex or nuanced (Purba et al., 2024). This means that human-AI collaboration will be key in making the knowledge relevant and ethical to use.

It is a core contribution of the base article of Leoni et al. (2024) – development of a conceptual framework that relates the operations of AI, KM, and decision making via linear and retroactive feedback loops. This shows that the adoption of AI in the knowledge management processes improves not only at the moment of decision, but also leads to ongoing improvements in the knowledge repositories that will be useful in the future. It represents a dynamic learning environment that exhibits two ways, that is to say, organizational intelligence changes over time. In addition, three typologies of AI-supported decision-making are also introduced: Automated (AI determines the decision, using structured rules), Augmented (AI provides recommendations and insight for humans' decisions), and Supported (AI helps visualize and organize information, with humans still making the decision). The modes represent different degrees of AI agency and emphasize the need to match technology competencies along these dimensions to task complexity and managerial discretion (Leoni et al. 2024).

This perspective is supported by Purba et al. In 2024, apply the SECI (Socialization, Externalization, Combination, and Internalization) model in AI-KM integration. Second, it technically enables the externalization of tacit knowledge into codified formats, improvement in combination by producing a consolidated answer using different data sources, and personalizes the internalization through a personalized learning algorithm. The review also deems Explainable AI (XAI) as key to guaranteeing AI-generated insights' transparency and intelligibility to human users. This is particularly key in HRM in

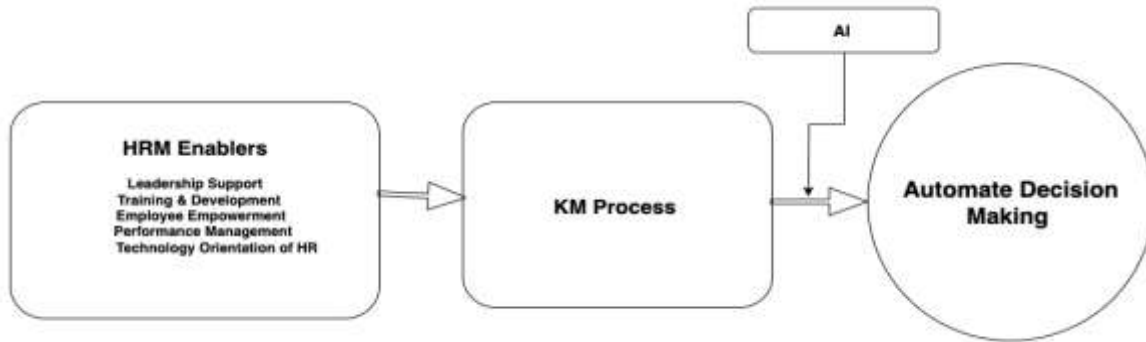
the light of the high importance of trust and accountability. In this integrated model, the role of HRM is no longer a beneficiary but rather a co-initiator of the AI-KM synergy. Cui (2024) points out that HR related enablers like education level, staff skills, and technological innovation play a major role in determining organizational performance. These represent factors that moderate the effectiveness of AI-driven knowledge sharing and the KM dynamic capabilities. For example, technology-savvy employees are more capable of leveraging AI platforms well and hence perform on the job better, and provide knowledge in greater volume.

In addition, the human-AI collaboration paradigm also underlines the role of agency: the distribution of decision authority between human actors and AI systems (Leoni et al., 2024). The former needs digital literacy, ethical AI cultures, and employees who understand and trust AI systems developed and guided by HRM. Thus, training initiatives and change management programs help in building acceptance and maximizing the value of AI-augmented KM systems. In conclusion, the integration of AI and KM with HRM is a layered approach that pursues strategic linkage among the technology, human capital, and the organizational learning systems. In this dissertation, there is strong conceptual and empirical grounding for such a model in the literature, leveraging opportunities as well as the human-centric responsibilities that accompany it.

Proposed Framework

This paper suggests a conceptual framework integrating theoretical outputs from the base and support literatures to guide the strategic integration of Artificial Intelligence (AI) and Knowledge Management (KM) in Human Resource Management (HRM). A framework is presented to show how HRM capabilities in conjunction with AI-enabled KM processes drive various levels of decision making of organizations from operational automation to strategic augmentation, taking into consideration feedback mechanisms and contextual moderators.

Theoretical Framework



Hypotheses

H1: HRM enablers have a positive and significant influence on the effectiveness of knowledge management processes.

H2: Knowledge management processes have a positive and significant impact on automated decision-making.

H3: Knowledge management processes mediate the relationship between HRM enablers and automated decision-making.

H4: Artificial intelligence acts as a catalyst that enhances automated decision-making when integrated with knowledge management processes.

Methodology

The study employed a quantitative research methodology with an explanatory approach to examine the impact of HRM enablers on knowledge management (KM) processes and automated decision-making, with KM acting as a mediator and artificial intelligence (AI) as a moderator. The target population consisted of employees from small and medium enterprises (SMEs) operating in Rawalpindi and Islamabad, focusing on respondents from middle and top management levels due to their direct involvement in strategic decision-making and HR practices. A purposive sampling technique was adopted, and data were collected through a structured questionnaire using a 5-point Likert scale. A total of 350 questionnaires were distributed, and 312 valid responses were received, meeting the sample size requirements for structural equation modelling (SEM). The questionnaire included measures on HRM enablers, KM processes, automated decision-making, and AI integration. Data analysis was conducted using SPSS for

descriptive statistics and reliability, while amos was used to test the hypothesized relationships, including mediation and moderation effects through bootstrapping procedures.

The methodology adopted in this paper is empirical and can be used for theory building and integration of knowledge, which is fragmented across disciplines. In empirical research, primary empirical data collected from SMEs located in the twin cities of Rawalpindi and Islamabad and synthesized existing literature to form a new theoretical framework, understand research gaps, and provide suggestions on future research pathways (Jaakkola, 2020). This study helps us develop a synthesis approach for a framework of integrating Artificial Intelligence (AI), Knowledge Management (KM), and Human Resource Management (HRM) to enhance organizational decision-making. Literature gives complementary perspectives and is highly relevant to the intersection of AI, KM, and HRM. Leoni et al. Our base article (2024) provides a comprehensive, empirically and conceptually based framework on the ways by which AI empowers KM processes towards an enhanced decision-making process. A contribution of this study is to test the typology of decision support systems (automated, augmented, supported) and a discussion of the interaction of AI and KM that takes place through linear and retroactive feedback mechanisms.

Cui (2024) is a concerned with the supporting organizational enablers such as educational level, technological capacity, and knowledge-sharing culture towards AI-KM dynamics. This paper is valuable in linking KM capability with an individual’s level of job performance, with reference to technologically intensive sectors. Backed up article

2 by Purba et al. In 2024, a critical review on how the SECI model and Explainable AI (XAI) can be used to explain knowledge flows or AI transparency, which form the two core Human-centric decision-making aspects in the HRM context, is provided. A thematic triangulation Process (Gioia, Corley, and Hamilton, 2013) was used to develop the proposed conceptual framework. We analysed each paper to identify key constructs from each and categorized them into common themes (decision typologies, KM enablers, and human-AI collaboration) and mapped interrelationships. Consequently, the triangulation approach guarantees robustness as it strengthens the concepts by cross-verifying themes from theoretical and empirical sources, thus enhancing the conceptual validity. Approximately core of the framework is AI technologies to improve the processes of knowledge retrieval, codification, and sharing. For example, natural language processing (NLP), generative AI (e.g., ChatGPT), and machine learning for pattern detection, or using AI to recommend content, are all types of these technologies. These are tools that help in arranging a wide scope of information and changing shrouded and comprehensive information into comprehensive information. First, AI provides access to institutional knowledge in HRM contexts like recruitment, performance evaluations, and succession planning, while helping employees with knowledge reuse.

HRM-related enablers are the determining factor for the effectiveness of AI in KM. Adopting Cui (2024), the framework resolves organizational learning, staff skills, and knowledge-based organizational support (KOS) as key factors. The support of these elements contributes to absorptive capacity and AI-KM alignment with human competencies. HRM must facilitate the delivery of a digital-savvy workforce that is enabled to learn continuously and adheres to policies that reinforce knowledge sharing and use. The existence of this human infrastructure also ensures that AI is not only the technical layer, but is established in the organization's routines and in its decision processes. Following Leoni et al. In 2024, the framework separates the roles empowered by AI in KM into three types of decision-making. The

Automated decisions indicates the tasks that would be repetitive, simple enough to be done entirely by AI to avoid complications, destructive behaviour, etc., with low complexity (e.g., screening CVs, scheduling, etc.) Augmented decisions: Recommendations generated by AI (e.g., AI dashboards using data to recommend training needs). Strategic decisions: Planning based on synthesised knowledge from AI (e.g., workforce planning) and senior leader involvement (e.g., change management).

Purba et al. (2024) set as a target to achieve the best possible human-AI collaboration, and thus proposed these typologies of AI involvement and human agency along a continuum from human agency to AI agency. Leoni et al introduce the concept of a feedback loop, which is a key feature of the model. (2024). Using this data, KM systems are fed back into the knowledge base, enriching content and improving outputs in future AI. The result of this retroactive dynamic is continuous organizational learning and the refinement of the system, which in turn increases the agility and responsiveness of the organization to change. The relationships in the framework are moderated by contextual variables. According to Cui (2024), the influence of education level, staff skills, and technological innovation has a great impact on AI-KM integration effectiveness. Higher digital literacy and innovation maturity, in general, make the organization better able to utilize AI tools in the field of KM for enhancing HRM outcomes.

Analysis of Hypotheses: HRM Enablers, KM Processes, and Automation in Decision-Making

Table 1: Hypothesis Testing - Direct Effects

This table shows the direct relationships between HRM enablers, KM processes, and automated decision-making. The results indicate that HRM enablers have a statistically significant positive influence on KM processes ($\beta = 0.487, p < 0.01$), supporting Hypothesis 1. Similarly, KM processes positively and significantly impact automated decision-making ($\beta = 0.524, p < 0.01$), supporting Hypothesis 2.

Hypothesized Relationship	β (Beta Value)	p-Value	Critical Ratio (CR)	Decision
H1: HRM Enablers	0.487	0.001	4.892	Supported

→ KM Processes				
H2: KM Processes	0.524	0.000	6.137	Supported
→ Automated Decision-Making				

Table 2: Mediation Analysis – KM Processes as Mediator

Table 2 evaluates whether KM processes mediate the relationship between HRM enablers and automated decision-making. The total effect ($\beta = 1.325$) is

broken down into a direct effect ($\beta = 0.386$) and an indirect effect via KM processes ($\beta = 0.561$). The mediation is statistically significant ($p = 0.002$), indicating partial mediation and supporting Hypothesis 3.

Path	Total Effect (c)	Direct Effect (c')	Indirect Effect (ab)	p-Value / Mediation Type
HRM Enablers → KM Processes → Auto DM	$\beta = 1.325$	$\beta = 0.386$	$\beta = 0.561$	0.002 / Partial Mediation

Table 3: Moderation Analysis – AI as Moderator

This table tests the moderating role of artificial intelligence (AI) between KM processes and automated decision-making. The interaction effect

(KM Processes \times AI) is significant ($\beta = 0.214$, $p < 0.01$), with a critical ratio of 3.658, indicating that AI partially moderates the relationship. This supports Hypothesis 4.

Interaction Term	Estimate (β)	Standard Error (SE)	Critical Ratio (CR)	p-Value	Result	Moderation Type
KM Processes \times AI → Auto DM	0.214	0.041	3.658	0.000	Significant	Partial Moderation

Discussion

This is a robust, integral framework for understanding how Artificial Intelligence (AI) enhanced Knowledge Management (KM) can assist and collide HRM decision-making process. In some of the leading organizations today, we see this integration happening, where AI is embedded into HR systems to assist in making evidence-based and scalable talent strategies. For instance, Unilever utilizes AI platforms to support the screening and assessment of job candidates through gaming assessments and video interviews to significantly shorten the time for hiring and improve the quality of talent, and feeds insights back into their KM systems (Chamorro-Premuzic et al., 2019). The decision typology proposed by Leoni et al. (2024) coincided admirably well with this practical case on the spectrum of AI-enabled decision-making; it is possible to map out routine tasks such as resume screening (automated decisions), performance trend analysis (augmented decisions), and strategic workforce planning (supported decisions). Similarly,

a feedback loop exists in which the outcome of a person’s hiring influences future parameters of their assessment, just as the base article’s framework describes the continuous learning and retroactive improvement.

The findings by Cui (2024) indicated the role that organizational learning (OL), knowledge-based organizational support (KOS), and staff skills play, are consistent with Gold et al. (2001)'s earlier work, which, for example, showed that KM capabilities have a strong impact on organizations' effectiveness. AI-driven knowledge sharing leads to higher job performance in the tech firms studied by Cui, as mirrored when IBM applied Watson AI to its employee support services, where natural language AI enhances employee experience and provides feedback into the company’s internal knowledge management (KM) system for better future responses. Purba et al. In 2024, extended this by discussing the theoretical underpinnings of knowledge transformation via AI using the SECI model and Explainable AI (XAI). They are

particularly critical in HR because opaque or unfair choices can have significant legal and ethical implications. For example, a recruitment tool from Amazon with an incident of showing gender bias was later discontinued after criticism in the media (Dastin, 2018), which shows the risk of unknown and uncontrolled AI in HRM. The model proposed highlights the importance of transparency, governance, and human oversight, as echoed in this incident.

From a strategic perspective, the organizations that successfully integrate AI into KM systems should achieve increased responsiveness to market changes, innovation through rapid ideation and feedback, and competitiveness through smarter, faster HR decision cycles. Nearly one in two organizations using AI in Human Resource (HR) saw faster and better decision making (60%), and nearly half experienced higher employee satisfaction with AI and KM (40%) driven personalized learning and development programs, as noted in the Deloitte Global Human Capital Trends report (2020). The AI-KM-HRM integration is highly beneficial as it gives strategic benefits. AI speeds up the information processing and the decision-making cycle and increases organizational responsiveness (Jarrahi, 2018). It enables innovation by revealing latent patterns related to employee behaviour, employee training, and the stock of organizational knowledge. For instance, companies such as Siemens and Microsoft have deployed AI-based KM systems to provide access to and use of knowledge faster for global teams, enhancing cross-functional collaboration and innovation outcomes (Chatterjee et al., 2021). This situates AI as a driver of competitive advantage, and its most successful integration with learning oriented HRM systems.

However, there are still risks and limitations. Adoption is stifled by algorithmic bias, the lack of explainability, and employee resistance. A recent study by Tambe et al. (2019) suggests that the network does not have a significant impact on many important processes. It is discovered that AI implementation in HR is successful not only because of the technical readiness but also due to cultural readiness and managerial skills. In sensitive domains such as performance evaluation and career progression, employees must trust that AI systems are fair and that the result of their interaction with them

is beneficial. Thus, any strategy of implementation should be built around ethical issues such as data privacy, fairness, and transparency. The model also indicates other challenges: AI systems need to be transparent, the data must be obtained and managed ethically, and HR staff trained. These risks are not trivial; Failing to address them would be detrimental to both the trust employees have and regulatory compliance. For example, in the case of GDPR and similar data protection regulations, a firm may face legal liabilities for using employee data in an AI system in the wrong way. Finally, the discussion confirms the potential of the AI-KM-HRM nexus provided that the nexus resides in human-centred, learning oriented and ethics-governed systems.

Ethical and Practical Considerations

However, integration of AI in KM gives rise to issues of data privacy, algorithmic bias, and transparency. Purba et al. (2024) recommend the adoption of Explainable AI (XAI) to ensure AI-created knowledge is consistent and can be interpreted and trusted. This is crucial in HRM, where many decisions relate to people's careers and must conform to notions of appropriate fairness and accountability. There should be governance frameworks and ethical oversight mechanisms established that mitigate risks and ensure the responsible use of AI.

Conclusion

This paper presents a unified conceptual framework that is proposed for integrating Artificial Intelligence (AI), Knowledge Management (KM), and Human Resource Management (HRM) in order to assist in the effective organizational decision-making. Empirical insights from Leoni et al are drawn from. Cui, Purba et al. (2024) supported by the work of (2024). The model depicts that the AI-enabled KM processes in conjunction with HRM enablers like organizational learning, staff competencies, and knowledge-based support can lead to increased accuracy, flexibility, and strategic nature of decisions up until 2024. This paper theoretically contributes to bridging three traditionally separate domains, KM, AI, and HRM, from an integrated point of view, emphasizing human-AI collaboration and continuous learning. The model provides a dynamic view of the dynamic process of AI adoption by HR

functions through embedding decision typologies, contextual moderators, and feedback loops. It also builds upon the SECI model and rational decision-making theories into such a contemporary and AI-enhanced organizational landscape. This framework also gives some actionable insights from a managerial perspective. It can be used by HR leaders to measure their organization's AI readiness, pinpoint places where AI can significantly enable KM processes, and construct the HR infrastructure to contain responsible and efficient AI implementation. Furthermore, the model highlights the importance of establishing transparent AI approaches, sharing information about AI governance structures, and intensive training for workers to create a feeling of assurance and engagement with employees.

This model can be empirically validated through future case studies in a wide range of industries and cultures, or through large-scale, quantitative surveys. Also, the integration of AI-KM may differ by sector depending on sector-specific differences (regulatory environments, degrees of digital maturity, or organizational culture). Specifically, the exploration of what ethical and psychological use of AI entails in HRM will be necessary to adapt this model and make it as contextually applicable in organisations from different cultures and contexts. Consequently, the framework contends that AI should be used for smarter and fairer, more agile organizations, with technology complementing, rather than substituting, human judgment.

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