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Agentic AI in Human Resource Management: Autonomous Decision Systems and Organizational Governance

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ABSTRACT

Purpose: The paper explores the transformative potential of agentic artificial intelligence (AI) in human resource management (HRM), specifically on the autonomous decision-making aspects and the governance problems that they create within the organization. Instead of offering a qualitative breakaway from traditional AI/ML tools used in HR settings, agentic AI is goal-directed, multi-step reasoning, adaptive planning, and tool orchestration, implying a qualitative shift.
Design/Methodology/Approach: This paper stands based on systematic conceptual review of the existing literature and combines such theories as Resource-Based View (RBV), Institutional Theory, Socio-Technical Systems (STS) Theory, and AMO Theory to create a new conceptual model. Seven research propositions, which are based on theoretical foundations, are developed and an empirical research design is suggested to be validated in the future.
Findings: The paper proposes four governance imperatives transparency, accountability, bias reduction, and human control, because of which organizations are required to mediate the implementation of agentic AI in the key HR functions.
Research Limitations: Conceptual, these propositions and framework have not yet been empirically tested. The use of previously published works could result in limited scope of rapidly emerging agentic AI developments. In theoretical terms, the contextual focus on emerging economies is appropriate, but it could limit cross-sectoral generalizability to advanced economy situations.
Managerial Implications: HR professionals and HR policy makers should create governance frameworks before using agentic AI in critical HR areas like hiring, performance measurement, and workforce planning.
Originality/Value: The paper contributes in three ways: It proposes actionable governance propositions that are relevant for both practice and policy making.

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Introduction

The future of artificial intelligence (AI) in organizations has been characterized by a trend of moving away the concept of limited, task-oriented tools towards more autonomous, adaptive and self-directed systems. The recent rise of machine learning (ML), natural language processing (NLP) and deep neural networks has facilitated AI in executing cognitively challenging tasks that only professional human experts used to undertake (Brynjolfsson & McAfee, 2014; Haenlein & Kaplan, 2019). However, currently, there is a more significant change: the advent of agentic AI – systems that can plan and execute multi-step plans, invoke external tools, hold contextual memory, and execute complex goal-driven workflows with little human oversight (Wang et al., 2024). This change in passive analytical tools to active decision makers radically alters the scope, responsibility and governance of AI in organizations.

The human resource management (HRM) has been a high-profile area of AI use. Data-driven AI tools have revolutionized recruitment screening, predictive attrition modeling, support of performance appraisal, and personalized learning recommenddations (Tambe et al., 2019; Budhwar et al., 2022). Traditional AI applications in HRM act as more of analytical aids: They take in inputs, produce scores or suggestions and wait until someone chooses to act. This paradigm is upset by agentic AI. In contrast to passive recommendation systems, agentic systems are able to automatically deconstruct job descriptions, construct interview pipelines, issue conditional offers, schedule onboarding, and even start performance improvement plans – they can complete multi-stage HR workflows without constant human oversight (Park et al., 2023; Wang et al., 2024). The repercussions to the HR governance, fairness to the employees, and institutional legitimacy are far-reaching.

Although the practice is developing at a very high rate, the academic knowledge about agentic AI in HRM is still young. The available literature on AI and HRM has focused mostly on algorithmic decision support (Cheng & Hackett, 2021), automation of e-recruitment (Pan et al., 2022), people analytics (Marler & Boudreau, 2017), and the ethical aspects of algorithmic bias (Raghavan et al., 2020; Bankins & Formosa, 2023). A minor yet increasing stream explores the overall socio-technical implications of AI-mediated HR processes (Bankins, 2021; Giermindl et al., 2022). Nonetheless, there is no systematic theoretical framework so far that aims at the agentic AI, as a specific type of autonomous decision-making technology, in the context of HRM. This is a large gap: Agentic AI poses qualitatively new accountability, transparency, and governance issues that are not sufficiently dealt with under the current frameworks.

The situation is aggravated further in the context of the emerging economies. The use of autonomous AI systems in HR decision-making has increased risks in countries like India, which have large, heterogeneous, and regulated labor markets, and whose statutory frameworks evolve. The use of algorithmic biases that are trained on unequal historical datasets can continue to perpetuate discrimination in hiring, appraisal, and promotions (Raghavan et al., 2020; Mehrabi et al., 2022). The National Strategy on Artificial Intelligence in India (NITI Aayog, 2018) recognizes the transformational potential of AI but does not go beyond referencing the possibility of autonomous agent systems in the governance of organizations. This gap in the regulation and theory needs a scholarly response.

Research Objectives

The research objectives of this paper include the following: (1) conceptualizing agentic AI and defining its distinguishing features compared to traditional AI/ML in HRM; (2) creating a conceptual framework based on theory to relate agentic AI implementation, HR functional areas, governance, and organizational performance, focusing specifically on India and emerging economies; (3) establishing research propositions that can be empirically tested; and (4) establishing governance.

Contribution

The paper has three contributions. First, it presents and theorizes the notion of agentic AI in HRM, contrasting it with previous AI/ML applications on the three dimensions of autonomy, adaptability, and decision scope. Second, it can be seen as having a multi-theoretic basis by combining the Resource-Based View, Institutional Theory, Socio-Technical Systems Theory, and AMO Theory,

which enables agentic AI to be embedded in the wider organizational dynamics. Third, it promotes both a governance framework and a collection of research propositions that are both theoretically rigorous and practically actionable, as a basis of future empirical investigation. The paper aligns with the interdisciplinary mission of Delhi Business Review of filling the gap between management theory, new technology and governance practice in the Indian and global organizational contexts.

Literature Review

The field of AI in organizations has grown at a fast pace with publications in various fields, such as information systems, human resource management, organizational behavior, and AI ethics. The review will be thematically organized to follow the intellectual path of the early AI tools in HRM to the new frontier of agentic AI and its governance issues.

Artificial Intelligence in Human Resource Management

The crossroads between AI and HRM have been a topic of considerable academic interest in the last ten years. In an influential early work, Tambe et al., (2019) outlined three key barriers to AI adoption in HRM: The lack of data quality, the problem of small n (small HR data sets) and ethical issues with algorithmic decision-making. In the systematic review of 190 studies, Vrontis et al., (2022) determined that the most frequent HR functions that could be transformed by AI are recruitment, performance management, and learning and development. Their review noted that there has always been a disconnect between the technical potential of AI and the responsible organization of AI.

The idea of autonomously configuring HR processes by AI-powered systems developed by Strohmeier (2020) prefigures the agentic paradigm. The Delphi study that he conducted revealed that HR professionals agreed that AI would gradually automate not only the processing of data but also the creation of recommendations and, to a growing degree, decisions. Budhwar et al., (2022) applied this discussion to the global HRM context, claiming that cross-cultural labor force relations pose opportunities and challenges to AI-based HR-related decisions, especially in heterogeneous labor markets in emerging economies. Empirically, Malik et al., (2022) showed that AI chatbots in HR can simultaneously be cost-effective and more personalized, thus supporting the efficiency hypothesis but posing the threat of depersonalization.

An accumulating body of critical scholarship has pointed out the dangers of algorithmic HRM. A strict definitional and theoretical review of HR algorithms by Cheng & Hackett (2021) demonstrated underlying contradictions between efficiency and predictive accuracy on the one hand and procedural fairness on the other. Pan et al., (2022) investigated the contextual factors that moderate the adoption of AI in the recruitment process and discovered that the organizational culture, regulatory environment, and managerial attitudes are major factors influencing adoption patterns. Giermindl et al., (2022) listed the dark sides of people analytics, such as surveillance risks, employee privacy violations, and loss of employee autonomy, which grow stronger as analytics platforms develop towards agentic operation.

The Concept of Agentic AI: Autonomy and Decision-Making

The term agentic AI is used to describe AI systems with goal-oriented behavior, adaptations, and the ability to perform multi-step tasks with little human supervision (Wang et al., 2024). Based on large language models (LLMs) and multi-agent systems, agentic systems contrast with traditional AI on a number of important dimensions: They have a persistent memory between tasks, they can invoke external tools and APIs, they can break down complex goals into subtasks, and they make dynamic plans in response to environmental feedback (Park et al., 2023). This transition was anticipated by Russell (2019) in the initial argument of his foundational thesis, that AI systems needed to transition to uncertainty-aware, preference-learning systems, rather than maximizing fixed goals – a transition that agentic systems now operationally seem to follow.

In a highly influential critique of large

language models, Bender et al., (2021) had predicted the dangers of implementing systems where the results are not always transparent, statistically skewed, and not tied to grounded reasoning. Such risks are compounded when such systems are accorded agentic power to make critical decisions in an organization. In their MIS Quarterly analysis, Lebovitz et al., (2021) showed that AI systems trained with expert-labeled data often tend to have systemic blind spots, which can be directly applied to the HR setting, with the training data being historically disproportionate workforce trends. The extensive survey of Wang et al., (2024) reported the architectural maturation of agents based on LLM – including planning, memory, tool use and multi-agent collaboration – as a validation that agentic AI has transitioned to a deployable technology.

Importantly, agentic AI is not a more competent variant of the current AI tools. Table 1 summarizes the major differences between traditional AI and agentic AI based on the dimensions that are applicable to HRM. According to the table, the key characteristics of agentic AI, such as temporal autonomy, self-directed planning, orchestration of tools and revision of goals, bring about governance issues that are qualitatively different than those of previous-generation HR analytics platforms.

HR Analytics, Automation, and Autonomy Continuum

HR analytics lies in the middle of the autonomy spectrum between the simplest form of data reporting and totally agentic decision-making systems. Marler & Boudreau (2017) have used an evidence-based taxonomy of HR analytics to differentiate between descriptive, predictive, and prescriptive applications. Tursunbayeva et al., (2018) delimited the conceptual frontiers of people analytics and its essence as evidence-based, data-informed HR decision support, which is an advisory but not an autonomous role. In a broad multi-disciplinary review, Dwivedi et al., (2021) mapped out the emerging agenda of AI research in any industry, determining that explainability, bias mitigation, and human-AI teaming are cross-cutting issues that directly apply to HR analytics.

The authors Mikalef & Gupta (2021) operationalized the concept of AI capability as an organizational resource and empirically proved

Table 1: Traditional AI Versus Agentic AI in HRM: A Comparative Analysis

Dimension	Traditional AI / ML in HRM	Agentic AI in HRM
Autonomy Level	Low – Human-in-the-loop for decisions	High – Multi-step execution with minimal oversight
Decision Scope	Single-task recommendations (e.g., resume scoring)	End-to-end process management (e.g., full recruitment cycle)
Planning Capability	Absent – Static model execution	Present – Dynamic task decomposition and re-planning
Memory & Context	Stateless – Each prediction is independent	Persistent – Retains context across sessions and actions
Tool Orchestration	None – Operates on pre-structured data inputs	Active – Invokes APIs, calendars, databases, communication tools
Adaptability	Fixed model; requires retraining for new contexts	In-context adaptation; updates behaviour from feedback
Governance Risk	Moderate – Bias in recommendations, explainability	High – Accountability gaps, opacity, unintended consequences
Key Sources	Cheng & Hackett (2021); Vrontis et al. (2022)	Wang et al. (2024); Park et al. (2023); Russell (2019)

Source: *Authors' construct*

that the concept of AI capability mediates the association between data infrastructure and organizational creativity in a positive way. Their results apply to HRM to the extent that they indicate that the organizational returns on AI, including in HR, hinge on the ability of the firm to assimilate, integrate and govern AI systems. The impacts of automation on the labor market, which Acemoglu & Restrepo (2022) also report, further put the stakes into perspective: With the development of AI systems, the substitution effect of skilled HR labor turns out to be a non-trivial case, altering the composition and competence needs of the HR function itself.

In this literature, special care is required in the Indian context. The number of employees in India is more than 500 million in the formal and informal sectors, and IT and services are some of the largest adopters of workforce management technologies in the world (NITI Aayog, 2018). However, the use of people analytics in Indian companies has been uneven, with giant conglomerates testing advanced AI-based HR solutions and most companies having no data infrastructure to support the most simple forms of analytics (Wamba-Taguimdje et al., 2020; Malik et al., 2022). This heterogeneity suggests that agentic AI governance systems in Indian HRM should take into consideration technological sophistication as well as developmental asymmetry.

Organizational Governance Challenges of AI

The management of AI within organizations has become a hot and disputed ground. In their survey of 84 AI ethics guidelines across 38 countries, Jobin et al., (2019) determined that five common principles existed: Transparency, justice and fairness, non-maleficence, responsibility, and privacy. Yet, they have observed that there are very big disjunctures between principles and mechanisms that can be enforced – a difficulty that is magnified when AI systems are acting on their own. Floridi & Cowls (2019) contributed to a cohesive set of five AI ethics principles, which are based on bioethics traditions, and that AI governance should eventually be implemented at the institutional level.

In a process lens of algorithmic decision-making within HRM, Bankins (2021) claimed that accountability in HR decisions mediated by AI is inherently spread out among developers, deployers, and users, which introduces accountability gaps that are hard to address using traditional HR policies. A study by Raghavan et al., (2020) found that claims by vendors of their tools to reduce bias were often false, and that they reinforced demographic inequalities based on gender, race, and educational backgrounds. Mehrabi et al., (2022) presented an in-depth taxonomy of the types of bias in machine learning, differentiating historical, representation, measurement, aggregation, and evaluation bias each of which appears differently in HR data-related contexts. Bankins & Formosa (2023) have explicitly linked AI in HRM to meaningful work theory and posited that autonomous AI decision systems have the potential to compromise the preconditions of employee flourishing by depersonalizing HR relationships, limiting the use of skills, and eliminating subjective meaning.

This literature continues to have critical gaps. First, practically all existing governance systems were built to work with passive AI/ ML tools, not with agentic systems; their usability in autonomous agents with the ability to plan and to exercise tool-use authority is constrained and largely unexplored. Second, the relationship between AI governance systems and organizational performance results is yet to be studied empirically. Third, the governance requirements of organizations in the emerging economies, which are confronted with unique regulatory, cultural and institutional environments, have been given inadequate theoretical focus. These three gaps have been the focus of this paper.

Theoretical Foundation

The paper combines four theoretical lenses that are complementary to form a multi-level perspective of agentic AI in HRM. All the theories cover different aspects of the phenomenon: organizational value creation (RBV), institutional legitimacy pressures (Institutional Theory), human-AI system design (STS Theory), and HR practice effectiveness (AMO Theory). Collectively,

Table 2: Selected Literature Synthesis — Agentic AI and HRM Governance

Author(s) & Year	Focus Area	Key Findings	Gap Identified
Tambe et al., (2019)	AI challenges in HRM	Data quality, small-n, and ethics are central barriers	No framework for autonomous AI
Marler & Boudreau (2017)	HR Analytics	Taxonomy of descriptive, predictive, prescriptive analytics	Overlooks agentic autonomy
Cheng & Hackett (2021)	Algorithms in HRM	Tension between predictive accuracy and procedural fairness	Agentic multi-step planning not addressed
Bankins (2021)	Algorithmic HRM decisions	Accountability is distributed; governance gaps persist	No empirical measurement model
Budhwar et al., (2022)	International AI-HRM	Context moderates AI adoption; emerging economies underrepresented	Agentic AI not theorized
Pan et al., (2022)	AI in recruitment	Culture, regulation, and management attitudes drive adoption	No governance propositions
Giermindl et al., (2022)	People analytics risks	Surveillance, privacy, and autonomy erosion	Agentic systems not considered
Bankins & Formosa (2023)	AI and meaningful work	Autonomous AI undermines meaningful work conditions	Governance framework absent
Wang et al., (2024)	LLM-based agents survey	Architecture of agentic AI: planning, memory, tool use	HRM application not addressed

Source: *Authors' construct*

they give a conceptually consistent scaffolding of the conceptual framework and propositions that are to be developed in the following sections.

Resource-Based View (RBV)

The Resource-Based View by Barney (1991) assumes that a long-term competitive advantage is based on organizational resources that are valuable, unique, imitable and non-substitutable (VRIN). Applied to agentic AI in HRM, this framework implies that the ability to launch, manage, and continually enhance autonomous systems of HR decision-making is a unique organizational capability, which is hard to duplicate without similar investments in data infrastructure, governance procedures, and human-AI collaboration skills. This rationale has been empirically proven by Mikalef & Gupta (2021) who show that the combination of technological, relational, and human resources (AI capability) is positively correlated with organizational creativity and performance. In their meta-analysis of the outcomes of HRM, Jiang et al., (2012) also demonstrated that HR systems create competitive advantage by mediating processes such as employee knowledge, motivation, and opportunity – exactly the aspects of agentic AI that can be systematically enhanced.

Importantly, RBV also warns against considering technology as an undifferentiated resource. Unless agentic AI systems have strong governance measures, they might undermine and not add value to competitive advantage, especially where governance failures lead to reputational losses, regulatory fines, or staff disengagement. The VRIN framework, therefore, is applicable to agentic AI systems, in general, as well as to the organizational governance capabilities that make agentic AI systems strategically valuable.

Institutional Theory

DiMaggio & Powell (1983) have shown that organizations do not necessarily engage in practices because of efficiency-related factors, but as a reaction to coercive, normative, and

mimetic institutional pressures that influence conformity to acceptable forms of organization. Institutional Theory applied to agentic AI in HRM predicts the AI governance practices to appear in a combination of regulatory compulsion (coercive isomorphism), the practice of professional norms transmitted through HR associations and management consultancies (normative isomorphism), and benchmarking against industry leaders (mimetic isomorphism). Such a framework is especially relevant to India, where AI-related regulatory frameworks in the employment sector are still in their early development and where the normative influence of multinational corporations operating in the nation dictates the domestic regulation practices more and more.

Jobin et al., (2019) noted that, in many cases, AI ethics guidelines are not backed by enforcement mechanisms, which means that they are more of a normative than a regulatory tool. In agentic AI in HRM, it means that the governance legitimacy can be less technically abiding and more observable organizational adherence to open and responsible HR AI practices, a dynamic that aligns with the focus on ceremonial adoption in the Institutional Theory. This opinion is supported by Floridi & Cowls (2019) who propose that the institutional anchoring of trustworthy AI governance should be done on various levels: firm, industry, and regulatory.

Socio-Technical Systems (STS) Theory

The Socio-Technical Systems Theory is a viewpoint based on the work of Trist & Bamforth (1951) with the coal-mining experiments and developed by Baxter & Sommerville (2011) when the authors claim that the work system is comprised of the inter-dependent social and technical subsystems and that the work systems are optimally performed when the social and technical subsystems are optimized When applied to agentic AI in HRM, the STS Theory underlines that autonomous AI agents are not technical entities but social agents within organizational work systems. Their relationships with the HR professionals, managers, and employees are socio-technical arrangements that should be carefully designed.

The STS Theory suggests that successful implementation of agentic AI in HRM requires focusing on the performance of the algorithms as well as the human roles, team structures, and organizational culture within which the system is placed. By using a process-theoretic lens, Bankins (2021) illustrated that the transparency and equity of AI-mediated HR judgments are determined by the way the human-AI work system is designed in the decision-making process. Siau & Wang (2020), who analyzed the ethics of AI through the prism of human-computer interaction, also proposed a similar view on the matter: That ethical AI within organizations is obtained based on system design decisions that introduce human controls and value resonance - a prescriptively socio-technical conclusion.

AMO Theory

The Ability-Motivation-Opportunity (AMO) Theory proposed by Appelbaum et al., (2000) assumes that the performance of workers is a product of the three conditions: Ability to perform, motivation to perform and opportunity to perform. Jiang et al., (2012) have built AMO as a sound mediating model in which HR practices can affect organizational outcomes, illustrating that HRM systems create performance impacts by their effects on abilities, motivational levels, and empowerment statuses of employees.

Applied to agentic AI, AMO Theory results in a two-level frame of analysis. At the employee level, agentic AI can add ability (with real-time skill gap analysis and personal development), increase motivation (with immediate and data-driven performance feedback and career paths), and increase opportunities (with less friction to internal mobility processes). Nevertheless, agentic AI may negatively impact motivation (by creating a sense of surveillance and depersonalization) and limit opportunity (by using algorithmic gatekeeping that harms underrepresented populations) at the same time. On the organizational level, AMO Theory indicates that the usefulness of agentic AI as an HRM tool depends on the capacity of the firm to govern (technical literacy and policy capacity), the organizational incentive to govern (ethical culture and leadership commitment) and the structural potential to govern (regulatory clarity and data infrastructure).

Table 3: Theoretical Frameworks Applied to Agentic AI in HRM

Theory	Core Proposition	Application to Agentic AI in HRM	Governance Implication
Resource-Based View (Barney, 1991)	Competitive advantage from VRIN resources	Agentic AI + governance capability = strategic HR resource	Governance capacity is co-determinant of AI value
Institutional Theory (DiMaggio & Powell, 1983)	Organizations conform to institutional pressures for legitimacy	AI governance adoption driven by coercive/normative/mimetic pressures	Regulatory clarity and professional norms are governance drivers
Socio-Technical Systems Theory (Baxter & Sommerville, 2011)	Joint optimization of social and technical subsystems	Agentic AI is a socio-technical actor requiring human system co-design	Human oversight roles must be intentionally designed
AMO Theory (Appelbaum et al., 2000; Jiang et al., 2012)	Performance = f(Ability × Motivation × Opportunity)	AI augments employee AMO; poor governance degrades all three	Governance mediates whether AI enhances or undermines AMO

Source: *Authors' construct*

Conceptual Framework

Based on the theoretical insights presented above and gaps in the literature, the paper presents a multi-tiered Agentic AI-HRM Governance Framework (AAHGF). In the framework, there are four interrelated layers, including: (1) Agentic AI Characteristics (autonomous agent layer); (2) HR Functional Application Domains; (3) Governance Mechanisms; and (4) Organizational Outcomes. Figure 1 shows the conceptual framework of the AAHGF.

Layer 1: Agentic AI Characteristics

The upper layer determines five characteristics of agentic AI systems that apply to HRM deployment. Autonomy is the ability of the system to start and implement the multi-step HR processes without the need to have human approval in every step. Goal-directedness refers to the capability of the system to understand the high-level organizational HR goals and break them down into subtasks with actions. Multi-step planning refers to the time ability to order actions by day or week to achieve more complicated HR goals – such as overseeing an end-to-end talent acquisition campaign. The adaptive memory helps the system to store the context of the past interactions and update its models as a reaction to new information. Tool orchestration includes the capacity of the system to activate and organize external systems like HR information systems (HRIS), calendar interfaces, assessment platforms, and communication channels in the support of HR functions (Wang et al., 2024; Park et al., 2023).

Level 2: HR Functional Application Domains

The implications of agentic AI applications to governance differ by the area of application, which covers all fundamental HR functions. In talent acquisition, agentic systems have the ability to analyse job requirements, find candidates, screen applications, perform structured digital interviews, assessments, and conditional offers (Pan et al., 2022; Raghavan et al., 2020). Within performance management, agentic AI may observe streams of productivity data, create real-time performance stories, detect patterns of underperformance, and create guided development discussions without having to wait until an annual review period (Bankins, 2021). When it comes to learning and development, agentic tutoring systems are capable of identifying each person on a case-by-case basis, crafting personalized learning journeys, and dynamically delivering content (Dwivedi et al., 2021). Compensation AI agents are able to compare salary information, simulate equity situations, and suggest compensation changes, which have direct legal and

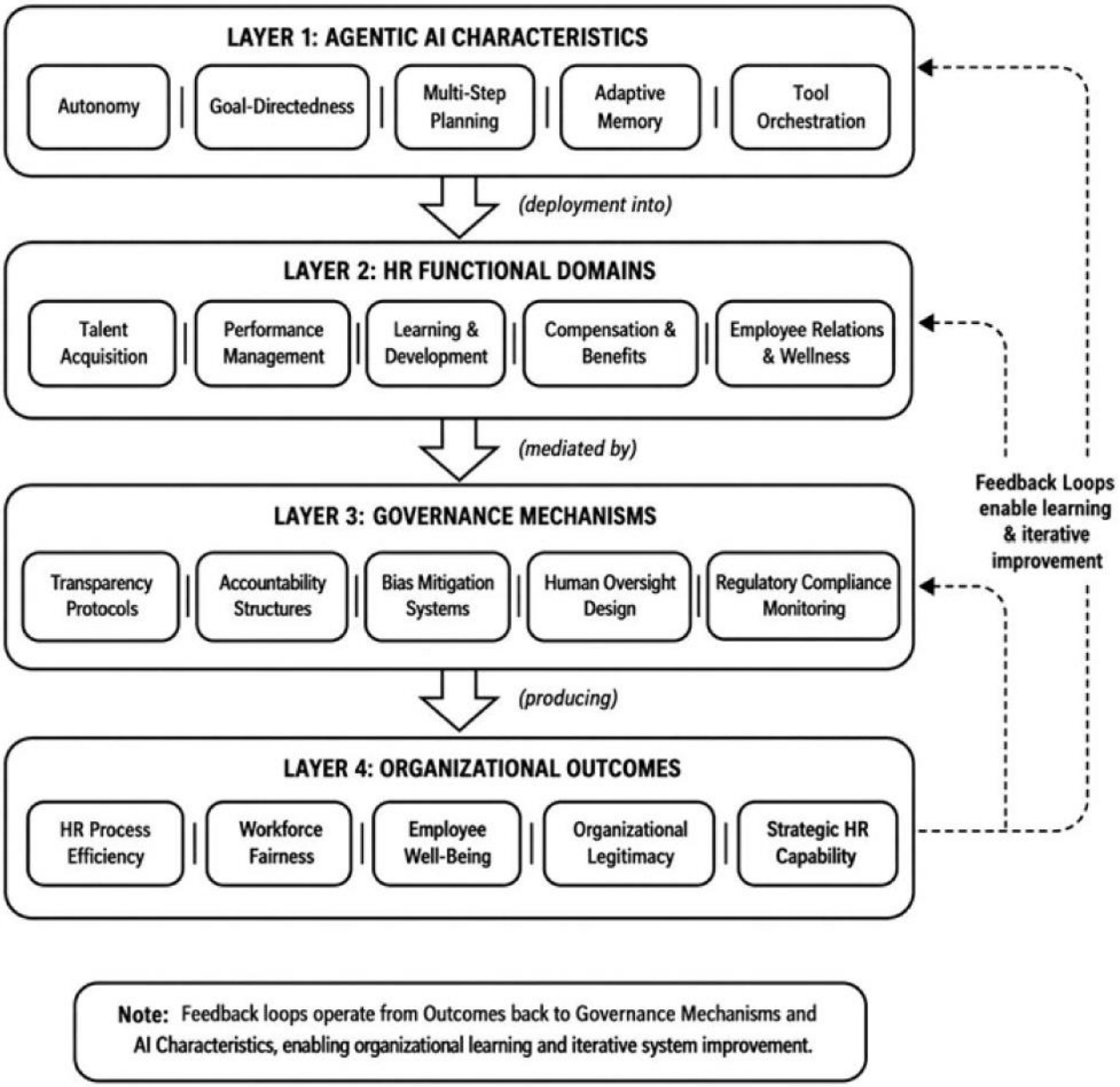


Figure 1: Agentic AI-HRM Governance Framework (AAHGF)

Source: *Authors' construct*

equity consequences. Engagement indicators, wellness-related route resources, and handling escalation channels of grievances can be tracked using agentic systems in employee relations, which might need particularly close governance to prevent over-surveillance (Giermindl et al., 2022).

Layer 3: Governance Mechanisms

The key mediating layer between the deployment of agentic AI and organizational results is governance mechanisms. There are five governor constructs in the framework. Transparency policies demand that agentic AI actions be made transparent to the impacted workers, human resource managers and regulators – in response to the vagueness of sophisticated neural structures. Accountability structures are also how responsibility is allocated in cases of agentic AI making consequential HR decisions, which are complicated to distribute in distributed human-AI systems

(Bankins, 2021). Bias mitigation systems are a way that operationalizes the identification, quantification, and remediation of demographic differences in AI-based HR outcomes (Raghavan et al., 2020; Mehrabi et al., 2022). The design of human oversight specifies the roles, decision rights, and intervention procedures in which human HR professionals would oversee, override and refine agentic AI behaviors, directly based on the principle of joint optimization of STS Theory (Baxter & Sommerville, 2011). Monitoring regulatory compliance helps to make sure that agentic AI activity complies with the existing data protection, labor, and anti-discrimination laws - an activity that will be particularly relevant to the changing legal environment in India (NITI Aayog, 2018).

Layer 4: Organizational Outcomes

The framework predicts an increase in five outcome dimensions when agentic AI is properly controlled. HR process efficiency indicates how fast, large-scale, and cost-effective AI-enhanced HR processes are. Workforce fairness refers to the fairness of HR decisions made among the demographic groups. Employee welfare includes objective (stress, workload) and subjective (meaningfulness, perceived fairness) aspects – features of ethical analysis in both works by Bankins & Formosa (2023). Organizational legitimacy shows how stakeholders think that the application of AI in HR decisions by the organization is accountable and reliable, which is dynamic in the manner that the Institutional Theory highlights social approval. Strategic HR capability embodies the RBV propositions that agentic AI, governed well, makes up a hard-to-replicate HR resource embedded within an organization (Barney, 1991; Mikalef & Gupta, 2021).

Research Propositions

Based on the theoretical underpinnings and the conceptual framework developed above, this paper develops seven research propositions. These propositions are supposed to be testable empirically and are based on the theoretical processes that are known in the AAHGF. These form a research agenda on which empirical research on agentic AI in HRM can be based.

Agentic AI and HR Process Efficiency

The argument of efficiency in AI usage in HRM is proven to be strong when it comes to traditional applications of analytics (Malik et al., 2022; Wamba-Taguimdje et al., 2020). It is estimated that agentic AI will amplify these efficiency benefits through its ability to make the use of multi-stage HR processes at scale and speed unattainable to human HR professionals acting independently. This suggestion is backed by the RBV viewpoint: Agentic AI as a VRIN organizational tool will result in higher HR operational efficiency compared to traditional AI tools.

Proposition 1 (P1): The organizations that have a higher level of agentic AI implementation in HRM will have a much more efficient HR processes (based on time-to-hire, cost-per-hire, appraisal cycle time, and the breadth of L&D personalization) than the organizations implementing conventional AI or manual HR processes, ceteris paribus.

Agentic AI, Governance, and Workforce Fairness

The benefits of agentic AI can never be achieved without the associated governance measures that will ensure that algorithmic bias does not lead to unfair workforce results. Raghavan et al., (2020) revealed that AI recruiting systems often reproduce past discrimination, whereas Mehrabi et al., (2022) established that discrimination in ML systems works in various directions. In the absence of active governance of bias mitigation, the scope of autonomous decisions of agentic AI only magnifies these effects.

Proposition 2 (P2): The positive association between the intensity of agentic AI deployment and the efficiency of HR processes will be weakened by the bias mitigation governance weakness: the less well-developed organizations will have a lower net efficiency gain because of compliance costs, litigation exposure, and reputational punishment because of discriminatory automated decisions.

Agentic AI and Employee Well-Being

Based on the AMO Theory and the meaningful work framework introduced by Bankins & Formosa (2023), the connection between the

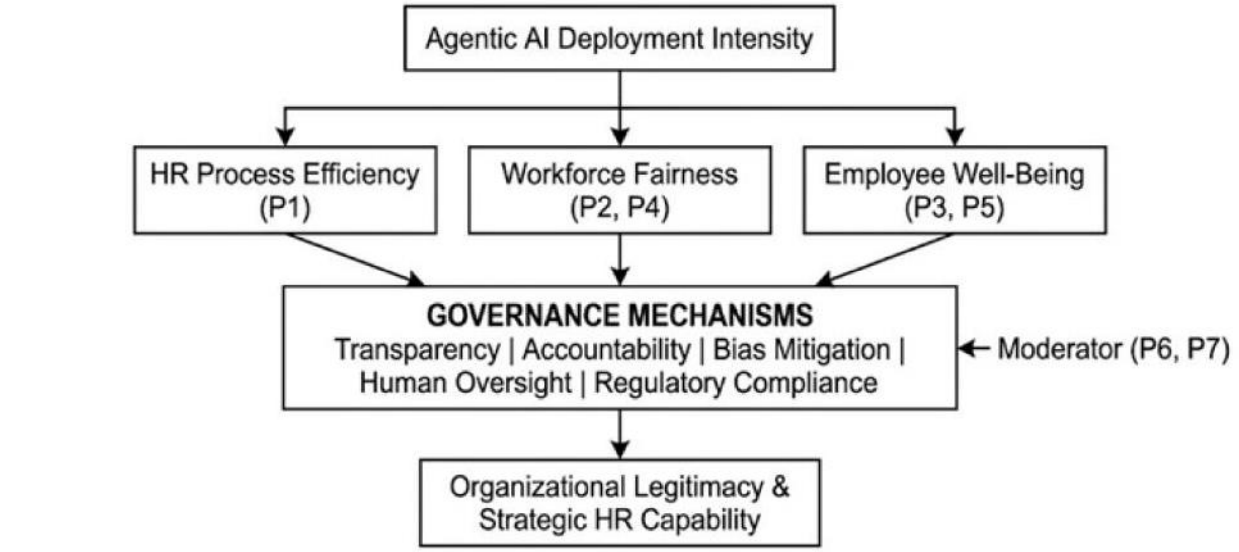


Figure 2: Research Propositions Model

Source: *Authors' construct*

implementation of agentic AI and the well-being of employees is likely to depend on the level of human agency maintained in the HR relationship between AI and humans. By eliminating human HR contact in favor of agentic AI, without maintaining channels of employee voice, appeal, and relational interaction, the risk is that psychological conditions of meaningful work (autonomy, purpose and social belonging) are undermined.

Proposition 3 (P3): Employee subjective well-being (perceived fairness, job meaningfulness, and HR relationship quality) will be negatively related to higher agentic AI implementation in HR functions without human oversight and appeal systems, and positively related to well-being with well-established human oversight.

Transparency Mechanisms and Perceived Fairness

One of the main principles of many AI ethics frameworks is transparency (Jobin et al., 2019; Floridi & Cowls, 2019). Transparency in the HRM context means that employees should be aware of the foundation on which agentic AI has made a decision that can impact their career. The Institutional Theory suggests that the commitment of organizational culture to an open AI HR practice will be the standard expectation as the stakeholders gain awareness of AI regulation.

Proposition 4 (P4): Implementing AI transparency mechanisms (explainable decision outputs, audit trails and employee notification protocols) in agentic HRM systems will positively correlate with employee-perceived procedural fairness, organizational trust, and acceptance of AI-mediated HR decisions.

Accountability Structures and Institutional Legitimacy

One key problem with agentic AI use in HRM is that accountability is distributed among technology developers, HR systems implementers, and managers of the organisation, introducing accountability gaps that Bankins (2021) claimed to be one of the key governance failure modes. Organizations will be in a better position to react to AI governance failures and retain institutional legitimacy when they have accountability structures, such as assigning explicit ownership, audit responsibility, and redress mechanisms.

Proposition 5 (P5): The institutionalization of agentic AI responsibility systems (such as the

appointment of AI governing bodies, auditing, and employee redress) will positively correlate with institutional legitimacy in the organization as perceived by staff, regulatory authorities, and third parties.

Governance Capability as Strategic HR Resource

Combining RBV and AMO Theory, it is suggested that the organizational ability to regulate agentic AI in HRM, such as the technical know-how to audit AI systems, the policy frameworks to regulate their application, and the cultural norms to regulate employee-AI relationships, is a VRIN organizational resource per se. This governing ability is what makes the difference between agentic AI deployment, creating either net strategic value or net strategic risk.

Proposition 6 (P6): Organizational AI governance capability (in terms of policy formalization, governance staff expertise, audit frequency, and ethical AI training programs) will be associated with better strategic HR performance resulting of agentic AI deployment (reduced involuntary attrition, increased talent quality, and improved employer brand) than low AI governance capability.

Emerging Economy Context Moderation

The intersection of the institutional Theory and the Indian HRM literature is in indicating that the governance environment plays a crucial role in moderating the relationship between agentic AI deployment and organizational outcomes (NITI Aayog, 2018; Budhwar et al., 2022). The issues of agentic AI governance are amplified in the context of emerging economies with less robust regulatory enforcement, a more diverse workforce, and less digital literacy.

Proposition 7 (P7): Negative impacts of weak AI governance on the fairness of the workforce and the well-being of employees will be more pronounced in the emerging economy organizational setting (e.g., India, South-East Asia, Sub-Saharan Africa) than in developed economy setting because of the differences in institutional enforcement capabilities, the heterogeneity of the workforce demographic, and the level of regulatory maturity.

Methodology

Rationale for Conceptual Approach

The paper follows a conceptual approach, which is compatible with the epistemological requirements of a study of an emergent phenomenon that rapidly changes, and that has not yet been studied with validated measurement scales and longitudinal data. The specific technology category of agentic AI only started making its way to the deployment context of organizations between 2023 and 2025; its HRM applications are thus still in the pre-paradigmatic stage of academic knowledge. The role of conceptual papers is crucial here: They provide theoretical background, define the boundary conditions, suggest the empirically testable constructs, and guide the future data collection activities (Duan et al., 2019; Dwivedi et al., 2021). This methodology aligns with that of Bankins (2021), Cheng & Hackett (2021) and Budhwar et al., (2022), who each utilized conceptual-theoretical frameworks to further the AI-HRM literature without conducting large-scale empirical tests.

The conceptual validity in this paper is attained in three ways. First, theoretical triangulation: the framework combines four very well-known theories, namely RBV, Institutional Theory, STS Theory, and AMO Theory, and each of them, in its turn, lends support to the propositions of the core at a different level of ontology. Second, logical consistency: every proposition can be traced to certain theoretical processes and empirical regularities that have been reported in the previous literature. Third, empirical pre-specification: the propositions are stated with adequate specifications to come up with testable hypotheses to be used in future survey-based or case-based research designs.

Proposed Empirical Validation Design

In order to provide the conduction of the conceptual framework towards the empirical study, this section identifies a research design that can be used in testing the propositions raised in Section 5. Phase 1 will use a quantitative, cross-sectional survey design with longitudinal, case study research in Phase 2. Phase 1 target population will include HR directors, CHRO-level executives, and HR technology managers in organizations that have reported AI-enabled HRM systems, and

are in the manufacturing, services, and IT industries in India. With a minimum of 250 organizations, structural equation modeling (SEM) is suggested to have sufficient statistical power.

Measurement Constructs

The constructs of interest would be operationalized using Likert-scale survey instruments (1 = strongly disagree, 5 = strongly agree), which have been validated. The scale of Agentic AI Deployment Intensity would be an eight-item scale assessing the scope and level of autonomous AI application in HR functions based on the scale of AI Capability that Mikalef & Gupta (2021) developed. The scale of Governance Mechanism Quality would consist of 20 items based on five sub-dimensions (transpa-rency, accountability, bias mitigation, human oversight, and regulatory compliance) and would be grounded on the ethics principles taxonomy of Jobin et al., (2019). HR Process Efficiency would rely on objective organizational data (time-to-hire, cost-per-hire, time-to-appraise) with manager-rated process effectiveness. The Utrecht Work Engagement Scale (UWES) and a five-item AI-specific fairness perception scale would be used to measure Employee Well-Being. A six-item reputational and regulatory compliance scale would be the measure of organizational Legitimacy.

Analytical Approach

The suggested method of analysis follows in three phases. To determine the dimensionality and psychometric properties of all multi-item scales, first, Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) based on IBM SPSS and AMOS software would be used. The Cronbach alpha (α 0.70 and above) and Composite Reliability (CR 0.70 and above) would be used to measure the construct reliability, the Average Variance Extracted (AVE 0.50 and above) and the heterotrait-monomethod (HTMT) ratios would be used to measure the discriminant validity. Second, the directional propositions in the research model, such as moderation effects defined in Propositions 2, 3 and 7, would be tested with Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 4.0. PLS-SEM is especially suitable in exploratory-confirmatory studies of new constructs (Hair et al., 2017). Third, the emergent economy moderation hypothesis (P7) would be tested with the use of multi-group analysis (MGA) that would compare India-based organizations with international standards established using the broader sample.

The ethical issues in data collection would be informed consent of organizational and individual respondents, anonymity of all HR data, and adherence to India Personal Data Protection framework. Since the data of organizational AI governance is sensitive, a snowball sampling method would be used to supplement purposive organizational sampling to access HR technology decision-makers.

Discussion

The propositions and conceptual framework formulated in this paper are open to a number of substantive debates regarding the intersection between AI technology, organizational management and governance. This part provides a more detailed discussion of the theoretical and practical implications of the AAHGF, frames the analysis in the context of HRM and AI literature, and explains in which circumstances agentic AI is most likely to produce positive or negative organizational performance.

Theoretical Implications

The initial and the most basic theoretical implication is the necessity to draw the line between agentic AI and the previous-generation AI/ML tools as the qualitatively different governance issue. Existing models of AI in HRM, such as those by Cheng & Hackett (2021), Bankins (2021), and Budhwar et al., (2022), have been designed based on passive, recommendation-generating systems. The agentic paradigm (marked by goal-pursuit persistence, re-planning, and autonomous orchestration of tools) challenges many of the main assumptions of these models (Wang et al., 2024). Above all, it is no longer possible to assume that a human decision-maker always intervenes between the output of AI and the action of the organization. This puts the centre of control no longer in the human decision-making process but in the design, operation

parameters and monitoring infrastructure of the AI system.

The multi-theoretic approach taken in this case provides other insights than each lens separately. RBV sheds light on the inequality in the value creation of organizations: The ones investing in the governance capability and technical AI capability will perform better than those using AI deployment as a technical activity only. It aligns with the empirical conclusion that performance impacts of AI capability are mediated by organizational absorptive capacity, as found by Mikalef & Gupta (2021). Institutional Theory incorporates a macro-level view: Agentic AI governance practices will be diffused following isomorphic patterns and initially motivated by regulatory compulsion within high-risk deployment areas (e.g., hiring, compensation) and eventually normalized via professional and competitive mechanisms. The contribution of STS Theory is prescriptive: it requires that the governance structures should not be designed as focused on technology, but rather on the socio-technical set-up in its entirety: The role, competence, and authority of human agents of oversight.

Perhaps the most subtle implication is that of the AMO Theory: That agentic AI is not in itself inherently good or bad in terms of employee outcomes, but that it has purely conditional effects based on its design and control. A system agentic HR that enhances employee capability (by supporting personalized learning), honors employee motivation (by making transparent and fair decisions), and increases employee opportunity (by making talent decisions without bias) will result in positive AMO implications. When the identical system is implemented without these governance conditions, it will have the opposite effect, i.e., decreasing the chances of using skills, perception of procedural justice, and reducing access to developmental resources by disadvantaged groups (Bankins & Formosa, 2023; Raghavan et al., 2020).

Implications for HR Managers and Organizations

To the HR managers, the AAHGF would mean a complete change of the HR itself. With operational HR implementation being taken over by agentic AI, the strategic merit of human professionals is progressively in AI governance: Defining the goals, moral standards, and performance indicators that autonomous systems will adhere to; establishing human control mechanisms that maintain procedural fairness; and making sense of the AI-generated information in the qualitative, contextual, and relational aspects of workforce management that are beyond the capacity of autonomous systems to replicate. This demands new HR capabilities such as AI literacy, data ethics, and algorithmic auditing – capabilities not yet systematically taught in HR education and professional development courses.

Organizations have a wider strategic option: To look at agentic AI governance as a compliance cost or as a strategic investment. The latter framing is highly supported by the RBV logic developed in this paper. Companies that establish their own governance frameworks, educate HR personnel on AI governance, and invest in ongoing algorithmic auditing will, over time, build governance capabilities that will become real competitive advantages in talent marketplaces, especially as employees, regulators and investors become increasingly suspicious about AI practices in organizational decision making. The growing attention to the social governance criterion of algorithmic responsibility as an element of the ESG movement supports this strategic rationale even further.

The Indian context, in particular, has been placed in a paradoxical position as large conglomerates/IT services companies have the technical capacity to apply agentic AI to HRM on a scale, but they are based in institutions in which the norms of governance are still in the crystallization phase. This offers a first-mover governance bonanza: The responsible agentic AI frameworks developed by firms that lead in to regulatory requirements will determine the normative rules that come to be codified in the future – a dynamic that aligns with normative isomorphism in Institutional Theory. This strategic posture is supported by a favorable policy framework supported by recommendations of

NITI Aayog (2018) on responsible adoption of AI, although yet to be fully operationalized in the employment regulation.

Managerial Implications

The paper leads to a number of implications which are directly practical to organizational leaders and HR practitioners.

- *Governance Architecture:* HR leaders must create an AI Governance Committee that is cross-functional (HR, Legal, IT, Ethics/ Compliance) to monitor AI agentic systems implementation, its ongoing enhancement, and improvement. This committee is supposed to determine deployment limits, give changes to the algorithms and present governance measurements to the board.
- *Explainability by Design:* All agentic AI uses in HR decision-making must include explainability features that produce decision stories in plain language that are accessible to the employees who are being impacted. It is not only an ethical but a practical necessity: employees that are informed about the AI decisions will be more inclined to accept it and less inclined to issue legal claims (Floridi & Cowls, 2019).
- *Bias Auditing as a Standard Operating Procedure*: Each agentic AI system in all HR functions should be audited at pre-deployment and annually, and in India, caste-biased audits should be conducted (to be done on gender, caste, religion, age, disability, and educational background disparities). The results of bias audits should be communicated both internally to HR leaders and, depending on regulatory frameworks, publicly.
- *HR Competency Transformation:* Organisations need to reskill HR workers around an AI-enhanced job description that focuses on AI oversight, ethical judgment, relational coaching, and managing organisational change – competencies that do not overlap with agentic AI competencies. This capability can be enhanced with the help of partnerships with business schools and AI ethics organizations.
- *Human Override Protocols:* Exceedingly automated agentic HR systems must not deny human decision-making rights at crucial points: Final hiring, termination or disciplinary measures, compensation determination, and interventions to mental health of employees. These human-in-the-loop checks guard organizational responsibility as well as the dignity of the employees.

Policy Implications

The governance issues as discussed in this paper are not only limited to particular organizations but also to the regulatory and policy environment within which the organization is operating. The policy implications listed below are promoted to be considered by lawmakers, regulators, and professional organizations- specifically, in the context of the developing AI regulation in India.

- *Employment AI Legislation in India:* In India, there is no particular legislation on AI use in the employment decision-making process. The Digital Personal Data Protection Act (2023) deals with privacy of data but makes no specific regulations on the use of algorithms in making employment choices. Specialized AI-in-employment regulation, similar to the AI Act that will soon be introduced in the European Union, that categorizes AI in recruitment and performance management as high-risk, is urgently required. This control must include prescriptive pre-deployment impact assessment, bias-auditing, and right to notification of employees.
- *Mandatory Disclosure Standards:* National regulators such as the Ministry of Labour and Employment and SEBI (in case of listed companies) ought to establish and implement AI governance reporting in HR by making organizations obliged to declare the field of autonomous AI application in employment decisions in their annual reports and Corporate Social Responsibility (CSR) reports. This would establish accountability incentives in a market fashion.
- *Professional Standards of Algorithmic HR:* Sector-specific codes of AI governance should be created to regulate HR practice by professional bodies, including the National HRD Network (NHRD), the Confederation of Indian Industry (CII) and the chapter of the Society

of Human Resource Management (SHRM) India, to establish professional standards of agentic AI use and management in employment relations. Such codes would direct normative isomorphic pressures to responsible AI governance.

- *Public Investment in AI Governance Infrastructure:* Regulators and multilateral organizations must invest in research and demonstration projects that establish technical and governance capacity to conduct agentic AI auditing in HR, especially among small and medium enterprises (SMEs) and employers in informal sectors, who cannot afford to develop proprietary governance systems. The AI governance infrastructure is especially useful in public goods in the context of emerging economies.

Limitations and Future Research

This paper notes a few limitations that, at the same time, outline possibilities in future research. First, since it is a conceptual paper, the AAHGF and the seven propositions are theoretically based but have not been empirically tested. The framework requires future empirical research, both quantitative survey studies and qualitative case research, to confirm the constructs, boundary conditions, and causal mechanisms of the framework. Section 6 gives the proposed empirical design as a starting point of this agenda.

Second, the analysis of emerging economies within the paper is mainly based on India, as it draws on the NITI Aayog strategy and Indian HRM literature. A comparative study across various emerging economies such as China, Brazil, South Africa, and Indonesia would add depth to the governance system by revealing inter-institutional differences in regulatory, cultural and labour market environments that mediate the AI-HRM governance nexus.

Third, the AAHGF considers agentic AI a relatively homogeneous category. In reality, agentic AI systems can differ significantly in terms of architecture, capability profile, and autonomy level, ranging between simple workflow automation agents to multi-agent systems with the capability to plan the workforce of an organization on a global scale. Further studies are required to create finer-grained taxonomies of agentic AI in the HRM domain and to investigate whether governance scales as a linear or non-linear function of agentic capability.

Fourth, the organizational and governance level of analysis perspective of the paper keeps the focus on staff opinions about agentic AI in HRM under theorized. The next generation of research ought to be focused on individual-level antecedents of employee acceptance or resistance towards AI-mediated HR decisions, based on technology acceptance models, organizational justice theory, and the literature on trust. Specific attention should be paid to the impact of demographic factors (such as gender, age, education, and occupational level) in the determinants of reactions to algorithmic HR governance.

Fifth, agentic AI technology is dynamic and rapidly changing, so the technical premises of the framework can change more quickly than they can be studied by the research community. To gain insight into the dynamics of governance over time, longitudinal research designs that follow organizations across multiple generations of agentic AI implementation will be critical. Researchers have been urged to work directly with entities that are experimenting with agentic AI systems so that they can produce theoretically informed practice-based insights.

Conclusion

This paper has presented the argument that agentic AI, characterized by its independence, goal-directedness, multi-step planning ability, long-term memory, and tool coordination, is a qualitative change in the nature of AI in HRM. In contrast to previous-generation analytics tools, which provide advice to human decision-makers, agentic systems are capable of operating to make consequential HR decisions at scale, speed and scope that can effectively restructure the architecture of organizational HR practice. This revolution creates both massive efficiency and customization advantages, but also creates governance issues: In terms of transparency, accountability, bias, and human control, which are poorly addressed by current HRM models.

The resulting Agentic AI-HRM Governance Framework (AAHGF) incorporates the Resource-Based

View, Institutional Theory, Socio-Technical Systems Theory, and AMO Theory into a conceptual framework with multiple levels that cut across agentic AI properties, HR functional domains, governance mechanisms, and organizational outcomes. The above seven research propositions go beyond just being theoretically based and actionable in practice as a future research agenda. To HR managers, the central message of the paper is straightforward: agentic AI can be valuable in HRM, but not in itself, but rather, conditional upon the organizational dedication to developing the governance capability, in addition to the technical capability. To policymakers, especially in India and emerging economies, the paper highlights the dire need to hasten efforts towards regulatory and professional frameworks of autonomous AI in employment before its use outpaces its regulation.

The age of agentic AI in organizations has started. The decision that organizations, regulators, and academics make in the coming few years will significantly determine whether it will enhance or undermine the tenets of fair, effective, and humane HRM. The present paper provides a theoretical and conceptual basis of making those decisions prudently.

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