

ORIGINAL CONTRIBUTION

Leadership Sense-Making of Workforce Value in AI-Enabled Talent Management: A Qualitative Inquiry

Rudsada Kaewsaeng-on¹, Asma Zeeshan^{2*}, Kashif Hussain³

^{1,2}Department of Business Administration, Prince of Songkla University Campus, Pattani, Thailand

²Asia Pacific University of Technology and Innovation, Kuala Lumpur, Malaysia

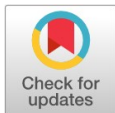
²Assistant professor, Bahria University, Islamabad, Pakistan

³School of Global Hospitality and Tourism, Asia Pacific University of Technology and Innovation, Kuala Lumpur, Malaysia

Abstract— Artificial intelligence is transforming how organizations assess, select, and develop talent, shifting workforce evaluation from static, retrospective criteria toward dynamic, predictive, algorithm-based models. Despite rapid technological growth, little is known about how organizational leaders interpret and use algorithmic outputs when assessing workforce value. Prior research has emphasized technology performance and adoption outcomes while overlooking the conceptual, normative, and social dimensions of decision-making at the human–algorithm interface—an omission that matters because algorithmic outputs become organizational action through meaning-making, not data processing alone. This qualitative study examined how senior leaders make sense of workforce value within AI-enabled talent management systems, focusing on the cognitive, ethical, and social dimensions of that process. Twenty-two senior leaders across four sectors (technology, finance, healthcare, and manufacturing) participated in semi-structured interviews, analyzed using a six-phase thematic analysis framework. Five interrelated themes emerged: a shift toward capability and adaptability as measures of value, tension between human judgment and algorithmic authority, ethical concerns regarding fairness, transparency, and trust, emotional and social complexities in leader decision-making, and evolving skill requirements for leading in AI-supported environments. Drawing on Sense making Theory, the findings introduce ethical mediation as a distinct, practice-based leadership construct in AI-enabled human resource management and offer recommendations for developing leader capabilities in responsible AI governance and human-centered HRM system design.

Index Terms— Human capital, Artificial intelligence, Leadership, Sense-making, Talent management, Thematic analysis

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Introduction

Over the last decade, organizations have radically changed how they define, assess, and use their most basic resource: people. The rapid development and institutionalization of AI are fundamentally reorganizing the operational and epistemic principles of HRM. Traditional evaluative systems that are traditionally based on fixed measures like tenure, tier of position, and ex post performance measures are being replaced by algorithmically based, predictive models that favor future potential, behavioral indicators, and adaptability (Cooke et al., 2026; Jarrahi et al., 2021;

*Corresponding Author: smaz.buic@bahria.edu.pk

Raisch & Krakowski, 2021; Scarbrough et al., 2024). These approaches rely on machine learning, natural language processing, and people analytics to produce probabilistic estimates of employee value, so organizations can focus on what employees have already done rather than what they are expected to do (Boudreau & Cascio, 2017; Huang & Rust, 2018). This shift is not only technological but also interpretive, as workforce value is now constructed through an interaction between algorithmic evaluations and human judgment (Kellogg et al., 2020; Meijerink et al., 2015; Minbaeva, 2020; Minbaeva & Navrbjerg, 2023). Practically, this shift creates significant urgency. Recent industry reports suggest that greater than 75 percent of large organizations currently utilize one or more types of AI-enabled HR tools, however, little attention has been paid to providing managers with training to interpret or question AI-generated assessments, let alone how to ethically mediate them as part of an organizational development strategy (Deloitte, 2024). Thus, it is not uncommon for leaders to be expected to make high-risk decisions regarding staffing, including hiring, promotion, and succession planning in collaboration with systems whose logic they may not fully comprehend or even reasonably question. This represents a critical operational gap between technological capacity and human capacity to interpret and question AI-generated assessments. Organizations, policy makers, and HR practitioners alike are just starting to come to grips with this gap.

Leadership as an interpretive role is very important and has not been studied under this new paradigm. By definition, AI systems are effective pattern-recognition and prediction systems, but they do not create contextual meaning or account for the multifaceted socio-emotional nature of human work (Dwivedi et al., 2023; Huang & Rust, 2018). Instead, leaders provide an interpretive link between algorithmic outcomes and organizational choice. This interpretive task aligns with sense-making theory, which defines meaning as dynamic, socially situated, and influenced by ambiguity, equivocality, and the unavoidable need to act in uncertain situations (Maitlis & Christianson, 2014; Weber et al., 2022; Weick, 1995). Above all, AI does not resolve this ambiguity, it changes it. Leaders must navigate predictive models, conflicting information messages, and align machine-generated knowledge with experiential knowledge, organizational norms, and contextual judgment (Faraj et al., 2018; Jarrahi, 2018; Kellogg et al., 2020). Beyond leadership as an interpretive role, it can be seen as an expanded form of sense-making in which cognitive human abilities are not completely supplanted by algorithmic intelligence in AI-enabled HRM (Balasubramanian et al., 2022; Jarrahi et al., 2021).

Although much research exists on AI in HRM, prior work has generally focused on the performance characteristics of systems adopted for HRM purposes, the degree of success achieved through adoption, and concerns about governing these systems. However, few studies have examined how leaders interpret or act on results generated by AI-enabled HRM systems. Specifically, few studies have addressed how leaders validate AI-generated assessments, challenge them, translate them into actionable workforce decisions, or address the ethical and relational implications of doing so. Therefore, this study addresses that gap by exploring how leaders construct meaning around AI-generated assessments used to support workforce decisions. Organizations lack a full understanding of how leaders cognitively assess and ethically evaluate assessments produced by AI systems used in Talent Management. Evidence from numerous empirical studies suggests that the rate at which organizations have implemented AI in HRM far exceeds their ability to develop frameworks enabling leaders to interact with these systems responsibly (Meijerink et al., 2015; Raisch & Krakowski, 2021; Scarbrough et al., 2024; Sharma et al., 2025). That disparity is consequential because when leaders do not have clear and structured frameworks to guide their interpretation of AI generated assessments, they risk unconditionally deferring to algorithmic interpretations thereby diminishing due process in personnel matters (procedural justice), reducing employee confidence in the organization (employee trust), and decreasing accountability for employment decisions (organizational accountability) (Benabou & Touhami, 2025; Kellogg et al., 2020). The issue is thus both technological and fundamentally interpretive.

That interpretation reflects a subjective experience that is not always easy. Because leaders' continued attempts to align the output produced by technology with organizational reality that cannot be precisely defined through data produce a continued process of interpretation/validation/revision. These conditions cannot occur anecdotally, they reflect broader, more significant issues: meaning does not reside in data but in socially situated interpretive practices (Maitlis, 2005; Sandberg & Tsoukas, 2020). This paper identifies how using AI for personnel-related decisions may create perceptions of distrust and inequity due to a lack of transparency or fairness, and can damage the social fabric within organizations (Floridi et al., 2018; Kellogg et al., 2020; Meijerink et al., 2015). As a result, leaders must strike a balance between the potential benefits of using AI to improve the scale and efficiency of their decision-making while ensuring the principles of procedural justice, transparency, and respect for human dignity, all of which are essential to maintaining organizational legitimacy (Dwivedi et al., 2023; Murray et al., 2021). Upon reviewing prior studies, we identify a clear research gap. Although recent work has described the technical capabilities and organization-wide outcomes of AI-HR systems Dwivedi et al. (2023), Huang and Rust (2018), and Scarbrough et al. (2024), three critical areas still need exploration. First, researchers have not empirically studied how individual leaders interpret and make sense of the AI-based talent data generated by their organizations, particularly how they validate, contextually understand, and sometimes reject algorithmic recommendations. However, Raisch and Krakowski (2021) and Balasubramanian et al. (2022) have begun to examine these issues theoretically. Second, researchers have not specifically described or theorized the leadership practice of ethical mediation that leaders must complete when sharing information about AI-driven employee-related decisions with staff, what this study calls "ethical mediation," although Cooke et al. (2026) and Murray et al. (2021) have started to describe the relational and ethical aspects of communication in AI-HRM systems. Lastly, researchers have not empirically examined how previous sense-making research applies to AI-driven HRM. Weick (1995) developed his original sense-making framework, which was later expanded Maitlis and Christianson (2014) and Sandberg and Tsoukas (2020) to include digital transformation, strategic ambiguity, and crisis. However, none of these frameworks were designed to apply directly to the specific interpretive challenges algorithm-governed talent systems pose for senior leaders. Overall, this study aims to fill the gap in our knowledge regarding how senior organizational leaders interpret, negotiate, and ethically mediate AI-generated

workforce assessments within AI-enabled talent management practices.

Research questions

Based on the previously identified gaps in research, this study addresses the following research questions:

RQ1: How do senior organizational leaders interpret, construct, and negotiate workforce value within AI-enabled talent management environments?

RQ2: What cognitive, ethical, and relational tensions do leaders experience when incorporating algorithmic outputs into significant workforce decisions?

RQ3: To what extent does leaders' interpretive practice in AI-enabled HRM contexts modify or extend existing sense making theory?

RQ4: How is ethical mediation enacted as a leadership practice within AI-enabled HRM, and what are its dimensions, antecedents, and outcomes?

Research objectives

This study addresses the aforementioned research questions by pursuing the following objectives:

1. To investigate how senior leaders develop and communicate workforce value in AI-enabled talent management environments.
2. To identify the cognitive, ethical, and relational dimensions of leadership sense making at the human–algorithm interface.
3. To extend sense making theory into the under examined domain of AI-facilitated HRM.
4. To introduce and theorize ethical mediation as a distinct leadership practice in AI-enabled HRM, specifying its dimensions, antecedents, outcomes, and boundary conditions within algorithmically informed organizational decision-making.

Literature Review

The evolution of Human Capital Theory

Human Capital has undergone significant, transformative development over the past couple of decades. It has evolved from its traditional view as primarily an economic concept to a more multi-dimensional and holistic perspective on how workers contribute to their organizations. Classically, human capital was viewed as the total of all knowledge and skills acquired through education and experience, and the value placed on those knowledge and skill sets was determined by the worker's productivity and the organization's efficiency (Becker, 1993).

More contemporary research has expanded the definitional parameters of human capital in many ways. Researchers are beginning to identify intangible and context-specific characteristics such as flexibility, resilience, mental health, and employee engagement as key contributors to workforce value (Guest, 2017; Minbaeva & Navrbjerg, 2023; Wright & McMahan, 2011). Further, human capital is increasingly seen as an emergent social construction created through interactions among individual agency, organizational systems, and technological systems (Boudreau & Cascio, 2017; Cooke et al., 2026), rather than something that exists solely within an individual. This new conceptualization of human capital has both strategic and practical implications. If human capital is dynamic and relational rather than static and individualistic, organizations must develop measurement and evaluation tools that reflect this reality. As a result, AI use in HRM is increasing. Organizations are seeking more responsive and prescriptive approaches to identifying and developing their human capital.

AI-enabled HRM: Capabilities, risks, and organizational implications

Integrating AI into HRM has helped accelerate the translation of human capital theory into theoretical and practical applications in organizational practice. Introduced AI systems have become widely adopted in key HR processes, such as recruitment, performance analysis, talent analytics, workforce planning, and succession management, allowing companies to process large amounts of structured and unstructured data and generate predictive data that could previously be analyzed solely by humans (Dwivedi et al., 2023; Scarbrough et al., 2024; Sharma et al., 2025). This technological capability has propelled a major shift from descriptive and diagnostic HR analytics to prescriptive and predictive analytics, fundamentally redefining how organizations discover, evaluate, and develop talent (Huang & Rust, 2018; Minbaeva & Navrbjerg, 2023). Recent high-volume reviews have affirmed that AI is becoming a center of efficiency, standardization, and scalability in HR systems, especially in high-volume recruitment and performance management settings. Meanwhile, interdisciplinary studies point to the rapid development of AI-HRM research, which is linked to the growing strategic prominence of technology in digitized organizations.

Despite these advances, numerous researchers have identified several critical issues associated with using AI in HRM. One of the most significant issues identified is algorithmic opacity. Most AI systems used in organizational decision-making are black boxes that produce statistically powerful yet analytically opaque results, making it difficult to understand how decisions are made or to challenge flawed outcomes (Rudin, 2019). This ambiguity is not only a technical inconvenience, its accountability loopholes are significant and hard to address, and the threat of algorithmic

bias only compounds the problem. Scholars remain divided here. While some argue that explainability tools can sufficiently address algorithmic opacity Rudin (2019), others contend that interpretability is structurally incompatible with the complexity of deep learning models used in HR contexts Kellogg et al. (2020), leaving this debate unresolved in the literature. As the work of AI systems is based on historical data, it can encode, reproduce, and, under some conditions, amplify social inequalities (Mehrabi et al., 2021), which, in turn, is a well-known threat to diversity, equity, and inclusion in hiring, promotion, and evaluation (Benabou & Touhami, 2025; Raghavan et al., 2020). Systematic reviews have characterized this as a twofold effect: AI can reduce standardization and even structural inequalities unless it is closely regulated.

Sense-making theory: Foundations and organizational applications

The initial idea of sense-making theory, proposed by Karl Weick (1995) and later elaborated by Maitlis and Christianson (2014), offers an invaluable framework for understanding how leaders solve interpretative dilemmas that AI brings to an organization. In a nutshell, sense making theory rests on the assumption that human beings and organizations do not immediately process information, instead, they make sense through a retrospective, ongoing, socially embedded process of interpretation. Ambiguity and equivocality do not need to be removed, they are aspects of organizational life that contribute to sense-making. This knowledge is particularly relevant in the AI-enabled space, where AI does not eliminate ambiguity but creates new, more complex forms of it. Today, leaders need to make sense of probabilistic outputs from systems they may not fully understand, balance conflicting data signals, and combine machine-based evaluations with experience, interpersonal knowledge, and organizational context (Dwivedi et al., 2023; Jarrahi et al., 2021). More recent work has gone further, suggesting that intangible but organizationally essential aspects of human work, such as creativity, empathy, collaboration, and contextual judgment, are often absent in AI systems, thus, human interpretive intervention is not only desirable but structurally necessary to make well-balanced and responsible decisions.

Leadership as interpretive practice in AI-enabled environments

AI-enabled HRM leadership can thus be seen as a highly interpretive and socially situated practice. Leaders do not simply accept algorithmic results. Instead, they actively sense-make, refracting, contextualizing, affirming, and occasionally questioning algorithmic outputs to align them with organizational values, ethical commitments, and relational realities (Cooke et al., 2026; Raisch & Krakowski, 2021). Recent data indicate that the success of AI implementation is strongly moderated by leaders' AI literacy: the more analytically informed their understanding, the better they can interpret algorithmic knowledge and apply it responsibly. This supports the theoretical understanding of leadership in AI-driven worlds as an extended sense-making process in which human thinking is not replaced by technological prowess (Balasubramanian et al., 2022; Jarrahi et al., 2021). This is vividly portrayed by narrative evidence in previous studies. According to one executive, it is a powerful system, but it does not replace judgment, it requires better judgment, which is why they call this the augmentation paradox. AI clearly improves analytical capacity, but it cannot be operated without enhanced human interpretive effort (Dwivedi et al., 2023; Raisch & Krakowski, 2021). As cognitive requirements rise, theory cannot overlook the relational and ethical aspects of AI-mediated leadership. In opaque algorithmic decision-making, employees can be significantly affected by perceiving that decisions impacting their careers were made without considering them, which can lead to severe outcomes for trust, perceived fairness, and organizational commitment (Kellogg et al., 2020; Meijerink et al., 2015). Leaders also mediate the relationship between AI-based HRM systems and the processes that create and reinforce relational cohesion and organizational legitimacy. Leaders can create narratives that help build the relationships needed to support relational cohesion and organizational legitimacy (Floridi et al., 2018; Murray et al., 2021).

Theoretical framework

This study draws on Weick (1995) theory of organizational sensemaking. This theory is chosen due to its direct relevance to how individuals and groups construct meaning given ambiguous, equivocal, and uncertain conditions, conditions that are structurally inherent in AI-driven decision-making environments. According to sense making theory, meaning is not found but rather enacted: it is a retrospective, socially situated, and action-oriented process through which actors create adequate explanations sufficient to allow for organizational responses (Maitlis & Christianson, 2014; Weick, 1995). Because AI does not remove ambiguity in evaluating personnel, it merely re-configures it by providing probabilistic outputs that require active human interpretation before action, making this theoretical lens particularly well-suited to this investigation (Balasubramanian et al., 2022; Jarrahi et al., 2021).

This study's framework comprises three analytical dimensions derived from previous studies. The first analytical dimension involves the cognitive aspect: How do leaders evaluate, validate, and contextualize algorithmic outputs in relation to experiential and organizational knowledge? (Raisch & Krakowski, 2021). The second analytical dimension involves the ethical aspect: How do leaders address fairness, transparency, and accountability when communicating/implementing AI-based decisions? (Floridi et al., 2018; Meijerink et al., 2015; Murray et al., 2021). The third analytical dimension involves the relational aspect: How do leaders establish/trust-building interpersonal relations/organizational cohesion when establishing/consequential decisions are made with partial reliance on non-human systems? (Cooke et al., 2026; Kellogg et al., 2020).

In summary, the three conceptual dimensions outlined above collectively provide the theoretical architecture against which this study examines the process of leadership sense-making in AI-enabled HRM. Figure 1 depicts the conceptual framework illustrated in this paper. This conceptual framework views sense-making as the overarching lens through which the analysis of each of the three dimensions (cognitive, ethical, and relational) that operate at the human-machine interface can occur.

Ethical mediation: Conceptual definition and theoretical positioning

Ethical mediation is defined as the active, iterative, and socially embedded leadership practice of translating AI-generated workforce assessments into decisions that are cognitively validated, ethically justifiable, relationally communicated, and organizationally legitimate. It is not a disposition or trait, but a practice-level competency enacted at the human–algorithm interface. As a construct, ethical mediation consists of three core dimensions: (i) interpretive validation which is the cognitive work of scrutinizing, contextualizing, and selectively accepting or overriding algorithmic outputs, (ii) communicative transparency which is the relational labor of explaining AI-informed decisions to affected employees in ways that preserve dignity and trust, and (iii) moral accountability which is the ongoing reflexive responsibility leaders assume for outcomes that are jointly produced by human and algorithmic agency. The antecedents of ethical mediation include: the opacity of algorithmic systems (which creates interpretive demand), organizational cultures of accountability, leaders' AI literacy, and the ethical stakes associated with consequential HRM decisions (e.g., promotion, succession). Its outcomes include: perceived procedural fairness among employees, organizational trust, reduced accountability vacuums, and the legitimation of AI-assisted decisions within relational organizational contexts.

Ethical mediation is conceptually distinct from, though theoretically related to, several adjacent constructs. It differs from ethical leadership Brown et al. (2005), which refers to a broad moral character orientation and role-modeling of ethical conduct, by being specifically situated at the human–algorithm interface and tied to the interpretive demands of AI-mediated decision contexts. It differs from responsible leadership Maak and Pless (2006), which emphasizes stakeholder relationships and strategic-level accountability, by foregrounding the micro-level communicative and interpretive practice through which algorithmic outputs are rendered organizationally intelligible. It extends beyond AI governance frameworks (Floridi et al., 2018), EU AI Act, (2024), which are largely prescriptive and system-level, by theorizing how humans enact governance values at the point of organizational decision-making. Finally, it differs from algorithmic accountability Kellogg et al. (2020), which focuses on technical audibility and legal compliance, by emphasizing the relational and communicative labor that leaders perform regardless of whether formal accountability mechanisms exist. Ethical mediation is thus positioned as a meso-level leadership construct that bridges normative AI governance theory and the micro-level interpretive practices documented in sense-making research. Its boundaries are defined by the presence of algorithmically mediated, high-stakes decisions affecting human capital, it does not apply to routine or fully automated low-stakes processes where no meaningful interpretive leadership is required.

Positioning sense-making against alternative explanations

Several theoretical traditions could plausibly inform the interpretation of AI-enabled leadership in talent management. Algorithmic management theory usefully explains how digital systems structure control, monitoring, and coordination, but its primary concern is governing labor through algorithmic systems rather than the interpretive work senior leaders do when translating workforce assessments into consequential organizational decisions. Responsible leadership theory helps explain ethical and stakeholder-oriented leadership obligations. Still, it is less suited to explaining the micro-processes through which leaders make sense of ambiguous, probabilistic, and often opaque algorithmic outputs in specific decision episodes. Institutional theory can illuminate how organizations respond to legitimacy pressures and adopt AI-enabled practices under normative or regulatory expectations. Still, it does not by itself provide a sufficiently fine-grained account of how leaders interpret, negotiate, and enact those systems in practice. Socio-materiality and technology enactment theory each offer valuable insight into the co-constitutive relationship between technology, actors, and organizational context, yet they are broader in ontological scope than the present study's specific interest in meaning construction under ambiguity.

Research gap and theoretical propositions

The existing literature offers an advanced view of AI's transformative potential in HRM, alongside its significant constraints. What it has yet to cover sufficiently, however, is the embodied experience of factual interpretation among leaders who interface these technological capabilities with human organizational realities. The most common area of research has been either system-level outcomes, which consist of recruitment efficiency, predictive accuracy, process standardization, or normative governance questions regarding what organizations ought to do to implement AI responsibly (Cooke et al., 2026; Raisch & Krakowski, 2021; Scarbrough et al., 2024). Very little attention has focused on the micro-level, practice-centered question of how leaders make sense of AI-generated outputs in practice-based organizational settings, how they bargain over interpretive dilemmas, how they cope with ethical ambiguity, and how they maintain relational trust as they translate algorithmic cues into consequential choices. This gap is theoretically important because, as sense-making theory has shown, the quality of any interpretive process is a

key determinant of the quality of the decisions and actions that result. Efforts to enhance AI governance and integration cannot be complete without understanding how leaders interpret AI outputs. Table I below compares the results of prior studies with those of the current study.

Ethical mediation operates at three analytically distinct levels: the cognitive level (validating and contextualizing algorithmic outputs), the communicative level (translating those outputs into humanly intelligible and defensible narratives for affected parties), and the moral level (assuming and distributing accountability for decisions that are jointly produced by human and non-human agency). These levels correspond to the three analytical dimensions of the conceptual framework and anchor the construct empirically in the themes that follow.

Table I
Research gap

Studies	Key Contribution	Shortcoming	This Study's Response
Maitlis & Christianson (2014) and Weick (1995)	Sense-Making has been framed as a socially embedded, ambiguity driven processes of meaning creation	Studies have Not Applied Sense Making Theory to Algorithmic Decision Making in Human Mediated Organizations	Extends sense-making theory into AI-enabled HRM, demonstrating how AI reconfigures rather than resolves interpretive complexity
Raisch & Krakowski (2021)	Human-AI Collaboration has been defined as augmentation rather than replacement, Introduced the Augmentation Paradox	No Study Examines How Leaders Experientially Navigates These Tensions in HR Specific Contexts	Provides empirical, narrative evidence of how leaders live and manage the augmentation paradox in talent management
Mehrabi et al. (2021), Benabou & Touhami (2025)	Document Algorithmic Bias Risks in AI Systems, Implications for Diversity and Fairness	Focused on System-Level Biases Rather Than How Leaders Interpret, Respond To Or Contest Biased Outputs From Algorithms	Examines leaders' ethical sense-making and their role as ethical mediators in AI-influenced decision processes
Kellogg et al. (2020), and Meijerink et al. (2015)	Explore How Algorithmic Management Influences Employee Trust, Autonomy, and Perceptions of Fairness	Under-explored Role Of Leadership In Mediating Employee Perceptions Of AI-Driven Evaluation Processes	Foregrounds the communicative and relational leadership work required to sustain trust in AI-mediated HR environments
Minbaeva & Navrbjerg (2023) and Cooke et al. (2026)	Examine strategic and organizational dimensions of AI adoption in HRM	Lacked Qualitative Depth Concerning Leaders' Interpretative Practices And Subjective Experiences With AI Tools	Offers rich, interview-based insight into how leaders construct and revise their understanding of workforce value through AI interaction
Floridi et al. (2018) and Murray et al. (2021)	Provide Ethical AI Principles and Governance Frameworks for Responsible HR Practice	Prescriptive Rather Than Practitioner-Grounded Nature Of Most Governance Frameworks	Develops the concept of ethical mediation as an empirically grounded leadership function, bridging governance theory and organizational practice
Dwivedi et al. (2023) and Scarbrough et al. (2024)	Review Current State-of-the-art Research Landscape in AI-HRM and Identifying Trends in Predictive Analytics	Micro-level sense-making processes of individual leaders were not the focus	Provides a qualitative, practice-level account that complements macro-level trend analyses with human-scale interpretive depth

Methodology

Research design

This study adopts a qualitative, interpretive design because the research questions focus on how senior leaders make sense of AI-generated assessments in consequential talent-management decisions. A qualitative approach is appropriate because the aim is not statistical generalization, but contextual understanding of how leaders interpret, negotiate, and act on algorithmic outputs in practice. Reflexive thematic analysis was selected because it allows patterned meaning to be identified across diverse organizational settings while remaining compatible with the study's interest in leadership sense-making. As a qualitative method, it does not presume social reality as a constant, objective object, but as something that people create when they experience, interpret, and relate to each other (Saunders et al., 2019). This ontological stance resembles a hypothetical construct of the sense-making theory, which takes meaning as an emergent, contextual, and socially situated, yet not fixed and pre-given one (Maitlis & Christianson, 2014; Weick, 1995). When AI-assisted HRM requires leaders to make high-stakes decisions with human implications and relies on ambiguous algorithmic outputs, qualitative research will deepen our understanding of how this process unfolds and yield a more advanced, empirically supported description. Unlike previous attempts to discover universal truths or generalized patterns, this study aims to produce richly detailed contextual insights that can complement both theoretical richness and applied implications for organizations seeking to adapt to the complexities of integrating AI.

Study population

The researcher selected participants using purposeful sampling. The researcher selected respondents who were entitled to express their opinions, had experienced the intersection of AI systems and talent management decision-making, and worked in professions where decisions could no longer be seen as merely incidental or mystical features of their job description. Therefore, the sample included representatives from top management within organizations, consisting of HR directors, departmental heads, and academic administrators, as well as from various departments within organizations. This cross-sectoral diversity was intentionally targeted to capture a wide range of institutional contexts, AI system types, and leadership cultures, enabling deeper analytical depth and greater transferability of the results.

Twenty-two Senior Leaders from five different industries completed the study. The industries included Technology ($n = 6$), Financial Services ($n = 5$), Healthcare ($n = 4$), Manufacturing ($n = 4$), Professional Services ($n = 3$). Participants were based in major cities across Pakistan, including Karachi, Lahore, Multan, Peshawar, Quetta, and Islamabad. While the study maintained sector diversity, it also achieved cross-contextual breadth. Demographically, participants had 8 to 27 years of leadership experience ($M = 16.3$ years), with 13 male and 9 female respondents. Organizational size ranged from mid-sized enterprises (500–2,000 employees) to large multinational corporations (>10,000 employees). Initial recruitment used professional networks and institutional contacts, and subsequent participants were identified through purposive chain referral to reach theoretical saturation (Braun, 2016). Saturation was defined not as the exhaustion of all possible variation, but as the point at which additional interviews no longer generated substantively new codes regarding leaders' interpretive, ethical, and relational engagement with AI-enabled HRM, and instead deepened already identified thematic patterns.

Participation was not based on seniority alone. To be included in the study, participants had to satisfy four criteria: (1) hold a senior role with decision authority in talent management, workforce planning, performance management, recruitment, promotion, or succession, (2) report direct involvement with at least one AI-enabled HRM system used in their organization, (3) describe at least one concrete decision episode in which algorithmic output informed, challenged, or shaped managerial judgment, and (4) specify the type of system involved, including whether it was commercially purchased, internally developed, or configured as a hybrid solution. We assessed these criteria during recruitment and reconfirmed them at the start of each interview through screening questions on the system used, the HR process supported, duration of deployment, and the participant's role in interpreting or acting on the output. To improve contextual transparency, Table II summarizes the AI-enabled HRM environments represented in the sample. The table shows the types of systems participants engaged with, the breadth of adoption, and each participant's role in interpreting or acting on AI-generated outputs.

Table II
Organizational AI-HRM context of participants

ID	Sector & Location	Gender	Senior Role	HR Domains Supported by AI	Tool Type	Duration (Years)	Adoption Level	Decision Role
P1	Technology (Karachi)	F	HR Director	Recruitment screening, workforce planning	Commercial	2.0	Partial	Final decision-maker
P2	Technology (Lahore)	M	Head of People & Culture	Employee engagement, retention prediction	Hybrid	1.5	Pilot	Influencer, recommends tools
P3	Technology (Islamabad)	F	Chief People Officer	Talent acquisition, performance, L&D	Hybrid	3.0	Embedded	Strategic owner & budget holder
P4	Technology (Peshawar)	M	HR Business Partner (Sr.)	Scheduling optimization, chatbots	Commercial	1.0	Partial	Operational user with input
P5	Technology (Karachi)	M	Talent Acquisition Lead	CV screening, candidate matching, scheduling	Commercial	2.5	Embedded	Co-decision-maker
P6	Technology (Lahore)	F	VP of Global Talent	Workforce analytics, leadership succession	Internal	4.0	Embedded	Final decision-maker
P7	Financial Services (Karachi)	M	Chief Human Resources Officer	Fraud detection in HR, payroll automation, comp	Internal	3.0	Embedded	Strategic owner & budget holder
P8	Financial Services (Lahore)	M	Head of HR Operations	Background checks, compliance tracking, benefits	Commercial	2.0	Partial	Co-decision-maker

Organizational AI-HRM context of participants

ID	Sector & Location	Gender	Senior Role	HR Domains Supported by AI	Tool Type	Duration (Years)	Adoption Level	Decision Role
P9	Financial Services (Islamabad)	F	Head of Talent Management	Skill gap analysis, personalized learning paths	Hybrid	1.5	Pilot	Influencer, recommends tools
P10	Financial Services (Multan)	M	Senior HR Manager	Attendance tracking, basic sentiment analysis	Commercial	1.0	Pilot	Operational user with input
P11	Financial Services (Faisalabad)	F	Head of Rewards & Benefits	Predictive turnover mapping, comp optimization	Hybrid	2.0	Partial	Co-decision-maker
P12	Healthcare (Lahore)	M	Director Human Resources	Shift allocation, nurse fatigue predictive modeling	Hybrid	2.5	Embedded	Final decision-maker
P13	Healthcare (Karachi)	F	Head of Medical Staffing	Credential verification, automated sourcing	Commercial	1.5	Partial	Influencer, recommends tools
P14	Healthcare (Rawalpindi)	M	HR Business Partner (Sr.)	Dynamic scheduling, onboarding workflows	Commercial	2.0	Partial	Operational user with input
P15	Healthcare (Quetta)	M	Chief People Officer	Wellness tracking, cultural alignment metrics	Internal	1.0	Pilot	Strategic owner & budget holder
P16	Manufacturing (Karachi)	F	Group Head of HR	Labor union sentiment tracking, safety compliance	Internal	3.5	Embedded	Final decision-maker
P17	Manufacturing (Sialkot)	M	Director People & Ops	Workforce productivity analytics, shift balancing	Hybrid	2.0	Partial	Co-decision-maker
P18	Manufacturing (Gujranwala)	M	HR Operations Lead	Automated payroll queries, leave management	Commercial	1.0	Pilot	Operational user with input
P19	Manufacturing (Hyderabad)	F	Talent Acquisition Manager	Blue-collar high-volume sourcing, SMS bots	Commercial	1.5	Partial	Influencer, recommends tools
P20	Professional Services (Islamabad)	M	Partner - Human Capital	Billable hours optimization, skill matching	Hybrid	3.0	Embedded	Strategic owner & budget holder
P21	Professional Services (Karachi)	F	Head of HR Consulting	Outplacement predictive models, psychometrics	Commercial	2.0	Partial	Co-decision-maker
P22	Professional Services (Lahore)	M	Senior Director HR	Project-based team building, bench-strength analysis	Internal	1.5	Pilot	Final decision-maker

Data collection

The data were gathered through semi-structured interviews, which are ideal for research that aims to achieve both thematic consistency and individual depth. Unlike structured interviews, which limit participants to a set of response options, semi-structured interviews allow free exploration of participant-specific views and experiences while maintaining high consistency across the dataset, enabling systematic comparison (Kallio et al., 2016).

Table III provides an overview of the interview guide structure and examples of the questions to be used for each thematic area. Figure 1 presents the proposed study framework.

Table III
Interview guide structure and illustrative questions

Thematic Area	Focus	Illustrative Questions
Perceptions of Workforce Value	How leaders define and assess employee value in current organizational contexts	"what changes have you observed regarding what makes employees valuable over recent years?" / "What qualities or capabilities do you now prioritize when evaluating your team?"
Experiences with AI Tools and Systems	Leaders' direct engagement with AI-enabled HR tools and their interpretations of AI outputs	"Can you describe the AI tools or systems your organization uses in talent management?" / "How do you typically respond when an AI recommendation conflicts with your own judgment?"
Leadership Decision-Making in AI Contexts	The cognitive, emotional, and ethical dimensions of decision-making in AI-mediated environments	"Can you walk me through a recent situation where AI data played a role in a significant decision?" / "How do you explain AI-driven decisions to employees who are affected by them?"
Ethical and Relational Dimensions	Leaders' awareness of fairness, trust, and accountability in AI-enabled evaluation processes	"What concerns, if any, do you have about the fairness or transparency of the AI systems you use?" / "How do you maintain trust with your team when AI is involved in evaluation decisions?"



Fig. 1 Research framework

Data analysis

The data were analyzed using thematic analysis following the six-phase framework developed by Braun and Clarke (2006, 2022), one of the most widely adopted and methodologically rigorous approaches to qualitative data analysis, particularly in research concerned with sense-making and lived experience. The analysis is best characterized as an abductive, theoretically informed thematic analysis rather than a purely inductive one. Initial coding was data-led, with close attention to participants' language, experiences, and recurring patterns across interviews. In later stages, theme refinement involved iterative movement between the empirical material and sensitizing concepts drawn from sense-making theory, augmented intelligence theory, AI governance scholarship, and socio-technical systems theory. These frameworks did not function as a rigid a priori coding template, instead, they deepened interpretation, sharpened conceptual distinctions, and located the findings within existing theoretical debates (Braun & Clarke, 2006).

To increase rigor and transparency in the coding process, the lead researcher developed initial codes independently. After developing the initial codes, another independent researcher with expertise in qualitative human resources research coded a subset of the data (five transcripts). Using Cohen's kappa, the study assessed intercoder reliability and achieved $\kappa = .81$, indicating strong agreement and consistency within the coding framework (Landis & Koch, 1977).

Findings

This section presents the findings in a primarily data-near form, emphasizing how participants described their experiences working with AI-enabled HRM systems in their own organizational settings. Table IV illustrates the structural path used to derive the thematic coding framework illustrated below. It also shows the analytical route taken to develop each theme. It allows the reader to determine whether each theme developed is

grounded in the raw data. Table V presents the distribution of thematic evidence across participants, demonstrating the breadth and consistency of each theme across the sample.

Table IV
Thematic coding framework

Final Theme	Subtheme	Representative Initial Codes	No. of Sources
T1: Restructuring of Workforce Value	From credentials to capabilities	"adaptability over tenure," "potential not performance," "learning agility matters more now"	18
	Algorithmically constructed value	co- "system flags potential I'd have missed," "data changes how I see the team," "value is now partly calculated"	15
T2: Human Judgment vs. Algorithmic Authority	Epistemic tension	"I trust my gut more than the score," "the number feels too certain," "model doesn't know what I know"	20
	Selective deference	"I use it as a starting point," "override when context demands," "it confirms but doesn't decide"	17
T3: Ethical Tensions in AI-Mediated Decisions	Fairness concerns	"worried it replicates old biases," "hard to explain why it scored them low," "feels unfair to the employee"	19
	Transparency deficit	"I can't defend what I don't understand," "employees want reasons not scores," "black box problem"	16
T4: Emotional and Relational Complexity	Affective burden	"it's a difficult conversation when the data says one thing," "I feel responsible for humanizing it," "numbers don't feel the loss"	14
	Relational mediation	"my job is to keep the person in the process," "trust breaks when it feels mechanical," "I translate, not just transmit"	13
T5: Reconfigured Leadership Competencies	AI literacy demands	"had to learn what the model actually does," "understanding limitations is part of the job," "can't lead what you don't understand"	16
	Ethical mediation as competency	"balancing efficiency with dignity," "responsible for the human interpretation," "the system needs a conscience"	15

Inter-rater reliability for the coding framework was confirmed at $\kappa = .81$ Cohen (1960), based on a second researcher independently coding 20% of the data set. The team determined final themes through consensus review of all discrepancies.

Table V
Distribution of thematic evidence across participants

Theme	Participants Contributing Evidence	% of Sample
T1: Restructuring of Workforce Value	P1, P2, P4, P5, P7, P8, P10, P11, P13, P14, P16, P17, P19, P20, P21, P22	73%
T2: Human Judgment vs. Algorithmic Authority	P1–P22 (all participants)	100%
T3: Ethical Tensions	P2, P3, P5, P6, P8, P9, P11, P12, P14, P15, P17, P18, P20, P21, P22	68%
T4: Emotional and Relational Complexity	P1, P3, P4, P6, P7, P9, P10, P12, P13, P15, P16, P18, P19	59%
T5: Reconfigured Leadership Competencies	P2, P4, P5, P7, P8, P10, P11, P14, P16, P17, P19, P20, P21, P22	64%

Theme 1: Reconfiguration of workforce value

This theme speaks to the sense-making concept of frame disruption, the moment when existing cognitive schemes become insufficient and new interpretive structures must be actively built (Weick, 1995). One of the most consistent and common findings across the data set was a radical reappraisal of how the leaders thought about workforce value. Participants noted a deliberate shift toward a more dynamic, capability-based, and prospect-oriented view of employee contribution, rather than the previously inert, tenure-based, retrospective approach. Previously, organizations hired individuals who were mostly judged by their experience and past results. With the introduction of AI-based analytics, the emphasis has shifted to what they will become and how readily they can adapt to an organization's rapidly changing requirements. P1 quote represents a dramatic difference in perspective: "The value is no longer how long someone has worked for this organization, but how quickly he/she can adapt

to changes,” and P2 quote also supports the first quote but with slightly different phrasing. “We look at how people learn, not what they have learned, since information is outdated too quickly today.” Participants have collectively recognized that past metrics are limited in a world where speed, continuous learning, and digital literacy are the current currency of workers’ relevance to organizations. Developing this new language matters analytically, it illustrates Weick (1995) idea of a sense-making rupture, a moment when previous conceptualizations become unsuitable and new ones must be consciously created. Leaders are not just revising their measurement tools, they are reconstructing their understanding of what constitutes human contributions in work contexts. This finding aligns with the new study of learning agility and human-AI complementarity that indicates that the most valuable workers in the technologically-enhanced working environment are those who can co-operate with intelligent systems and offer context-judgment that cannot be handled by intelligent systems (Brey & van der Marel, 2024; Forum, 2025).

Importantly, the respondents did not mention AI as either validating or accelerating the already existing notion of value. Instead, they represented AI systems as actively building and even disrupting their interpretive systems. The results of AI, like predictive performance scores, analytics of behavioral trends, and capability map tools, brought new informational inputs unfamiliar to leaders and not necessarily entirely ready to process them. P4 replied, “The system only gives patterns, and it is our responsibility to determine what the patterns tell us about our people,” and P7 said, “AI only shows correlations, and the system does not know what it is like. That is our work.” That suggests something important is at risk in the quality of AI-enabled evaluations: it does not eliminate the need for human judgment, it changes the conditions under which those judgments are made. The new information leaders must handle is more detailed and abstract than prior evaluation measures, yet statistically precise and virtually devoid of contextual reference. The separation between the outputs of the algorithms and human interpretation is not unique, however, it represents a widely held concern found throughout other empirical studies of late that argue that AI- derived insights should be selectively inserted into appropriate contexts to prevent misinterpretation of those outputs and over-reliance upon those outputs Raisch and Krakowski (2021), and is a significant structural characteristic of the data.

Respondents also shared narratives of deliberate defiance and AI ratings when a personal experience led them to question or ignore what the system determined. P14 commented, “There are times when the system puts a person down, but we are confident that they are so much more than the data. Just impossible to measure situations, there are situations which cannot be reflected in the data, which demand critical judgment.” The narratives show that the value of the workforce in AI-enabled environments is negotiated and socially constructed.

Theme 2: Interpretive tension between human judgment and AI

The theme captures the epistemological core of augmented sense-making: the continuous negotiation between human judgment and algorithmic certitude (Jarrahi et al., 2021; Raisch & Krakowski, 2021). The theme describes the interpretive contradiction that emerges between AI-based recommendations and a leader’s professional assessment. Some participants described this contradiction as infrequent or minimal, while others indicated that the contradictory interpretations were an ordinary and structurally entrenched element of their decision environment. As P3 explained: “There are instances where I find a recommendation from a system that contradicts my years of experience.” Similarly, P6 noted that “While AI may provide conclusions with great confidence, it doesn’t necessarily mean that they are correct.” These statements illustrate a central contradiction in the relationship between human judgment and AI-based judgment, namely that AI-based solutions generate conclusions with a degree of objectivity that can be challenging to challenge, especially in organizations where data-driven decision-making is becoming increasingly popularized, however, that objectivity is generally based on patterns rather than contextual knowledge. In contrast to AI-based solutions, leaders who understand this contradiction may find themselves in a precarious position: exercising skepticism toward results with institutionally recognized validity simply because they appear objective (Burton et al., 2019; Scarbrough et al., 2024).

Participants didn’t identify this tension as a choice between relying on humans or machines, nor did they define AI as untrustworthy or counterintuitive to good judgment, instead, they described it as a process of continuous negotiation between the human interpreter and the algorithm’s output. Both components continually inform and challenge each other, with neither taking precedence. In fact, P12 stated that “The system gives us one view of the case, but it’s just one piece of the whole story. We have to add our understanding of the individual to the picture,” which is exactly how Raisch and Krakowski (2021) describe the augmentation paradox. However, participants extended that idea: Augmentation is not a structural component of the system, it results from ongoing interpretive activity and requires continued epistemic work. Further, leaders must constantly mediate between two authoritative sources versus simply piling one source on top of another. P15 further explained that “AI allows us to spot patterns, but ultimately decisions require human judgment because individuals aren’t pattern-based.” Participants framed this concept as hybrid decision-making logics, i.e., organizations using both algorithmic rationality and human-based intuitions simultaneously (productively and/or tensively), while using these rationales together in decision-making processes (Raisch & Krakowski, 2021). Participants’ identification of this logic in their accounts represents a critical development since it represents evidence that leaders are not merely accepting AI as an additional resource but are actually creating new conceptualizations regarding the nature of their expertise, i.e., what they know, what the system knows, and how these two types of knowledge should be considered relative to each other in any specific context.

Beyond the cognitive aspect of this interpretive tension, participants offered insight into the emotional/psychological implications of participating in this type of decision-making. Specifically, participants reported experiencing anxiety related to deviating from an AI-generated recommendation regardless of the justification behind the deviation. For example, P14 noted that “Going against the system can feel like making

a calculated risk.” P17 similarly articulated this concern when he noted, “If you override the system and things don’t go right, you’ll take full blame. If you let the system tell you what to do and things don’t go right, that can be problematic too.” These quotes illustrate a unique dimension of AI-enabled leadership that has been largely ignored in both technological and governance-oriented research on AI adoption: the affective experiences of holding accountability for decisions made through combining human judgment and algorithmic judgments.

Theme 3: Ethical concerns and trust dynamics

This theme highlights an ethical consideration relevant to leadership sense-making, extending governance theory beyond the system-level to include the lived experiences of individual leaders (Floridi et al., 2018; Murray et al., 2021). One of the most emotionally evocative and organizationally effective aspects of AI-enabled talent management was ethical considerations based on data, which were classified as such in terms of sense-making in leadership. Fairness, transparency, accountability, and bias were repeatedly and sometimes vehemently addressed to the participants not as an abstract policy issue, but as a pressing and urgent aspect of their day-to-day professional activities. Leaders acknowledged AI systems’ analytical ability and were genuinely anxious about what the systems could not capture. P3 explained that “AI can analyze information, but is unable to comprehend individuals fully.” These remarks reflect a common understanding that algorithmic systems, regardless of how advanced they are, rely on a reductive conceptualization of human beings. This conceptualization is capable of quantifying behavioral outputs and map them to results but cannot explain the inherent complexity of individual situations, relationship backgrounds, and situational variables that responsible organizational decisions demand (Benabou & Touhami, 2025; Floridi et al., 2018). This restriction is not a trivial technical flaw of a technical nature, but a key difficulty of the AI-informed evaluation validity to leaders who recognize the fundamentality of their role as a relationship and humanizing one.

One of the most important concerns participants expressed was that, in practice, it is difficult to explain to employees affected by AI-driven decisions why those decisions were made. One of the most distressing experiences many leaders shared was having to explain their own reasoning behind conclusions drawn from systems they didn’t fully understand, where the logic behind those systems wasn’t well known to the individuals using them. As P6 noted: “The most difficult challenge in making a decision is explaining why the system determined it.” P6’s experience of being communicatively accountable-deficient aligns with one of the governance implications of black box AI described by Rudin (2019). The data illustrate what the technological literature does not: leaders’ moral discomfort when they are formally required to justify decisions they cannot see inside represents another layer of accountability in AI-mediated environments that requires organization-based remedies. P9 stated: “Employees have asked questions that employees cannot answer because employees do not understand how the system works.” P9’s comments illustrate the lack of transparency inherent in systems described as black-box AI. This lack of transparency leaves a governance void where accountability may be literally absent or unexpressible (Rudin, 2019). When a leader or employee cannot fully understand or question why a decision was made, the grounds for perceived fairness and legitimate authority are greatly compromised. The subjects were highly aware of these dynamics, they felt it was not only an organizational inconvenience but also a source of moral discomfort, as they were being asked to grant authority they could not convincingly justify or substantiate.

The consequences for trust were also tremendous. Respondents noted that employees were more likely to react negatively to decisions if they felt algorithms made them. They might have been fair and substantively well considered. One leader mentioned that once people are informed it was done with AI, even a just decision will be less trusted, and another said people will feel AI eliminates the human factor, which will be an obstacle. These observations suggest something significant about the social psychology of algorithmic authority: perceived humanity is not merely a function of accurate decision-making in an organizational context, but of perceived legitimacy. Workers must believe that those making decisions about their future have taken a personal interest in their cases, and implementing AI into the process can upset that perception even when the results are fair. A few participants also reported ethical and emotional pressure from what could be called diffused accountability, where humans and machines share responsibility for decisions, and the boundary is both organizationally unclear and personally uncomfortable. With P12 commenting, “I sometimes feel like I made decisions I did not make properly, as the system made me do so, and another commenting, “We are responsible for outputs we cannot fully interpret.” Collectively, these results affirm the current empirical research that adoption of AI in HRM can undermine the sense of perceived fairness and organizational trust unless it is accompanied by strong transparency, well-established governance rules, and long-term communicative interactions between leaders and their followers (Naoum et al., 2026; Newman et al., 2019).

Theme 4: Emotional and relational dimensions of leadership

This theme reveals a dimension of AI-enabled leadership that cognitive and procedural frameworks have largely overlooked: the affective and relational texture of interpretive work under algorithmic uncertainty (Maitlis & Christianson, 2014). Although the current literature on AI in HRM focuses largely on cognitive and procedural aspects of decision-making, one of this research’s most significant and distinctive findings is that AI deployment affects the emotional and relational aspects of leadership practice. Participants defined not only the intellectual issues of interpreting AI outputs but also the affective dimension of interpreting them amid uncertainty, responsibility, and interpersonal accountability. It was found that the experience of making a decision that has a great impact on the career of another individual, in part due to being based on information

that a system that one cannot fully question generates, was something that was truly burdensome in more than just professional discomfort. P10 explained that “I was caught between the numbers and the person, and that this was a type of moral and emotional conflict that was common throughout the dataset.” This aspect of the emotional dimension expands on Maitlis and Christianson (2014) concept of sensemaking, which is primarily framed cognitively, by showing that the interpretive labor involved in making decisions in AI-enabled environments is also emotional labor. Beyond processing conflicting knowledge claims, leaders feel the burden of making consequential decisions with incomplete information or, worse, algorithmically filtered information about very human circumstances. P12 indicated that “The most challenging situations aren’t when such information can’t be understood, it’s when you recognize something special about the person sitting across from you” after seeing what appears to be relevant information. As these examples illustrate, the emotional labor associated with leadership in AI-enabled environments is substantively distinct from traditional decision-making environments. It includes emotional labor related to epistemic uncertainty, relational responsibility, and moral accountability.

The human relations in this theme were also noteworthy. Some interviewees described how AI-mediated evaluation procedures transformed their relationships with team members, both positively and negatively, in some cases, they did not expect it and did not like it. When employees realized that AI systems were used to evaluate their performance or potential, the quality of the trust relationship between leader and employee was often impacted. Leaders reported spending a lot of time and communicative effort in what one participant referred to as making the process human again, proactively clarifying, situating, and even qualifying AI-generated inferences so that they could maintain the relational integrity of their leadership. P15 noted that “People do not simply desire to know what the decision is, but they desire to know that when the decision is being made, a human being considered them.” This finding is highlighted by what Maitlis and Christianson (2014) call communicative sense-making: the relational and discursive labor in which leaders create and exchange meaning in ways that maintain organizational unity and personal dignity. Leaders in AI-enabled worlds face a different kind of challenge than those in traditional AI worlds because, in traditional AI worlds, leaders must connect algorithms to human experiences in every important interaction.

Theme 5: Transformation of leadership competencies

The fifth and final theme addresses how integrating AI changes the competency requirements for organizational leaders, emphasizing big leaps rather than small steps. The theme focuses on the development implications of integrating AI into organizations’ operational processes. According to Weber et al. (2022), effective leadership in algorithm-governed organizations will require a fundamentally different approach than incremental skill development or continuing education. Participants’ assessments were consistent and unambiguous, the skills that constituted effective leadership in pre-AI organizational settings can no longer be relied on alone. Even skills like reading a spreadsheet, managing performance discussions, or making informed promotion choices have not been overtaken, but are now a subset of a larger, more complex range of interpretive, moral, and communicative skills that AI-driven environments demand. P8 mentioned that “It is important to know technology, but it is more even essential to know people now.” P11 provided probably the most succinct formulation of the shift: leadership today is about making sense of the data and translating it into something meaningful to people. All these descriptions relate to a shift in the role of leadership, where the ability to interpret analytically, reason ethically, and translate relations is now as core as any technical knowledge of the domain (Brey & van der Marel, 2024; Cooke et al., 2026).

This shift was felt not only in leadership work but also in the dispositions and orientations effective leadership demands. Participants described maintaining an unproductive algorithmic confidence alongside human skepticism in productive tension: not dismissing AI-generated information as unreliable, but not taking it as the final word, using it as one input among many. P20 described this transition vividly when he said, “I had to learn to fight the system without throwing it away, and to make my own judgment without ignoring data.” In other words, while AI-enabled leadership will certainly require significant skill-building and some of these skills will build on existing competencies, these are not mere additions to existing capabilities. Rather, they represent a qualitatively new form of professional competency, one that academic research has not yet fully articulated. Therefore, this finding challenges current conceptualizations of leadership development and argues for reconceptualizing what constitutes effective leadership competency in digitalized organizational environments (Cooke et al., 2026; Weber et al., 2022). P21 stated that “Leadership today is all about achieving a balance between machine logic and human understanding”. P22 added that “Communication has become more important since we have to provide answers not only to our decisions but to how those decisions were reached.” These stories describe an experiential basis for ongoing professional learning that cannot be easily developed through traditional training programs designed for different organizational conditions.

The participants identified a relatively wide development gap. P19 indicated that she had been trained to make decisions, not interpret algorithms, and therefore needed to learn to interpret algorithms. The implications for leadership development are clear: to support effective AI-enabled leadership practices, organizations cannot rely solely on providing workers with technical skills-upgrade opportunities. Instead, organizations must create opportunities to develop interpretative/ethical/communicative skills that enable workers to perform their jobs effectively (Forum, 2025; Weber et al., 2022). Table VI outlines the five themes, each theme’s primary characteristics, and representative narratives from major players that supported each theme in the data.

These five themes are not independent findings or separate views of leadership sense-making at the human-algorithm interface. Rather,

taken together they present an integrated view of the same process.

Table VI
Research findings

Theme	Core Dimension	Representative Participant Quote	Theoretical Resonance
Reconfiguration of Workforce Value	Shift from static, retrospective evaluation to dynamic, capability-based assessment	"Value is no longer about how long someone has been here, but how quickly they can evolve with change"	Human capital theory, anticipatory valuation (Brey & van der Marel, 2024)
Interpretive Tension Between Human Judgment and AI	Ongoing negotiation between algorithmic output and professional expertise	"The system provides a perspective, but it is only one part of the story"	Augmentation paradox, hybrid decision-making logics (Raisch & Krakowski, 2021)
Ethical Concerns and Trust Dynamics	Fairness, transparency, accountability, and trust in AI-mediated decisions	"The hardest part is not making the decision, but explaining why the system made it"	Algorithmic governance, ethical mediation (Floridi et al., 2018; Rudin, 2019)
Emotional and Relational Dimensions	Emotional labor and relational management in AI-enabled evaluation contexts	"People do not just want to know what the decision is, they want to know a human being thought about them"	Communicative sense-making (Maitlis & Christianson, 2014)
Transformation of Leadership Competencies	Emergence of hybrid, interpretive, and ethically grounded leadership capabilities	"I had to learn to question the system without dismissing it, and to trust my judgment without ignoring the data"	Digitally fluent leadership, adaptive competency frameworks (Weber et al., 2022)

Discussion

Before examining each finding in detail, it is worth situating the study's contributions within the current state of the literature across the three bodies of work it engages. In the AI-HRM literature, recent systematic reviews Cooke et al. (2026), Scarbrough et al. (2024), and Sharma et al. (2025) have converged on a consistent observation: scholarship has richly documented what AI systems do to organizations but has largely neglected how individual actors interpret and enact those systems in practice. The following discussions are presented in a format designed to express these dialogues clearly.

Sense-making reconfigured: AI as an interpretive trigger

The theoretical model applied within this research, sense-making theory, is relevant in the context of AI-based HRM, however, it is also required. According to Weick (1995), the continuously evolving and socially defined process of generating meaning within the ambiguous environment described above is the basis for viewing sense-making. What the findings add, though, is more than a simple affirmation of this suggestion. They demonstrate a qualitatively novel sense-making that the advent of AI presents, more iterative, more cognitively demanding, and more emotionally charged than the expressions of interpretive work that had been identified in previous organizational sense-making studies.

AI produces outputs that are not solutions to the data, but interpretive stimuli that participants elicit and respond to, rather than respond to, the need to make meaning. When participants explained that the system provides patterns that we have to make sense of for our colleagues, they were referring to this very dynamic. Sense-making does not begin with the algorithms' output, it begins with it providing leaders with a new kind of informational cue that is statistically certain but low in context. This produces what could be referred to as a second-order interpretive demand whereby leaders need to be able to make sense of the situation in the organization that they are considering, as well as make sense of the sense-making tool itself in terms of its reliability, its relevance, and its limitations before any results of the application of the tool could be considered meaningful. This conclusion builds on recent theoretical arguments by (Jarrahi et al., 2021; Maitlis & Christianson, 2014), who propose that digital technologies can increase interpretive complexity by raising the quantity of organizational cues and their obscurity. While Scarbrough et al. (2024) documented sense-making dynamics during organizational AI adoption broadly, their analysis remained at the system-implementation level. It did not examine the micro-level cognitive labor individual leaders perform daily when processing probabilistic HR outputs.

Workforce value as a socially negotiated construct

The re-evaluation of workforce value as revealed in the results is a significant addition to the human capital theory. Classical concepts of human capital treated workforce value as a comparatively unchanging, objectively quantifiable factor based on education, skill level, and historical productivity (Becker, 1993). This research questions this framing both empirically and theoretically. Respondents noted a deliberate shift from retroactive, credentials-based appraisal to dynamic, capabilities-based, future-oriented perceptions of employee worth. They attributed this

change to predictive analytics and behavioral scoring systems installed in their AI platforms, which shifted organizational focus to what employees have already achieved and what they are expected to bring to the organization in changing circumstances.

Additionally, Brey and van der Marel (2024) and Shumilova et al. (2026) expanded the concept of anticipatory valuation, arguing that AI tools shift organizational emphasis toward future possibilities. However, according to the results of this study, both the claims made by Brey and van der Marel (2024) are supported and complicated: leaders certainly employed a forward-looking evaluation perspective, yet at the same time, they resisted algorithmic representations of this perspective, instead choosing to utilize human judgment informed by contextual considerations when their perspectives conflicted with statistical certainty predictive scores. This suggests that anticipatory valuation, as theorized, underestimates the interpretive friction through which it is achieved in practice.

The automation-augmentation paradox in practice

The interpretive conflict respondents reported between human judgment and algorithmic authority provides strong empirical support for Raisch and Krakowski (2021) hypothesis on the automation-augmentation paradox. This paradox states that AI enhances human cognitive capabilities and concurrently generates additional levels of dependence, ambiguity, and decisional overload, none of which existed before the introduction of AI into organizational environments. This study's findings add empirical texture to this theoretical contradiction by showing how individual leaders experience, manage, and negotiate it in everyday professional practice. Burton et al. (2019) empirically examined how algorithmic decision systems redistribute accountability in organizational settings and found that diffuse responsibility consistently increases managers' risk perception. The present data extend this finding in an important direction: not only do leaders perceive increased risk, but they also experience what the findings term epistemic asymmetry: a structural pressure to defer to algorithmic authority even when their professional judgment diverges, a dynamic that Burton et al. (2019) identified at the organizational level but did not trace into the subjective experience of individual leaders. These results map to some of the fundamental dimensions illustrated in Table VII.

Table VII
Dimensions of the automation-augmentation paradox in leadership practice

Dimension	AI Contribution	Human Leadership Response	Resulting Tension
Analytical capacity	Predictive scoring, pattern recognition, behavioral analytics	Contextual interpretation, experiential re-evaluation	Competing epistemic authorities
Decision efficiency	Rapid, scalable recommendations across large datasets	Slower, relational, case-by-case judgment	Speed versus depth of understanding
Accountability	Algorithmic output shifts responsibility partially to the system	Leaders remain fully accountable for outcomes	Diffuse responsibility with concentrated accountability
Emotional labor	System outputs are affectively neutral	Leaders manage uncertainty, risk, and moral discomfort	Increased affective demands on human actors
Organizational legitimacy	Data-driven recommendations carry institutional authority	Human overrides require explicit justification	Pressure to conform versus professional obligation to contest

Ethical mediation as a core leadership function

Before elaborating on the empirical evidence, it is important to situate ethical mediation precisely within the construct landscape. Unlike ethical leadership, which is dispositional and broadly focused on modeling moral behavior Brown et al. (2005), ethical mediation is situationally activated, it is triggered by specific conditions: the presence of algorithmically generated recommendations that carry epistemic authority yet lack contextual completeness, and the need to communicate those recommendations to employees whose careers, trust, and dignity are at stake. Unlike algorithmic accountability frameworks, which define what systems must do to be auditable, ethical mediation defines what leaders must do to make accountability real in practice. In this sense, the construct occupies a unique theoretical niche: it is the organizational enactment of governance values.

One of the most significant theoretically derived findings from this study concerns the degree to which integrating AI redistributes and makes ethical accountability more (not less) complex. Implementing algorithmic systems in consequential HRM decisions does not decrease ethical complexity for leaders, it creates complexity in an area that current governance frameworks and leadership competency models have not fully conceptualized. When participants said they felt responsible for decisions they did not make themselves entirely, or for outcomes they could not fully describe, they were describing a technical, organizational, and ethical structural issue. This decentralization of responsibility between human and machine actors creates what this paper terms an accountability vacuum: responsibility is formally attributed to human leaders but de facto distributed across systems, algorithms, and institutional processes in ways that make meaningful accountability difficult to locate or enforce. Newman et al. (2019) and Naoum et al. (2026) have each demonstrated that employee perceptions of fairness in AI-mediated HRM decisions are significantly moderated by the quality of managerial communication surrounding those decisions. The concept of ethical mediation developed in this study provides the theoretical infrastructure that this empirical finding implicitly requires but has lacked, it names the leadership practice,

describes its constituent elements, and explains why it is not reducible to transparency or procedural justice as technical governance properties. In this sense, the present contribution moves the field from describing that leadership communication matters to theorizing how and why it functions as a distinct form of ethical labor.

One of this study’s principal theoretical contributions is developing ethical mediation as a leadership construct grounded in leaders’ lived experience at the human-algorithm interface. Ethical mediation refers to the interpretive, communicative, and moral work through which leaders transform AI-generated assessments into decisions that are statistically informed, ethically defensible, organizationally legitimate, and humanly comprehensible to those affected. This goes far beyond what existing responsible AI governance frameworks call transparency or explainability, which are largely technical aspects of system design rather than ongoing social and communicative practices (Floridi et al., 2018; Rudin, 2019). The findings suggest that AI-based HRM transparency is not an engineering characteristic that can be introduced into a system, but a quality that leaders must actively produce through long-term communicative, relational, and ethical reflexivity.

Theoretical contributions

The findings of this study generate several distinct and interrelated contributions to existing theoretical frameworks, summarized in Table VIII before each is briefly elaborated.

Table VIII Theoretical contributions of this study		
Theoretical Framework	Existing Position	This Study’s Contribution
Sense-making Theory Maitlis & Christianson (2014) and Weick (1995)	Sense-making as an ambiguity-driven, socially embedded interpretive process	Extends to AI-mediated contexts, demonstrates that AI functions as an interpretive trigger rather than an ambiguity-reducer, introduces the affective dimension of AI-enabled sense-making
Human Capital Theory Becker (1993) and Wright & McMahan (2011)	Workforce value as a measurable, relatively stable individual attribute	Reconceptualizes workforce value as socially negotiated, algorithmically co-constructed, and context-dependent, advances the concept of anticipatory valuation
Socio-Technical Systems Theory Faraj et al. (2018)	Value and practice as co-produced by human and technological subsystems	Foregrounds interpretive work as the central mechanism of human-technology integration, demonstrates that socio-technical alignment depends on sense-making practices, not structural design alone
Leadership Theory Raisch & Krakowski (2021),and Cooke et al. (2026)	Leadership as decision-making capacity augmented by AI	Reconceptualizes leadership as a hybrid, sense-making-driven practice, introduces ethical mediation as a core leadership function in AI-enabled organizational environments
Algorithmic Governance Floridi et al. (2018) and Rudin (2019)	Transparency and fairness as technical system properties	Reframes transparency as a social and communicative practice actively produced by leaders, extends governance theory into the micro-level domain of leadership practice

This helps address a long-standing gap between normative methods of AI ethics and empirical studies of their application (or non-application) in organizational practice.

Theoretical implications

Extending sense-making theory into AI-based HRM is a key advancement. Ethical mediation represents a more novel conceptual addition to the current body of work. Theoretically, this study extends our collective understanding of the three inter-related domains above. First, this study provides evidence that Weick (1995) seminal sense-making framework, developed largely in response to crises and strategic ambiguity in organizations, needs to be significantly extended to account for the specific ways AI-facilitated environments condition people’s interpretation. While AI may present new data to help humans understand their environment better, it presents a fundamentally unique form of data: statistically authoritative, devoid of contextual information, and difficult to dispute. The concept of second-order interpretive demand offers a precise way to describe this reconfiguration (Maitlis & Christianson, 2014; Sandberg & Tsoukas, 2020). Second, by reconceptualizing workforce value as a socially negotiated and algorithmically co-constructed phenomenon, the study extends human capital theory beyond its classical, asset-based framing toward a more dynamic and practice-oriented understanding (Boudreau & Cascio, 2017; Minbaeva & Navrbjerg, 2023). This has theoretical implications for strategic HRM research, which has increasingly adopted data-driven evaluation frameworks without adequately theorizing the interpretive labor through which those frameworks are enacted in practice. Third, the construct of ethical mediation fills a recognized gap between

normative AI governance theory, which addresses what responsible AI should look like, and the empirical reality of leadership practice, which determines what it becomes in organizational life (Floridi et al., 2018; Murray et al., 2021).

Practical implications

The findings offer concrete implications for organizations adopting AI in HRM. As shown in Table IX below, this study's recommendations apply to four related areas of organizational practice.

Table IX
Practical implications for AI-enabled HRM

Domain	Current Organizational Challenge	Evidence-Based Recommendation
Leadership Development	Leaders with training in pre-AI decision frameworks do not have the necessary interpretive and ethical skills for AI mediated environments	Design leadership programs to develop critical AI literacy, ethical reasoning, communicative translation ability and emotional resilience in an algorithmic uncertainty
AI System Design	Some HR AI tools focus more on predicting outcomes rather than making it human-readable, leading to transparency gaps	Design systems with explainability as an integral part of the design, not an afterthought, make sure that algorithmic outputs are traceable, open for questioning and contestation by leaders
Organizational Communication	The ways in which leaders communicate AI-informed decisions to impacted workers are often not well-defined	Establish communication protocols within an organization that enable leaders to transform algorithmic findings into narratives that are contextually relevant and credible to people
Governance and Accountability	Ambiguity and organizational risk can arise when there is a lack of clarity about who is accountable for the actions of humans or machines	Develop governance structures to establish decision ownership, incorporate human-in-the-loop processes, and set up governance frameworks for accountability of AI-driven HRM decisions and actions

Limitations and directions for future research

Several limitations should be acknowledged when interpreting this study's findings. First, while purposive sampling enabled the selection of information-rich participants, the sample of 22 senior leaders, though sufficient for thematic saturation, limits statistical generalizability to broader leadership populations. Because the sample is primarily drawn from Pakistan, the findings should be understood as contextually situated, future research should examine whether similar patterns of leadership sense-making emerge in settings with different regulatory regimes, technological infrastructures, and organizational cultures. The findings are analytically generalizable to theory rather than statistically representative of all organizational leaders engaging with AI-enabled HRM (Lilly, 1998; Patton, 2014). Readers should exercise caution when transferring these findings to organizational contexts that differ significantly in size, sector, regulatory environment, or technological maturity. Second, the sample's geographic scope necessarily reflects culturally specific leadership norms and institutional environments. The sense-making practices and ethical concerns identified here may manifest differently in organizational cultures with distinct orientations toward authority, algorithmic trust, and individual agency, and cross-cultural comparative research would be needed to determine the boundaries of transferability (Saunders et al., 2019). Because participants were drawn from organizations with different levels of AI-HRM maturity and different types of systems, the study prioritizes analytic depth and cross-context interpretive patterns over formal comparison of sectors or technologies. Third, as with all qualitative interview-based research, the data are self-reported and therefore susceptible to retrospective rationalization, social desirability bias, and participants' tendency to present their decision-making in professionally flattering terms. Although member checking and reflexive practices were employed to mitigate these risks, they cannot be eliminated (Braun & Clarke, 2022), Tracy, 2020). Fourth, because the study focuses exclusively on leadership perspectives, the employee experience of AI-mediated talent decisions, which may diverge meaningfully from leadership accounts, remains outside the scope of this inquiry and constitutes a significant avenue for future research. Because ethical mediation is developed here through qualitative, inductive theorization, it should be understood as a theoretically specified but still provisional construct that requires further refinement, discriminant validation against adjacent leadership concepts, and future scale development.

The findings of this study open several productive avenues for future investigation:

1. Longitudinal studies tracking how leadership sense-making practices and employee trust evolve as AI systems mature within organizations would provide temporal depth that single-point qualitative studies cannot offer (Burton et al., 2019).
2. Cross-cultural comparative research examining whether ethical mediation and augmented sense-making manifest differently across national and institutional contexts would establish the boundary conditions of the theoretical contributions made here.
3. Quantitative and mixed-methods studies operationalizing and measuring the constructs identified, including ethical mediation capacity, second-order interpretive demand, and AI-augmented sense-making, to test their relationships with leadership effectiveness, organizational trust,

and employee well-being (Raisch & Krakowski, 2021).

4. Employee-centered research capturing how workers experience and respond to AI-mediated evaluations, providing the relational counterpart to the leadership perspective foregrounded in this study (Kellogg et al., 2020; Meijerink et al., 2015).

5. AI system design research examining how explainability features, human-in-the-loop mechanisms, and governance structures mediate the interpretive and ethical labor demands documented here, bridging the gap between technical design and organizational practice (Benabou & Touhami, 2025; Jam et al., 2025; Rudin, 2019).

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