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“The System Says So”: Making Sense of AI-Driven HRM, Conditional Trust and Employee Well-Being in Saudi Arabian Organisations

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Article

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Abstract

Purpose

This study explores how employees in Saudi Arabian organisations perceive artificial intelligence (AI)-driven human resource management (HRM) and how their interpretations of the technology shape trust in HR systems and employee well-being.

Design/methodology/approach:

This qualitative study draws on 35 semi-structured interviews analysed using reflexive thematic analysis.

Findings:

Employees' perceptions of AI-driven HRM were shaped by transparency, human involvement, and contextual sensitivity. Employees expressed conditional trust in AI used for administrative tasks, but were more reluctant to trust it with consequential decisions such as performance appraisals. Concerns about dignity, autonomy, and mental well-being were closely linked to perceptions of AI-driven HRM as context-blind and overly reductive.

Originality/value:

By placing employee sensemaking at the centre of the analysis, this study clarifies how AI-driven HRM is interpreted in organisational settings and how such interpretations shape trust and well-being.

Practical implications:

The study highlights the need for a hybrid HRM model that combines technological efficiency with transparency, contextual awareness, and meaningful human oversight.

1. Introduction

Employee sensemaking involves continuously interpreting and acting on uncertain events (Weick, 1995). As artificial intelligence (AI) transforms industries, AI-driven human resource management (HRM) promises speed, consistency and informed decisions in selection, appraisal and training (García-Madurga et al., 2024; Gemmano et al., 2026). It also reshapes governance, power and accountability within employment relationships (Kellogg et al., 2020; Meijerink et al., 2021). Organisational efficiency expectations may therefore conflict with employees' experiences of evaluation and monitoring, raising concerns about autonomy, fairness and surveillance. Investment alone does not ensure employees

perceive benefits. This study examines how employees interpret AI-driven HRM and relate these interpretations to trust and well-being.

Against this backdrop, research emphasising technical adaptability, managerial performance, organisational readiness and effectiveness provides only a partial account of AI-driven HRM. Organisational benefits do not ensure that employees interpret practices as intended or regard them as legitimate and trustworthy. Research on algorithmic sensemaking and employee responses highlights the need to examine how interpretations and behavioural adaptations develop after implementation (Möhlmann et al., 2023; Rahman, 2021; Edwards et al., 2024). This interpretive focus is particularly important when systems influence performance decisions, career opportunities and relationships with management.

Employee responses to algorithmic HRM are therefore neither automatic nor uniform. Opacity, limited explanations and unclear decision criteria can obscure systems' operation and career implications. The relationship between employee sensemaking, trust and well-being nevertheless warrants closer examination. Beyond technical characteristics, employees interpret AI-driven HRM through organisational cues, previous experiences, interactions with managers and colleagues, and perceptions of fairness and accountability.

Such opacity obscures decision criteria, prioritised indicators and reasons for unfavourable outcomes. Employees draw on cues, experiences and organisational narratives to construct plausible explanations that inform fairness, legitimacy, trust and well-being. Anticipated evaluation may increase self-monitoring and self-discipline even without technical changes (Rahman, 2021; Edwards et al., 2024). Algorithmic HRM can thus exercise black-box power through employees' interpretations, alongside explicit managerial instructions and interpersonal interaction (Kellogg et al., 2020; Meijerink et al., 2021; Pasquale, 2015).

These interpretive challenges are particularly relevant to Saudi Arabia's digital transformation under Vision 2030. Hierarchical decision-making and constrained employee voice have been documented in some organisational settings, without characterising all Saudi organisations (Adham, 2022). Saudi studies report AI-enabled HR practices in chemicals and telecommunications (Alshahrani et al., 2025; Ramy, 2025), while wider research identifies concerns about trust, job loss, skills readiness, surveillance and data governance (Kaur and Gandolfi, 2023; Tambe et al., 2019; Pedrami and Vaezi, 2026; Vrontis et al., 2022). This context enables examination of employee interpretations where technological change intersects with expectations of human judgement, managerial authority and interpersonal relationships.

Drawing on Weick (1995), this study treats sensemaking as the mechanism through which AI-driven HRM acquires organisational meaning. It shifts attention from adoption and assumed technological effects to employees' everyday interpretations, assessments and responses. It examines legitimacy and conditional trust in relation to perceived transparency, fairness, contextual sensitivity, accountability and human involvement. Within Saudi Arabia's digital transformation, it also considers well-being through autonomy, dignity, security and organisational support. The research question is: How do employees and

HR professionals make sense of AI-driven HRM practices, and how do they describe the relationship between these interpretations, trust, and employee well-being?

2. Literature review

2.1 AI-driven HRM

AI supports HR data processing and decisions in recruitment, performance management, workforce analytics and employee development (Meijerink et al., 2021; Vrontis et al., 2022; Chilunjika et al., 2022). Awareness may support acceptance and readiness; limited understanding may foster scepticism, confusion and resistance (Benlian and Pinski, 2025; Venkatesh and Bala, 2008). Managerial emphasis on efficiency and outcomes only partly explains employee responses. These may vary with technology adoption attitudes.

Successful AI-driven HRM requires technological capability and organisational readiness. Governance, AI literacy, workforce preparation and employee participation support adoption (Pedrami and Vaezi, 2026; Benlian and Pinski, 2025; Arslan et al., 2022; Felemban et al., 2024). Readiness therefore extends beyond technical resources. Implementation also presents organisational and human challenges.

Moreover, readiness research emphasises infrastructure, governance, employee training and technological resources (Pedrami and Vaezi, 2026; Benlian and Pinski, 2025; Felemban et al., 2024). These capabilities enable implementation but only partly explain employees' everyday interpretations. Employees actively assess AI-driven HRM's implications for work, relationships and future employment. Interpretations may therefore vary across organisational contexts.

Depending on role and exposure, employees may perceive AI as supporting efficiency, enabling surveillance or threatening job security (Kellogg et al., 2020; Rahman, 2021; Schmid and Wiesche, 2026). Saudi sector-specific studies report managerial optimism about recruitment, performance evaluation, compensation and organisational effectiveness, alongside varied assessments of AI-enabled practices and work-life quality (Alshahrani et al., 2025; Ramy, 2025). Organisational readiness alone therefore appears insufficient to explain employee responses. These differences warrant examining employees' workplace interpretations of AI-driven HRM.

These differences warrant examining meaning construction beyond AI adoption factors. Employees' prior experiences, organisational relationships and perceptions of fairness, legitimacy and accountability inform their interpretations, attitudes and behaviours. Such processes may explain varying trust and well-being experiences across organisations using similar systems. Accordingly, sensemaking is the study's primary theoretical lens and interpretive mechanism linking AI-driven HRM conditions, trust and well-being, rather than merely describing perceptions.

2.2 Employee sensemaking in AI-driven HRM

Algorithmic complexity and opacity make sensemaking relevant to AI-driven HRM (Möhlmann et al., 2023; Rahman, 2021; Burrell, 2016). Employees draw on cues, experience, organisational communication and interactions with managers and colleagues. They use these resources to interpret system operations and implications for work and careers. These interpretations inform perceived legitimacy, trustworthiness and compatibility with work expectations.

Such uncertainty can also prompt behavioural adaptation. Employees may anticipate evaluation despite unclear metric generation or recommendation use (Kellogg et al., 2020; Rahman, 2021; Edwards et al., 2024). Opacity can inform interpretations of fairness, accountability and organisational legitimacy (Burrell, 2016; Newman et al., 2020). Responses may include self-monitoring, impression management and metric compliance despite unclear criteria.

Generative AI adds interpretive complexity through plausible but inaccurate outputs, complicating trust judgements for employees and HR professionals (Beutel et al., 2023). Limited AI literacy and opportunities for dialogue or challenge may heighten uncertainty, role ambiguity and concerns about unfair blame (Benlian and Pinski, 2025; Xu et al., 2024). Leadership and communication help interpret AI's alignment with organisational goals, values and ethical expectations (Xu et al., 2024; Madanchian et al., 2024; Ueno et al., 2022). Transparency, communication, human oversight and opportunities to question decisions also provide governance cues for assessing legitimacy.

A sensemaking perspective therefore treats employee responses as ongoing interpretations. Employees assess what AI-driven HRM signals about organisational priorities, managerial control and their own standing. Their responses extend beyond technological features. These interpretations inform trust, work experiences and well-being.

2.3 Trust in AI-driven HRM

Trust is central when algorithms inform recruitment, appraisal, promotion, compensation and career opportunities. It involves interpreting competence, fairness and legitimacy rather than automatically following adoption (Xu et al., 2024; Glikson and Woolley, 2020; Shukla et al., 2026). A sensemaking perspective therefore distinguishes trust in AI-enabled HR practices from trust in technology itself. Employees may recognise AI's technical usefulness while questioning the organisational processes governing its decisions.

Trust may be supported by transparency, explainability and meaningful human oversight (Xu et al., 2024; Shukla et al., 2026; Davidovic, 2023). Opaque scoring and unclear criteria can increase scepticism. Limited opportunities to challenge decisions may further undermine trust. Organisational justice and social exchange perspectives also highlight procedural fairness, respectful communication and accountability (Newman et al., 2020; Shukla et al., 2026; Hunkenschroer and Luetge, 2022; Mayer et al., 1995).

Trust judgements also reflect organisational and cultural contexts. Saudi sector-specific studies link HR practice evaluations to AI knowledge, use frequency, organisational role and perceived work-life quality

(Alshahrani et al., 2025; Ramy, 2025). Human review and clear communication may sustain legitimacy and reduce uncertainty (Xu et al., 2024; Shukla et al., 2026; Davidovic, 2023). Trust is thus conditional and socially embedded, informed by ongoing interpretations of transparency, fairness, accountability and organisational support alongside technical performance.

2.4 AI-driven HRM and employee well-being

AI-driven HRM has implications not only for organisational efficiency but also for employees' psychological and emotional experiences at work. When AI systems allocate tasks, monitor behaviour, or evaluate performance, employees may experience changes in autonomy, job security, and perceptions of organisational support (García-Madurga et al., 2024; Deranty and Corbin, 2024; Parent-Rocheleau and Parker, 2022; Kim and Kim, 2024). Research on algorithmic management suggests that employees are more likely to experience stress, disengagement, and emotional exhaustion when AI-driven evaluations are perceived as overly reductive, context-blind, or difficult to contest (Kellogg et al., 2020; Rahman, 2021; Edwards et al., 2024; Kim and Kim, 2024).

At the same time, AI does not inevitably produce negative outcomes. Well-being is increasingly understood as encompassing psychological health, sense of purpose, work-life balance, and feelings of security and support (Chingan Thottathil and Nandakumar, 2025). Studies from Saudi Arabia indicate that AI-driven HR practices may enhance empowerment and quality of work life when employees perceive them as fair, supportive, and designed to assist rather than replace human judgement (Ramy, 2025). Broader research similarly shows that participatory governance, transparency, data protection, and employee involvement can strengthen psychological safety and reduce the psychosocial risks of AI adoption (Davidovic, 2023; Lazazzara et al., 2025).

These findings suggest that the well-being effects of AI-driven HRM depend less on the technology itself than on how employees interpret and experience it. When AI systems are viewed as legitimate, transparent, and supported by meaningful human oversight, they may contribute to feelings of security, fairness, and balance at work; when perceived as intrusive, biased, or excessively controlling, they are more likely to generate anxiety, uncertainty, and reduced well-being (Rahman, 2021; Edwards et al., 2024; Kim and Kim, 2024). From an employee sensemaking perspective, such experiences reveal how employees interpret AI-mediated HR practices in relation to autonomy, fairness, security, and organisational support.

2.5 Research gap

Overall, existing research has substantially advanced understanding of AI adoption, organisational readiness, trust, and employee well-being in HRM. However, much of this literature examines these issues as separate organisational or technological factors, and comparatively less attention has been paid to the interpretive processes through which employees make sense of AI-driven HRM and how these interpretations shape trust and well-being. Drawing on sensemaking theory, the present study addresses this gap by examining how employees and HR professionals in Saudi organisations interpret AI-enabled HR practices and how these interpretations influence trust and employee well-being.

2.6 Conceptual framework

Using a sensemaking perspective (Weick, 1995), this research examines how HR professionals and employees in Saudi organisations interpret AI-driven HRM practices and how these interpretations shape trust and employee well-being. It considers AI-driven HRM not merely as a technological input but as a socio-technical arrangement that restructures evaluation, monitoring, and decision-making authority in ways that require ongoing interpretation. The proposed framework conceptualises employee sensemaking as the interpretive mechanism linking the socio-technical conditions of AI-driven HRM to conditional trust and differentiated well-being outcomes (Fig. 1).

2.6.1 Socio-technical conditions of AI-enabled HRM (context layer)

Within this framework, socio-technical readiness encompasses AI literacy and support, infrastructure, data quality, and governance supporting transparency, contestability and visible human oversight (Pedrami and Vaezi, 2026; Benlian and Pinski, 2025; Felemban et al., 2024; Davidovic, 2023). These conditions support intelligible explanations and accountability within organisational responsibilities (Appelbaum, 1997). Unclear communication, poor supervision or inadequate preparation may heighten confusion, insecurity and interpretive uncertainty. Together, these conditions contextualise employees' interpretations of AI-driven HRM's legitimacy, fairness and practical implications.

2.6.2 Employee sensemaking (interpretive mechanism)

Sensemaking explains how employees construct practical understandings of AI-driven HRM in ambiguous situations. Employees try to understand what the system considers valuable, how it makes decisions, and what consequences those decisions may have, and their interpretations are affected by their roles, proximity to AI-mediated decisions, and the signals provided by organisational governance (e.g., opportunities to ask questions, receive explanations, or appeal results). Sensemaking is thus the main mechanism linking organisational conditions to employee responses: through it, employees assess whether AI-enabled HR practices are understandable, fair, contextually suitable, and subject to meaningful human judgement, laying the foundation for subsequent trust or distrust.

2.6.3 Conditional trust (social condition)

Trust is conditional and socially embedded, reflecting perceived governance integrity, accountability and oversight, alongside outcome reliability, reasonableness and contextual fit (Shukla et al., 2026; Mayer et al., 1995). The framework distinguishes trust in the technical system from trust in its organisational governance. Visible governance and meaningful contestability do not make trust unconditional; opacity and limited human review may further constrain it. Employees may therefore recognise AI's usefulness or reliability while withholding trust because of errors or inadequate transparency, contextual sensitivity or accountability.

2.6.4 Employee well-being outcomes

The model conceptualises well-being as an outcome varying with organisational position, system exposure and governance. Perceived legitimacy, accountability and human oversight may support psychological safety, engagement and work-life quality. Opacity, surveillance and restricted voice may instead be associated with strain, anxiety and poorer work-life quality. Well-being is therefore understood through interpretive and trust processes connecting AI-driven HRM conditions with workplace experiences, rather than as a direct effect of adoption.

2.6.5 Human-centred AI governance (practical implication and feedback layer)

Human-centred AI governance is treated as a practical implication of the framework and a feedback mechanism. It comprises organisational arrangements that provide transparency, human oversight, accountability, contestability, and employee participation in AI-driven HRM. These governance mechanisms offer employees interpretive cues to understand, assess, and question AI-mediated HR decisions. In turn, employees' experiences of trust, distrust, and well-being can indicate where HRM practices require greater transparency, contextual sensitivity, human review, or opportunities for appeal. Within this framework, governance is therefore conceptualised as a feedback loop that can strengthen the legitimacy, accountability, and human-centredness of AI-driven HRM practices.

3. Methods

3.1 Research design

This qualitative study examined how HR professionals and employees interpreted AI-driven HRM within Saudi organisations. It explored how participants related these interpretations to trust and employee well-being. The design sought to understand meaning construction rather than measure predefined relationships between variables (Creswell and Poth, 2018; Tracy, 2020). It foregrounded subjective experiences of technological uncertainty, algorithmic decision-making and changing organisational relationships.

The interpretivist paradigm treated organisational realities as socially constructed through experience and interaction. Weick's (1995) sensemaking theory guided examination of employees' active interpretations through organisational cues, previous experiences and workplace interactions. The analysis considered transparency, fairness, contextual awareness, human oversight and accountability in relation to trust and well-being. AI-driven HRM was thus approached as a socially interpreted phenomenon, examining how employees negotiated its everyday meaning through experiences of control, evaluation, autonomy, fairness and human involvement. The study addressed the following research question:

How do employees and HR professionals make sense of AI-driven HRM practices, and how do they describe the relationship between these interpretations, trust, and employee well-being?

3.2 Research context

Saudi Arabia provides an appropriate setting for examining employee experiences of AI-driven HRM because organisations are rapidly integrating AI technologies as part of broader digital transformation initiatives under Saudi Arabia's Vision 2030. AI-enabled HR applications are increasingly being adopted across recruitment, performance management, workforce analytics, attendance systems, and employee development. At the same time, organisations differ considerably in their levels of technological maturity, governance arrangements, and employee engagement with AI, creating a context in which employees may interpret similar technologies in different ways. This diversity makes Saudi organisations an appropriate setting for exploring the sensemaking processes through which employees understand AI-driven HRM.

3.3 Participant recruitment and sampling

Purposive sampling identified individuals with direct experience of AI-enabled HRM who could provide rich accounts of its implementation and use (Patton, 2015). Of 52 invitees, 35 agreed and completed the study. Participants were anonymised as P1–P35 and included CEOs, managers, supervisors and employees in Saudi organisations. Their differing roles and involvement with AI-enabled HR practices provided diverse perspectives on governance, decision-making, employee experiences and workplace outcomes.

Sample adequacy was assessed analytically rather than statistically. Concurrent data collection and analysis allowed developing interpretations to inform subsequent interviews. Interviews continued until later accounts consistently repeated earlier ideas without materially new insights. This informed a pragmatic judgement of data adequacy, not exhausted meanings, acknowledging debates about saturation and its limited fit with reflexive thematic analysis (Guest et al., 2006; Malterud et al., 2016; Saunders et al., 2018; Braun and Clarke, 2021b).

3.4 Data collection

Semi-structured interviews were conducted between January and March 2026. This format combined flexibility with consistent coverage of AI-driven HRM, sensemaking, trust and well-being (Patton, 2015). The guide explored experiences of AI-enabled HR practices, interpretations of algorithmic decisions and their perceived implications for fairness, trust, accountability and well-being. Participants could introduce emerging issues, enabling in-depth exploration of sensemaking.

Interviews took place in Arabic, face-to-face or through secure videoconferencing, according to participants' location and availability. They lasted 45–75 minutes and were audio-recorded with informed consent. Transcripts were verbatim, anonymised and labelled P1–P35 for analysis and reporting. The author translated the material into English, and an academic at King Abdulaziz University reviewed translation accuracy.

3.5 Data analysis

All 35 transcripts (P1–P35) underwent reflexive thematic analysis (Braun and Clarke, 2019; Braun and Clarke, 2021a). This approach supported rich interpretive themes while recognising the researcher's active analytical role. Analysis focused on participants' interpretations of AI-driven HRM and their relationships with trust and well-being. Themes were developed through interpretation rather than frequency alone.

Analysis proceeded iteratively, beginning with repeated reading for familiarisation. Inductive codes remained close to participants' language, addressing algorithmic transparency, fairness, monitoring, human oversight, dignity, trust, uncertainty and psychological well-being. Cross-interview comparison identified patterns, similarities, differences and variations, developing descriptive codes into conceptually interpreted themes. Analysis connected four areas—AI-driven HRM as an organisational reality, employee sensemaking, conditional trust and well-being—while examining relationships between organisational conditions and employee interpretations.

Sensemaking theory served as a sensitising resource rather than a predetermined coding framework, supporting inductive theme development (Creswell and Poth, 2018). The conceptual framework was refined iteratively to reflect participants' experiences rather than imposed a priori. Deviant and disconfirming cases challenged emerging interpretations, while regular peer debriefing examined coding decisions and assumptions to strengthen credibility (Tracy, 2020). Statements were checked against original transcripts for accurate attribution and consistency with participants' responses.

3.6 Research quality and trustworthiness

Credibility was supported through prolonged data engagement, iterative comparison of codes and themes across P1–P35, examination of disconfirming cases and checks against original transcripts. Dependability was strengthened through transparent, systematic analysis documenting coding decisions and theme development. Reflexive memos and regular peer debriefing supported confirmability by enabling critical examination of interpretive assumptions. Rich descriptions of the research context, participant characteristics and organisational settings supported transferability, allowing readers to assess relevance to similar contexts (Creswell and Poth, 2018).

Table 1
Themes, representative codes and illustrative quotations

Main theme	Representative codes	Illustrative quotations
1. Conditional trust and the boundary of human authority	Routine administrative trust; transactional reliability; consequential scepticism; algorithmic transparency; human oversight; human-in-the-loop governance; perceived reduction of *wasta (personal connections)*	*"I trust the system for things that are easy, such as figuring out my leave time."* (P1) "The moment a machine is given the final say on a person's career without a human checking the logic, trust completely breaks down." (P19)
2. Behavioural adaptation and metric-oriented work	Metric-chasing; dashboard orientation; strategic compliance; gaming; risk aversion; innovation dampening; profile monitoring; digital self-surveillance	*"You start asking, will this improve my score? If not, it moves lower in priority."* (P6) "People will open those mandatory training modules on a second screen and just click through them while doing real work, just to get the green tick." (P19)
3. Algorithmic visibility, professional identity and context-blindness	Data-point identity; loss of professional dignity; invisible qualitative work; context-blind evaluation; procedural consistency; contextual injustice; reduced human recognition	*"Sometimes you feel like a data point instead of being a real human."* (P11) "The system captured what I had completed, but not the value I had added in ways that were harder to measure." (P34)
4. Accountability, managerial mediation and the "system says so" effect	Accountability displacement; responsibility deflection; "system says so"; managerial discretion; automated rejection; impersonal communication; managerial intervention; human buffering	*"When the answer is just, 'The system decided,' that's when I start losing trust."* (P30) "My manager's attitude didn't change. In fact, he was supportive and helped sort things out." (P22)
5. Digital modernisation, hierarchy and constrained employee voice	Digital transformation; Vision 2030; modernisation; technological prestige; institutional legitimacy; resistance framing; hierarchical constraints; employee voice; silent adaptation	*"There is a huge push for Digital Transformation and Vision 2030. Everyone wants to be modern and advanced."* (P1) "People don't complain openly. There's more silence than resistance." (P6)
6. Employee well-being and psychological strain	Continuous surveillance; performance anxiety; emotional exhaustion; background stress; uncertainty; forced compliance; reduced engagement; psychological pressure	*"It adds some anxiety. You feel like you are being watched 24/7."* (P1) "It leads to emotional exhaustion because you feel like you are constantly fighting a machine just to prove your worth." (P20)

4. Results

Reflexive thematic analysis of 35 transcripts developed six interrelated themes concerning employees' and HR professionals' interpretations of AI-driven HRM, trust and well-being. Participants' accounts linked their responses to perceived fairness, transparency and human oversight. The themes are presented below, with representative codes and quotations in Table 1. Figure 2 summarises the thematic structure developed from these accounts.

4.1 Conditional trust and the boundary of human authority

The first and most prominent theme concerned the **conditional nature of trust** in AI-driven HRM. Participants generally differentiated between the use of algorithmic systems for routine, factual, and administrative activities and their use in evaluative or consequential decisions. Automated systems were more readily accepted when they were perceived as processing information objectively, whereas trust became more tentative when systems were perceived to assess employees' value or determine career-related outcomes.

For routine activities such as leave calculation, attendance, training records, and certification information, participants described algorithmic systems as useful and relatively dependable. P1 explained, *"I trust the system for things that are easy, such as figuring out my leave time,"* while P23 similarly stated, *"I trust the system when it's dealing with factual information like training records, medical clearances, or certification dates."* P4 captured the distinction between technological accuracy and human interpretation by observing, *"I trust data-driven systems for operational accuracy, but I trust people to interpret the data fairly."*

The boundary became more pronounced when algorithmic systems were associated with performance evaluation, promotion, or other consequential decisions. P1 explained that although a system could record what an employee had done, it could not necessarily capture the circumstances surrounding that work: *"A machine can see what you did, but it cannot see how or why you did it."* Similarly, P21 stated, *"I trust them when they're used to organise information, not when they make important decisions on their own."* These accounts suggest that participants distinguished between computational competence and interpretive authority. The ability of a system to process information accurately did not automatically establish its legitimacy as a decision-maker.

Transparency and human review therefore emerged as important conditions of trust. P13 stated, *"I trust these systems as long as they are clear and straightforward, as reviewed by humans, and are there only for decision-support."* P18 similarly linked trust to transparency, emphasising the importance of knowing *"what data the system uses and how decisions are made."* P11 went further by arguing that consequential decisions should not be finalised without direct interaction between a manager and employee: *"I would make sure that no major decision, like a low rating, is final until a manager speaks directly with the employee and hears their perspective."*

However, contrasting accounts associated algorithmic systems with greater fairness through reduced favouritism. P26 described shortlisting based on recorded performance rather than relationships, while P32 valued qualifications and previous work over *"who knew whom."* These cases suggest that acceptance depended on what technology was perceived to correct or replace. Reducing favouritism could strengthen perceived fairness, whereas replacing contextual human judgement could undermine trust.

4.2 Behavioural adaptation and metric-oriented work

The second theme concerned how employees adapted their behaviour to the perceived requirements of algorithmic systems. Participants did not merely receive algorithmic evaluations; they described modifying their everyday priorities in anticipation of how their activities would be represented within digital systems. The resulting pattern involved increased attention to measurable indicators, strategic compliance, and continuous monitoring of personal records.

P6 described this shift succinctly: *"You start asking, will this improve my score? If not, it moves lower in priority."* P7 similarly observed, *"You start working to what the system measures. For promotion, you focus on activities that count in points."* These accounts indicate that the perceived logic of the system became a reference point for deciding which activities deserved attention. In this sense, employees were not simply being evaluated by algorithmic systems; they were increasingly organising their behaviour around anticipated algorithmic evaluation.

Some participants described more strategic forms of adaptation. P19 reported that employees could open mandatory training modules on a secondary screen and click through them while undertaking other work to obtain the required digital indicator. P20 described a comparable response in procurement, where employees divided larger contracts into smaller tasks because these could be closed more quickly and therefore produced more favourable dashboard indicators. Such practices suggest a distinction between formal compliance and substantive performance. The achievement of a positive digital indicator could become an objective in itself, even when it did not correspond to the underlying quality or strategic value of the work.

This adaptation was accompanied by increased self-monitoring. P12 stated, *"I constantly check if I'm hitting the right numbers to stay in the system's good books."* P22 similarly explained that after completing projects or training programmes, they no longer assumed that the information had been recorded automatically and instead checked their employee profile themselves. These accounts suggest that the system extended managerial evaluation into a form of employee self-surveillance, in which workers assumed responsibility for ensuring that their digital records remained accurate and favourable.

This pattern was not universal. P27 represented a contrasting case, explaining that the introduction of automated processes had not substantially changed how he performed his work: *"Not really. I still do my job the same way."* His response suggests that the effects of algorithmic HRM depended partly on the employee's level of exposure to algorithmically evaluated outcomes and the extent to which those outcomes were experienced as consequential.

4.3 Algorithmic visibility, professional identity and context-blindness

A third theme concerned the tension between employees' professional identities and the simplified representations produced by algorithmic HRM systems. Participants frequently described a discrepancy between the complexity of their actual work and what became visible through dashboards, scores, and other measurable indicators.

The experience was particularly evident in descriptions of being reduced to a numerical representation. P11 stated, *"Sometimes you feel like a data point instead of being a real human,"* while P9 similarly observed, *"When decisions are made by algorithms, I feel like just another data point."* P1 connected this reduction directly to the absence of interpersonal interaction, explaining that when a system determines a rating or bonus without a face-to-face discussion, the process feels *"cold and robotic."*

Participants also highlighted the invisibility of qualitative and relational contributions. P1 explained that the system recorded measurable digital activities such as completed tickets but failed to capture mentoring and strategic activities. P34 similarly described spending considerable time supporting colleagues and resolving employee issues that were not reflected in formal metrics, concluding that the system captured *"what I had completed, but not the value I had added in ways that were harder to measure."* P12 raised a related concern about talent identification, noting that employees could be represented primarily through their formal roles even though these did not reflect their complete skill sets.

A related pattern concerned the distinction between procedural consistency and contextual fairness. Participants acknowledged that algorithmic systems could apply the same rules to everyone and thereby reduce obvious favouritism. Yet consistency did not necessarily translate into perceived fairness. P1 captured this contradiction: *"It's fair because the rules are the same for everyone, with no favourites... but it feels unfair because it does not understand the context of our work."* P20 similarly argued that the absence of preferential treatment could itself become problematic when the system ignored the operational circumstances surrounding an employee's work.

The findings therefore suggest that participants evaluated algorithmic fairness at two levels. Procedural consistency was valued because it reduced arbitrary interpersonal variation, while contextual sensitivity was necessary for employees to regard an outcome as substantively fair. When the latter was absent, the formal equality of algorithmic rules could be interpreted as another form of unfairness. The findings indicate that employees continuously interpreted AI-driven HRM by evaluating fairness, transparency, contextual sensitivity, and dignity. These interconnected interpretive processes are summarised in Fig. 3.

4.4 Accountability, managerial mediation and the "system says so" effect

The fourth theme concerned the redistribution and, in some cases, diffusion of accountability following the introduction of algorithmic HRM. Participants described situations in which responsibility for decisions became difficult to locate because managers and HR personnel could attribute outcomes to the system rather than explaining or taking responsibility for the decision themselves.

P19 described this as an *"accountability vacuum,"* asking who would be responsible if an algorithmic decision adversely affected a high-performing employee. P20 similarly reported that when system errors affected evaluation outcomes, responsibility could move between HR and line management. The

concern was therefore not limited to inaccurate algorithmic outcomes; it also involved uncertainty about who had the authority and responsibility to correct them.

This issue was particularly visible in the recurring *"system says so"* response. P30 explained:

What bothered me wasn't the decision itself. It was that everyone kept saying, 'That's what the system says,' and nobody seemed willing to take ownership of it.

For P30, the problem was consequently not simply disagreement with an automated outcome but the absence of meaningful human engagement with the decision. P31 similarly observed that using the system as an explanation made it more difficult to understand what had actually occurred.

The data nevertheless revealed an important contrasting pattern: managerial intervention could restore trust and dignity. P22 described a supportive manager who helped resolve a system-related problem, explaining that the intervention reminded the employee that *"there was still a person behind the process, not just a screen making decisions."* P35 likewise reported feeling respected when the organisation reviewed concerns rather than simply asserting that the system was correct.

These contrasting accounts indicate that human involvement operated in two different ways. When managers used the system to avoid responsibility, algorithmic HRM became associated with distance and powerlessness. When managers intervened, explained decisions, and facilitated correction, human oversight acted as a relational buffer between employees and the automated system.

4.5 Digital modernisation, hierarchy and constrained employee voice

The fifth theme situated employee interpretations of AI-driven HRM within the wider organisational environment of rapid digital transformation in Saudi Arabia. Participants connected the adoption of AI and automation with organisational aspirations for modernisation and with the broader national emphasis on digital transformation under Vision 2030.

P1 described *"a huge push for Digital Transformation and Vision 2030"* and suggested that organisations sometimes adopt such systems partly to demonstrate that they are technologically advanced. P6 similarly observed that being *"data-driven and advanced"* had become part of the organisational image. These accounts indicate that AI-driven HRM could acquire symbolic significance beyond its immediate technical function: digitalisation could represent organisational progress, competitiveness, and alignment with broader modernisation priorities.

At the same time, this symbolic status could make criticism more difficult. P20 explained that employees who questioned system decisions could be perceived as *"resisting change or backward-thinking."* P6 similarly reported that employees did not necessarily complain openly because they understood that digitalisation represented the direction of the organisation.

The findings also indicated that the capacity to challenge algorithmic outcomes varied according to organisational position. P21 observed that junior staff could be less willing to question systems than senior academics because of organisational hierarchy. P20 described the difficulty of bypassing established lines of command to question a system that senior leadership had invested heavily in. Thus, opportunities to voice concerns were not experienced as equally distributed across organisational levels.

This pattern matters because participants did not describe resistance solely as open rejection. Instead, concerns could be expressed through silence, adaptation, private criticism, or strategic compliance. The absence of overt resistance therefore did not necessarily indicate acceptance. Rather, employees could accommodate algorithmic systems while simultaneously questioning their fairness or usefulness.

4.6 Employee well-being and psychological strain

Employee well-being was identified as a cross-cutting reported experience associated with how algorithmic HRM was interpreted and experienced. Participants associated persistent monitoring, context-blind evaluation, and uncertainty over automated outcomes with anxiety, pressure, and reduced psychological comfort.

P15 stated directly, *"The constant monitoring adds so much pressure; it affects my mental health."* P1 similarly described feeling as though employees were being watched *"24/7."* P19 connected algorithmic monitoring with an additional layer of mental strain, particularly where employees feared that a missed digital requirement could affect their careers.

Participants did not attribute psychological strain to automation alone. More negative well-being accounts were reported particularly when automation was interpreted as opaque, intrusive, context-blind, or difficult to challenge, whereas transparency, human review, and supportive managerial intervention were associated with less negative accounts. This pattern is consistent with the broader finding that the consequences of AI-driven HRM were conditional on the meanings employees attached to its operation and governance.

4.7 Integrative summary of the findings

The study findings reveal a process of conditional acceptance rather than simple acceptance or rejection of AI-driven HRM. Participants generally recognised the administrative value of algorithmic systems and, in some cases, their potential to increase consistency and reduce interpersonal favouritism. However, this acceptance became constrained when systems were perceived to replace rather than support human judgement, particularly in decisions involving performance, promotion, recognition, or employee status.

The findings also show that employees respond to algorithmic HRM through behavioural adaptation. They monitor their digital records, prioritise measurable activities, and in some cases strategically adjust their behaviour to satisfy system indicators. These responses can create a discrepancy between what organisations observe through dashboards and the substantive quality of work being performed.

At the relational level, algorithmic HRM also altered perceptions of professional identity and accountability. Employees questioned whether their qualitative contributions remained visible when performance was represented through simplified metrics, while automated decisions could create uncertainty regarding who was responsible for explaining or correcting adverse outcomes. Human managers therefore remained important intermediaries shaping employee experience: supportive intervention could restore trust, whereas reliance on the system as an accountability shield could intensify distrust.

Finally, these processes were embedded within a broader Saudi organisational environment characterised by rapid digital modernisation and unequal opportunities for employee voice. The findings consequently suggest that the meaning of AI-driven HRM is socially and organisationally contingent. The same technology could be interpreted as an efficiency-enhancing resource, a fairness mechanism, a surveillance device, or a constraint on professional autonomy depending on the employee's role, exposure, experience, and access to human review.

These findings provide the empirical foundation for the subsequent discussion, which interprets these patterns through Weick's (1995) sensemaking properties: identity construction, extracted cues, retrospection, social interaction, enactment, ongoing sensemaking, and plausibility (Fig. 3).

5. Discussion

The findings suggest that employees actively interpret and reconstruct the meaning of AI-driven HRM through ongoing sensemaking. The six themes from 35 interviews (Table 1) connect these responses to algorithmic cues, professional identities and social relationships. Employees also adapt their behaviour to the organisational realities created by automated systems. From Weick's (1995) perspective, AI-driven HRM thus involves ongoing interpretation and enactment, with employee responses shaped by these processes rather than technical capabilities alone.

Specifically, participants interpreted AI under uncertainty and limited transparency (Weick, 1995). They considered technical performance, work complexity, explanation, appeal and human judgement. Sensemaking linked organisational practices to perceived fairness, legitimacy and trust, supporting socio-technical perspectives (Meijerink et al., 2021; Appelbaum, 1997). This ongoing interpretation involved identity, retrospection, extracted cues, social interaction, enactment and plausibility (Weick, 1995).

A second contribution concerns conditional trust in AI-driven HRM. Extending organisational trust research (Mayer et al., 1995), participants accepted routine automation but approached consequential decisions cautiously. Trust depended on transparency, explainability, contestability and meaningful human oversight. Trust thus encompassed system capabilities and organisational governance: employees assessed decisions for accuracy, contextual appropriateness and legitimacy.

The findings also clarify fairness and algorithmic legitimacy in HRM. Participants valued consistent rules yet found them insufficient when systems overlooked unmeasured contributions, personal circumstances and professional judgement. Fairness required contextual sensitivity and employee voice, alongside transparency, contestability and accountability (Newman et al., 2020; Davidovic, 2023; Jabagi et al., 2025). Consistency could thus coexist with diminished professional recognition and dignity.

Sensemaking also translated into action. Prioritising measurable activities, monitoring profiles and strategic compliance illustrate enactment: employees help produce the algorithmic environment they interpret (Weick, 1995). These adaptations may generate data that managers read as productivity evidence, reinforcing reliance on algorithmic measurement. This recursive process suggests that employees may inadvertently strengthen the systems governing their behaviour.

These interpretations also illuminate well-being in the sixth theme. Participants associated transparency, support and human judgement with consistency and reduced uncertainty. Opacity, surveillance and contextual insensitivity were linked to stress, anxiety and concerns about autonomy and dignity. These accounts suggest that perceived governance and communication shaped well-being experiences without establishing measured effects.

Participants consistently favoured human-centred AI governance. They supported a hybrid approach in which AI informs rather than replaces managerial judgement. Human oversight, opportunities to explain individual circumstances and transparent review were considered essential to trust and dignity. This contributes to responsible AI governance debates by showing how employees define safeguards in everyday HR practices.

The Saudi context further situates these governance preferences. Vision 2030 has accelerated investment in AI-enabled HRM across public and private sectors. Complementing technological and managerial perspectives on adoption, the findings show how employees interpret change through organisational relationships, cultural expectations and governance arrangements. They suggest that effective implementation requires technological capability alongside transparency, fairness and meaningful employee participation in algorithmic decision-making.

These governance concerns also reveal displaced accountability when managers and HR personnel invoke system outputs to justify adverse decisions. This “accountability vacuum” leaves employees interpreting outcomes without explanation or dialogue, with implications for trust. Managerial explanation, intervention and correction provide relational support, suggesting that accountability requires transparency and human responsibility. Access nevertheless appeared unequal: authority, managerial access and organisational standing facilitated challenges, while junior employees remained cautious, locating sensemaking and contestability within organisational power relations.

Taken together, the six themes illustrate ongoing sensemaking through identity, extracted cues, retrospection, social interaction, plausibility and enactment (Weick, 1995). Employees interpret algorithmic cues through professional identities, shaping trust and behavioural adaptation, while

repeated encounters inform perceptions of fairness, accountability, dignity and well-being. New decisions prompt reassessment, and employees' actions help shape the environments they interpret. The study thus contributes an account of AI-driven HRM in which employee responses emerge through interactions between technology, identity, organisational relationships, hierarchy, governance and agency.

5.1 Strengths, limitations and future directions

The study offers an interpretive account linking employees' and HR professionals' experiences of AI-driven HRM to conditional trust and well-being. Its sensemaking lens extends technical and efficiency-based perspectives through participants' legitimisation, questioning and resistance. In-depth interviews across roles contextualised evaluation, monitoring, fairness, transparency and human oversight. The Saudi setting broadens algorithmic HRM and management research through employee interpretations in a comparatively underexplored Gulf context.

Four limitations qualify these strengths. First, the 35-participant sample provided rich insights into trust, dignity, fairness and well-being for analytical, not statistical, generalisation. Iterative collection and analysis yielded no materially new insights in later interviews, informing a pragmatic judgement of data adequacy consistent with reflexive thematic analysis, rather than fixed analytic saturation. Second, the cross-sectional design captures sensemaking at one time; longitudinal research could explore how system experience changes trust, fairness, transparency and well-being. Third, CEOs, managers, supervisors and employees were included, but vendors and designers were absent; their perspectives could clarify system design, implementation, justification and experiences across organisational levels. Fourth, accounts did not always distinguish AI-enabled HRM from conventional automation, and system exposure varied. Findings therefore reflect self-reported experiences of technologies as encountered and understood.

These limitations invite research into AI-driven HRM's social dynamics across organisational contexts. Longitudinal studies could trace sensemaking, trust and well-being throughout adoption across HR functions. Cross-sector and cross-institutional comparisons could explore how institutional and cultural values and labour market dynamics inform employee responses. Comparing employee, HR manager and system designer perspectives could clarify how their interactions shape trust and legitimacy.

6. Conclusions

Drawing on Weick (1995), this study examined employee and HR professional sensemaking of AI-driven HRM in Saudi organisations. Reflexive thematic analysis of 35 semi-structured interviews developed six interrelated themes connecting professional identity, organisational relationships and fairness with conditional trust, behavioural adaptation, accountability, hierarchy and well-being. Participants generally accepted routine automation but questioned consequential performance, promotion, talent selection and

career decisions. Acceptance depended on human judgement, contextual understanding, transparency and review.

Interpretations informed metric-oriented behaviour, strategic compliance, self-monitoring and occasional gaming. These adaptations illustrate enactment: prioritising measurable activities may reproduce constraining performance structures. Reducing expertise, relational work, mentoring and problem-solving to data points had perceived implications for professional recognition. Although consistent rules could reduce favouritism, participants distinguished uniform treatment from context-sensitive fairness.

Invoking “the system says so” left participants uncertain about responsibility and challenging errors. Supportive managerial intervention was associated with restored trust, suggesting a relational safeguard for organisational legitimacy. Vision 2030 conferred perceived symbolic legitimacy on adoption, while hierarchy could constrain voice when criticism was interpreted as resistance to organisational or national progress. Monitoring, evaluation uncertainty, metric pressure and profile maintenance were associated with anxiety and strain; transparent, supportive systems with human intervention offered perceived consistency, efficiency and protection against interpersonal bias.

Together, the findings frame AI-driven HRM as ongoing sensemaking and enactment involving opportunities to understand, question and participate in decisions. The contribution connects technology with employee agency, organisational relationships and governance rather than assuming direct effects. It supports human-centred governance: AI provides evidence and decision support, while consequential decisions retain meaningful human review, contextual interpretation, transparency and employee voice. These arrangements may support digital efficiency while protecting dignity, trust, autonomy and well-being.

Declarations

Conflict of interest

The author declares no competing interests.

Ethical approval

This study was approved by the Research Ethics Committee (REC), Faculty of Business, Rabigh, King Abdulaziz University (approval no. 2047-47, dated 20 December 2025). All methods were carried out in accordance with the Saudi Law of Ethics of Research on Living Creatures and its Implementing Regulations (National Committee of Bioethics, KACST), together with the applicable research ethics regulations and guidelines of the Deanship of Scientific Research at King Abdulaziz University. Informed consent was obtained from all participants.

Informed consent

Verbal informed consent was obtained from all participants before their interviews. Participants were informed about the purpose of the study, how their information would be kept confidential, and their right to withdraw at any time. Participation was voluntary.

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Author Contribution

F.K.A. conceived and designed the study, collected the data, conducted the analysis, interpreted the findings, and drafted and revised the manuscript. F.K.A. approved the final version for submission.

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Data Availability

Requests for access to de-identified interview data may be directed to the corresponding author and will be considered in accordance with participant confidentiality and applicable institutional ethics requirements.

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Figures

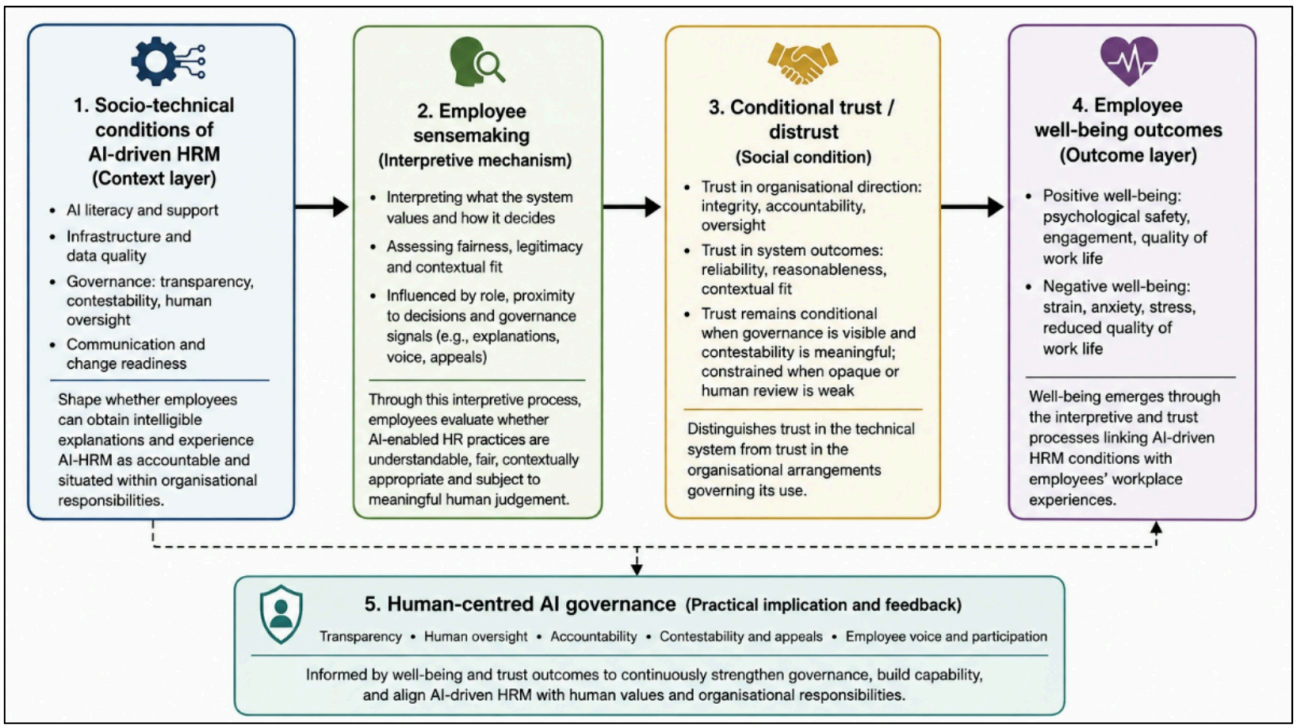


Figure 1

Process framework linking AI-driven HRM conditions, employee sensemaking, trust and well-being

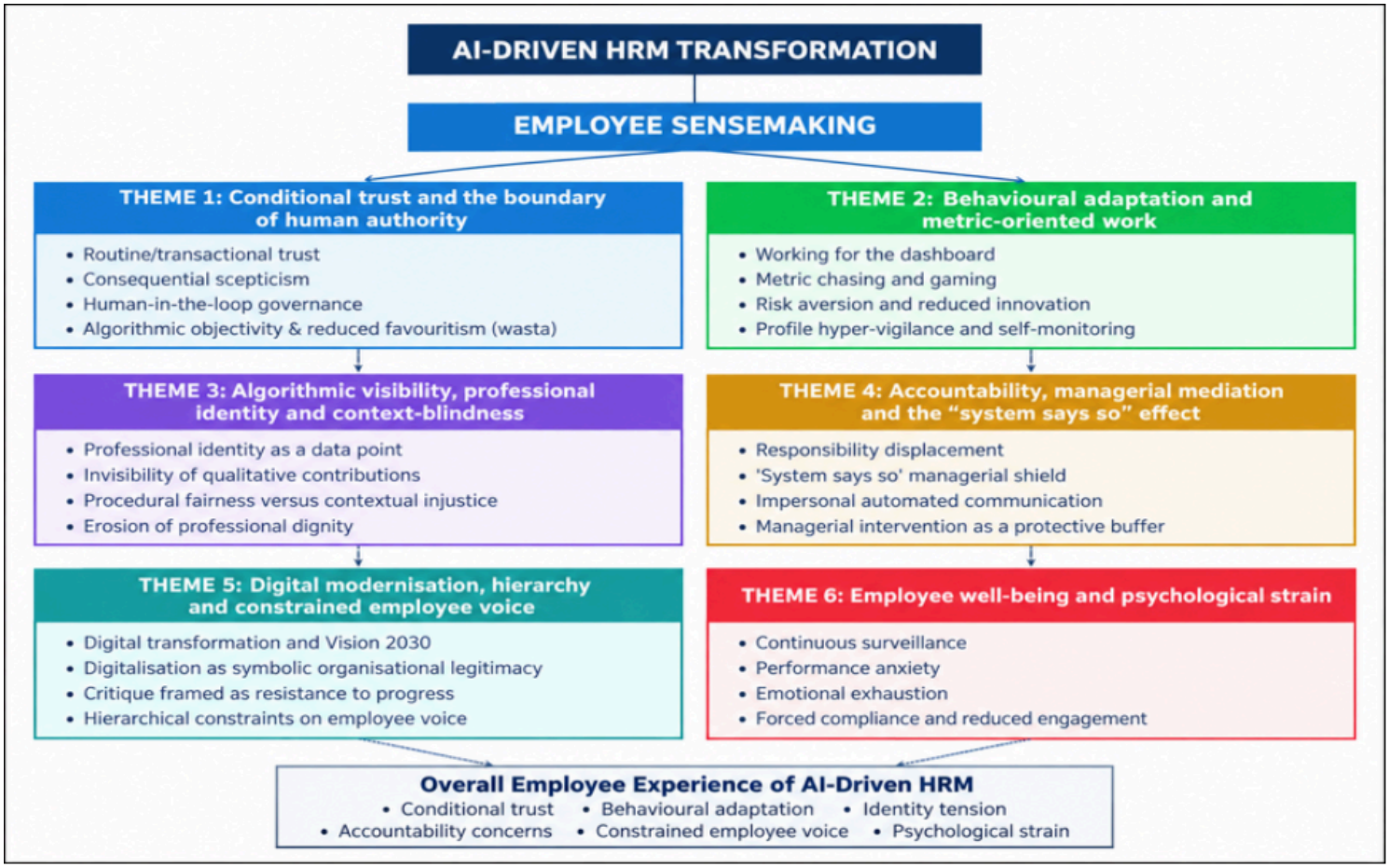


Figure 2

Thematic structure of employee sensemaking of AI-driven HRM

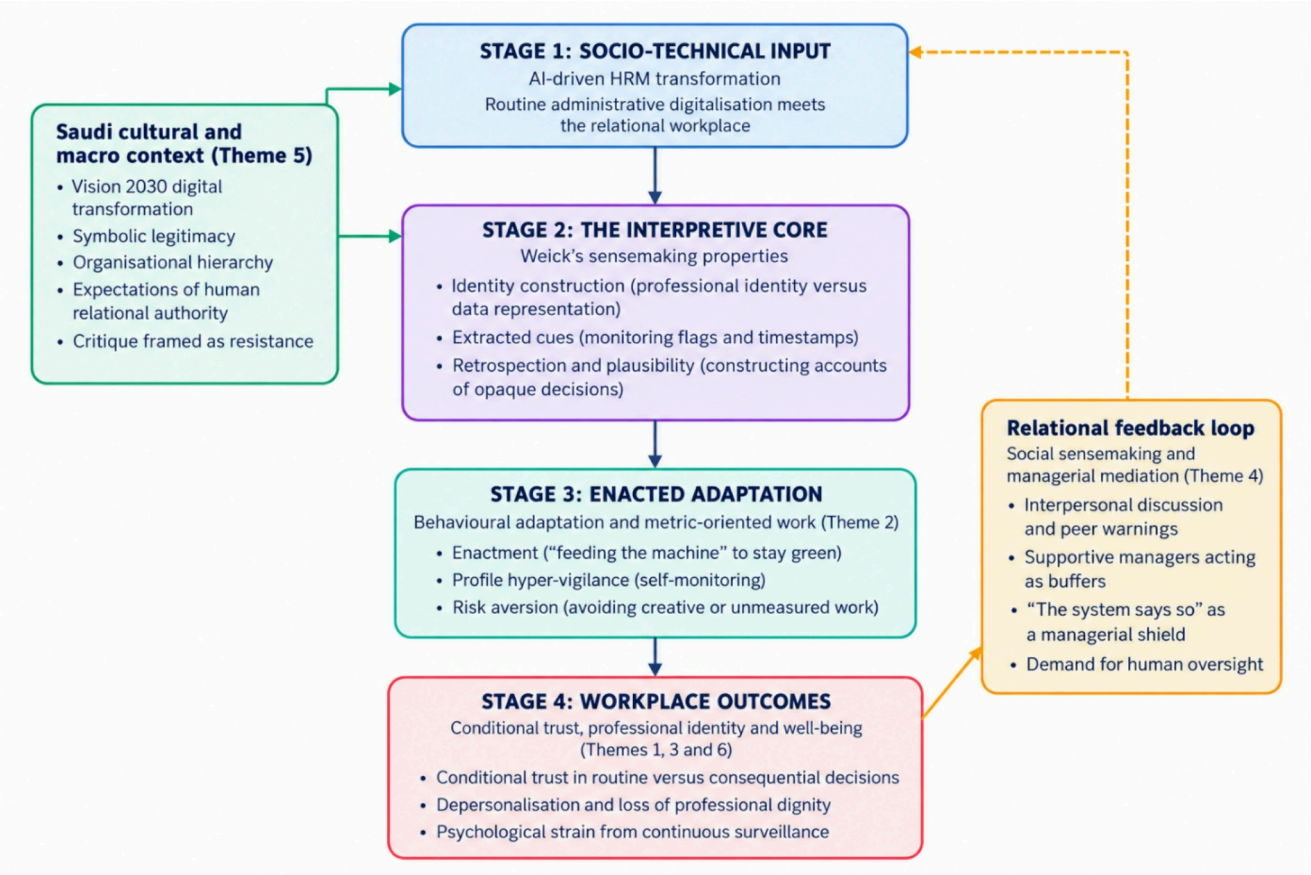


Figure 3

Conceptual model of employee sensemaking of AI-driven HRM in Saudi Arabia