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The role of human resource analytics in enhancing organisational performance and decision-making: A systematic literature review

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Orientation: The importance of human resource analytics (HRA) has been growing as organisations seek to enhance evidence-based decision-making and performance through data-driven human resource (HR) practices.

Research purpose: This study systematically examines and synthesises extant literature on HRA to illuminate its role in organisational decision-making and performance outcomes.

Motivation for the study: Despite growing investment in HRA, organisations report persistent disparities in value realisation. A synthesised framework identifying the processes, facilitators, and barriers defining successful HRA adoption is therefore needed.

Research approach/design and method: A systematic literature review of 68 peer-reviewed articles was conducted across varied industries and international settings, following the Preferred Reporting Items for Systematic reviews and Meta-Analyses framework.

Main findings: Analytics capability, data quality, HR-business partnership and decision-making quality are the four primary drivers of HRA effectiveness. These capabilities translate into improved performance when mediated by organisational culture, ethical governance and digital maturity.

Practical/managerial implications: Managers should invest in data literacy and analytical skills before deploying predictive models and ensure that foundational infrastructure and governance frameworks are in place to maximise HRA value.

Contribution/value-add: The review presents an integrative, multi-level framework that explains HRA's role in organisational performance and identifies seven priority directions for future research.

Keywords: Human Resource Analytics; Organisational Performance; People Analytics; Evidence-Based HRM; Decision-Making Quality; Data Governance; Artificial Intelligence in HRM; Digital Transformation.

Introduction

Human resource analytics (HRA) has evolved from simple descriptive reporting into sophisticated predictive and prescriptive systems that support evidence-based talent decisions and strategic workforce planning. As organisations become increasingly reliant on data-driven human resource management (HRM) to enhance agility, productivity and competitive advantage, HRA has emerged as a foundational capability enabling high-quality, timely decision-making. Despite its widespread adoption, studies indicate persistent contradictions regarding the actual impact of analytics on performance, and evidence confirms that analytics capability alone does not guarantee effective decision implementation (Bechter et al., 2022).

The barriers to realising HRA's strategic potential are well documented and include skills gaps, low analytics maturity, cultural resistance and strained relations between human resource (HR) and line management. Ekka and Singh (2022) demonstrate that adoption of analytics tools is heavily shaped by behavioural and motivational factors among HR professionals, irrespective of organisational investment levels, reflecting broader mismatches between technological potential and practical application. Recent reviews further document the fragmentation of this literature, noting the absence of integrative models that connect analytics inputs, decision mechanisms and performance outcomes (Goswami, 2025).

This systematic review addresses that gap by synthesising evidence from 68 peer-reviewed studies to examine how HR analytics can improve decision-making and organisational performance. Specifically, the review: (1) identifies the antecedents and mediators of effective HRA implementation; (2) proposes a multi-level conceptual model linking analytics inputs to strategic, tactical and operational performance; and (3) establishes five formal propositions to guide future empirical research.

The review makes three primary contributions to the literature. Firstly, it integrates Resource-Based View (RBV), Ability-Motivation-Opportunity (AMO) and Decision Theory frameworks to explain the HRA-performance nexus in a theoretically coherent manner. Secondly, it advances the discussion beyond Western, developed-economy contexts by systematically examining developing-country moderators. Thirdly, it provides formal testable propositions that bridge the review's descriptive synthesis with future quantitative and mixed-methods inquiry.

Conceptual framework

Before proceeding to the systematic methodology, it is important to establish the conceptual boundaries within which key constructs are operationalised in this review. Two constructs require careful definitional and typological treatment: HR Analytics and Organisational Performance.

Defining and typologising human resource analytics

In the context of this review, HRA refers to the systematic collection, analysis and utilisation of workforce data to support informed decisions throughout the employee life cycle. Human resource analytics encompasses four increasingly sophisticated forms. Descriptive analytics summarises historical workforce trends, including turnover rates and absenteeism patterns. Diagnostic analytics identifies the underlying causes of HR outcomes through correlation and root-cause analysis. Predictive analytics employs statistical modelling and machine learning to forecast future workforce behaviour and talent risks. Prescriptive analytics goes further by recommending specific interventions and optimal courses of action.

This typology is necessary because HRA value realisation is substantially determined by the form of analytics deployed and the level of organisational maturity required to implement it effectively (Bechter et al., 2022; Shet, 2025). Organisations at lower maturity levels that attempt to implement predictive or prescriptive analytics without adequate data infrastructure and interpretive capability are unlikely to realise value commensurate with their investment.

Conceptualising organisational performance

Organisational performance is treated in this review not as a homogeneous construct but as a multi-dimensional phenomenon comprising four interrelated domains. Financial performance encompasses cost reduction, revenue growth and return on human capital investment. Operational performance covers productivity, process efficiency and time-to-hire. Talent performance includes retention rates, engagement levels, and the quality of the leadership pipeline. Strategic agility refers to the organisation's capacity to adapt workforce strategy dynamically in response to environmental change (Cayrat & Boxall, 2022).

This disaggregation is analytically important because evidence indicates that the effects of HRA are not consistent across performance dimensions. For example, predictive analytics may produce measurable improvements in recruitment process efficiency without generating commensurate short-term financial returns (Cayrat & Boxall, 2022). A nuanced, multi-dimensional performance conception therefore provides greater fidelity to the evidence base than a single composite outcome variable would afford.

Research design

Databases and search strategy

To achieve methodological rigour and comprehensiveness while adhering to Q1 review standards, this study employed Scopus and the Web of Science Core Collection (WoS) as its primary bibliographic databases, selected for their extensive coverage of peer-reviewed management, HRM, and analytics literature and their established reliability in systematic reviews. A structured search plan was developed to identify publications examining the intersection of HR Analytics, decision-making and organisational performance.

Scopus search string

> TITLE-ABS-KEY((“HR analytics” OR “people analytics” OR “workforce analytics” OR “talent analytics” OR “data-driven HRM” OR “predictive HR” OR “AI in HRM”)) AND TITLE-ABS-KEY((“decision-making” OR “managerial decisions” OR “strategic HRM” OR “organisational performance” OR “productivity”))

Web of Science search string

> TS = (HR analytics OR people analytics OR workforce analytics OR data-driven human resource management) AND TS = (“organisational performance” OR evidence-based HRM OR decision-making)

Searches were conducted in November 2025, covering the 2010–2025 period, which spans both the early conceptual development and mature empirical phases of analytics adoption in HRM.

Inclusion and exclusion criteria

Stringent criteria were applied to ensure conceptual clarity and relevance. Included studies were peer-reviewed journal articles or full conference papers published in English between 2010 and 2025 that directly examined HR analytics in relation to decision-making quality, strategic or operational HR outcomes, or organisational performance, and that offered theoretical, empirical or mixed evidence concerning

HRA capability, data quality, technology infrastructure, HR-business alignment or decision processes.

Studies were excluded if they focused on human resource information systems (HRIS) without an analytics component, presented theoretical propositions without supporting evidence, were dissertations, book chapters, editorials or working papers, failed to relate HRA directly to decision-making or performance, were unavailable in English, or represented incomplete records. These criteria were applied consistently across both databases to ensure the review remained focused on analytically and empirically substantive contributions.

Methodological transparency and limitations

To maintain transparency in accordance with best practice in systematic reviewing, this section explicitly documents the methodological limitations of the present review and the procedures employed to mitigate associated risks.

Firstly, the review protocol was not pre-registered on any platform, such as International Prospective Register of Systematic Reviews (PROSPERO), prior to commencement. While this does not invalidate the findings, it constrains readers' ability to evaluate deviations from the a priori design and creates the possibility of post-hoc scope adjustments. Future iterations of this research agenda should employ prospective registration to strengthen methodological accountability.

Secondly, study selection was conducted by a single reviewer. Although dual screening was not feasible, structured re-evaluation procedures and consistency checks were implemented to approximate reliability in study selection. To mitigate selection bias, a structured, documented screening protocol was applied consistently at every decision point, with pre-defined inclusion rules operationalised as a decision tree. All borderline case studies meeting some but not all criteria were systematically re-evaluated against each criterion individually before a final inclusion or exclusion decision was recorded. To provide a supplementary reliability check, all excluded studies at the full-text screening stage (*n* = 276) were reviewed a second time in a separate pass, and 55 randomly selected records (20% of the excluded pool) were re-evaluated against the inclusion criteria to confirm consistency of application. No reversals from the original decisions were identified in this second-pass review.

Thirdly, a post-hoc quality appraisal was conducted of the 15 most-cited core studies included in the review, using the Critical Appraisal Skills Programme (CASP) Systematic Review Checklist as the adapted evaluation instrument. Appraisal findings are summarised in Table 1-A1. Studies evaluated ranged from strong (meeting all 10 CASP criteria) to moderate (meeting 6–7 criteria), with no included core study rated as weak. While this appraisal was not applied to all 68 studies, a limitation acknowledged, it provides a quality signal for the evidential backbone of the thematic synthesis.

Fourthly, grey literature was excluded to maintain focus on peer-reviewed scholarship, though this may limit practitioner-oriented insights. Fifth, no formal inter-rater reliability statistic can be reported given the single-reviewer design. These constraints are acknowledged as legitimate threats to validity. Given its characteristics, this review is most accurately classified as a systematically conducted structured narrative synthesis with Systematic Literature Review (SLR)-aligned methodology, rather than a fully dual-screened pre-registered SLR in the strictest methodological sense.

Preferred Reporting Items for Systematic reviews and Meta-Analyses flow and screening process

The review followed the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) 2020 framework to maximise transparency and reproducibility. Initial database searching yielded 1310 records. Following de-duplication (*n* = 312 duplicates removed), 998 unique studies were screened at the title and abstract level, resulting in the exclusion of 654 irrelevant records. Full-text evaluation was conducted on 344 articles, of which 276 were excluded because of non-journal format, off-topic focus or insufficient methodological clarity. The final sample comprised 68 studies included in the qualitative synthesis, as depicted in Figure 1 (PRISMA flow diagram).

Descriptive literature analysis

Geographic distribution of studies

The geographic distribution of HRA scholarship demonstrates a strong concentration in the United States and Western Europe (Figure 2), where digital transformation infrastructure, sophisticated HR technologies and established data

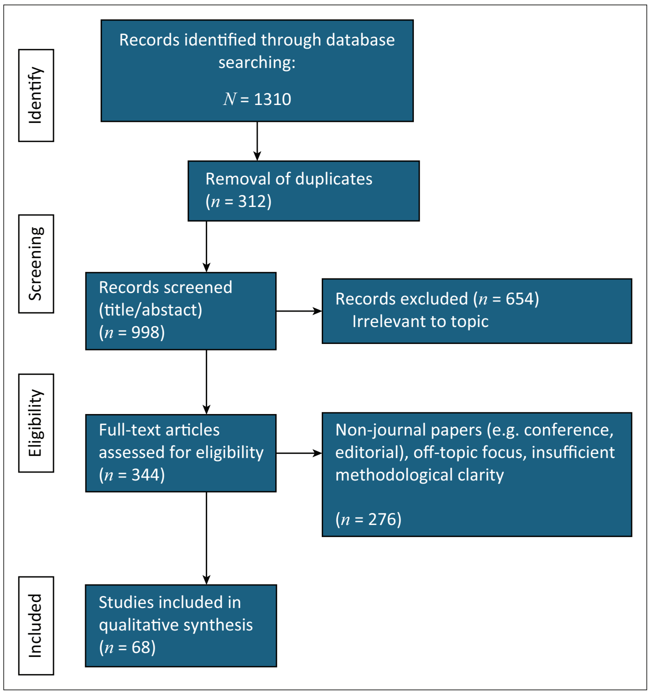


FIGURE 1: Preferred reporting items for systematic reviews and meta-analyses flow diagram.

ecosystems have long supported analytics-oriented HRM. These contexts provide the foundational debates on analytics capability, decision integration and organisational contingencies (Angrave et al., 2016; Marler & Boudreau, 2017; Peeters et al., 2020). Nordic, UK and Central European research institutions dominate recent empirical output, particularly studies on capability frameworks and evidence-based HRM (Bechter et al., 2022; Dahlbom et al., 2020).

Asian representation has grown markedly since 2020, particularly from India, China, Sri Lanka and Indonesia, where digitalisation and the adoption of HR technology have driven empirical shifts towards workforce analytics and cross-cultural dynamics. Contributions from the Middle East have focused primarily on artificial intelligence (AI) integration and recruitment analytics (Alaghbari et al., 2024; Hourani, 2025). Africa and Latin America remain substantially underrepresented (Oladipupo & Falola, 2020), signalling an important direction for future comparative research.

Moderating role of developing country contexts

Conditions in developing economies moderate the HRA-performance relationship through five primary mechanisms. Firstly, infrastructure constraints, such as fragmented HRIS adoption, limited digital connectivity and unequal access to cloud-based analytics, reduce the effectiveness of data quality and technology infrastructure as enablers of performance (Oladipupo & Falola, 2020; Siddiqua et al., 2023). Secondly, critical shortages of data science and analytical skills in HR functions limit the translation of insights into action, particularly in non-information technology (IT) industries (Alexandro, 2025; Kiran et al., 2022). Thirdly, the varied data protection regulatory landscapes across South Asia and Sub-Saharan Africa create uncertainty about algorithmic decision-making, potentially inhibiting the adoption of analytics (Bahuguna et al., 2024). Fourthly, collectivist cultural norms and hierarchical decision-making traditions moderate the extent to which analytics recommendations are enacted in managerial practice (Herdiansyah et al., 2025). Fifthly, the digital divide between urban, technology-intensive organisations and rural, public-sector, or informal-economy organisations means that most developing-country firms remain at the descriptive analytics stage, necessitating investment in foundational infrastructure before advanced analytics can generate performance benefits (Oladipupo & Falola, 2020; Siddiqua et al., 2023).

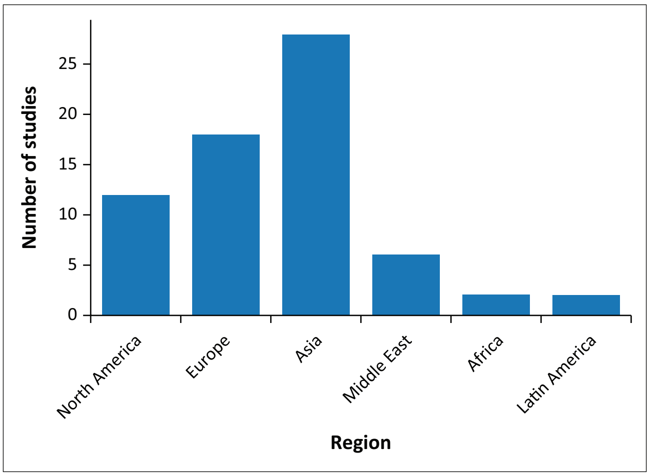
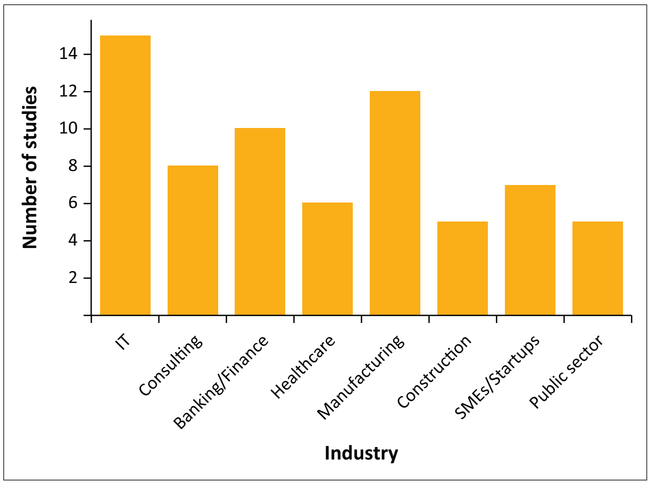


FIGURE 2: Geographic distribution of studies.

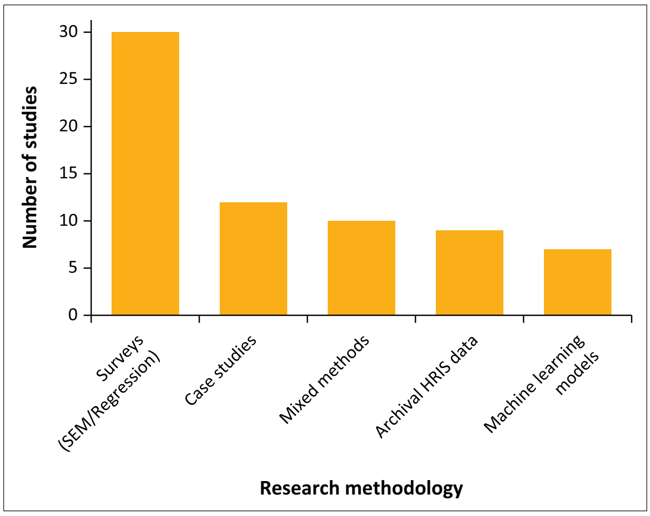
Industry and methodological trends

Human resource analytics research is most concentrated in IT, consulting, high-tech manufacturing, banking, healthcare and construction (Figure 3), with high-technology and data-intensive industries predictably leading adoption given their technological preparedness and compatibility between analytics systems and workforce complexity (Mushtaq et al., 2024). Methodologically, survey-based quantitative studies using regression, structural equation modelling (SEM) or multi-level modelling dominate the corpus, followed by case studies, mixed-methods approaches, archival HRIS data analyses and machine-learning-based models (Figure 4) (Arora & Mittal, 2024; Cayrat & Boxall, 2022; Hamja et al., 2025).



IT, information technology; SME, small and medium-sized enterprises.

FIGURE 3: Industry distribution.



HRIS, human resource information system; SEM, structural equation modelling.

FIGURE 4: Methodological trends.

Significant methodological gaps remain. Longitudinal research designs are rare, limiting understanding of how analytics capabilities evolve over time. Experimental and quasi-experimental designs are scarce, and research rarely examines how analytics interventions reshape managerial cognition or strategic reasoning. These gaps point to the need for advanced multi-wave and experimental methodologies in future research programmes.

Research development of human resource analytics over time

Human resource analytics scholarship has developed in three discernible waves. Between 2010 and 2015, research focused primarily on conceptual frameworks and articulating the strategic potential of workforce analytics (Angrave et al., 2016; Lal, 2015). Between 2016 and 2020, attention shifted toward predictive analytics, talent management applications and analytics-enabled performance improvement, with evidence-based HRM models that link analytics to decision quality emerging prominently (Dahlbom et al., 2020; McCartney & Fu, 2021). The 2021–2025 period represents a phase of rapid acceleration driven by AI, machine learning and digital HR ecosystems, accompanied by growing scrutiny of algorithmic fairness, data governance and the ethical dimensions of analytics-intensive HRM (Bahuguna et al., 2024; Kulikowski, 2024; Shet, 2025).

Thematic synthesis

Thematic analysis of the 68 included studies reveals four overarching, mutually reinforcing themes that explain how HRA improves organisational decision-making and performance: analytics capability, data quality and technology infrastructure, HR-business partnership and decision-making quality. These themes demonstrate the multi-tiered pathway through which analytics transforms raw data into strategic value.

Thematic synthesis, conceptual clustering, and triangulation of methodological patterns across the 68 studies reveal seven predominant research streams that characterise the current state of HRA scholarship. Future research opportunities arising from these streams are summarised in Table 2.

Human resource analytics capability

Human resource analytics capability emerges as the foundational pillar enabling analytics adoption, integration and performance transformation. Research consistently identifies capability as multifaceted, encompassing analytical aptitude, leadership support, technological preparedness and an evidence-based HRM culture. Organisations with higher capability levels exhibit greater precision, velocity and consistency in analytics execution (Arora & Mittal, 2024; Marler & Martin, 2024). However, capability gaps remain common: HR practitioners frequently lack the statistical, technological, and interpretive skills needed to translate insights into action, a challenge anticipated in early accounts of HR's readiness deficit for big data (Angrave et al., 2016). Shaping capability depends not only on individual skill but also on structural enablers, including training investment, leadership motivation and market context (Bechter et al., 2022; Kaur & Gupta, 2024).

Data quality and technology infrastructure

Effective HRA implementation is contingent on high-quality data and robust technological infrastructure. Research on AI-based HR systems and predictive modelling consistently demonstrates that the quality of analytics outputs is directly determined by the quality, integration and availability of underlying HR data (Bagiyam et al., 2024; Wang et al., 2025). Data entry errors and cross-system inconsistencies undermine confidence in decisions and erode the perceived value of analytics outputs (Dahake et al., 2024). Advancing technologies, including machine learning, IoT-based workforce tracking, blockchain-enabled records and intelligent HR systems, expand analytical possibilities but also introduce challenges related to transparency, algorithmic bias and operational risk (Abel et al., 2024; Alzyoud et al., 2024; Bankar & Shukla, 2023; Bhati, 2024; Chavan et al., 2024; Kulikowski, 2024; Lakshmi, 2025; Mangla, 2023; Murale et al., 2024; Nimmagadda et al., 2024; Sonar et al., 2025). Explainable machine learning approaches in attrition prediction studies demonstrate that transparency is central to gaining acceptance from HR managers and employees of analytics-driven decisions (Hamja et al., 2025).

Human resource–business partnership

Analytics generates organisational value only when HR works in close collaboration with business leaders and line managers. Effective HR-business relationships enable the translation of analytical evidence into strategic programmes, strengthen the credibility of HR recommendations and generate organisational buy-in for data-driven interventions (Gupta & Sharma, 2023; McCartney & Fu, 2021). Evidence indicates that analytics adoption rates are higher in organisations where HR engages with business units through digital enterprise platforms and integrated decision-support systems (Gupta & Sharma, 2022; Rusilowati et al., 2025). Persistent barriers to effective partnership, including siloed HR functions, a lack of managerial trust and misalignment between HR and business strategies, continue to limit the effectiveness of analytics in many organisations (Cayrat & Boxall, 2022; Mushtaq et al., 2024).

Decision-making quality

The ultimate value of HRA is manifested in its enhancement of decision quality at strategic, tactical and operational levels. Analytics has been shown to reduce cognitive bias, improve predictive precision and support scenario reasoning in talent decision-making (Sasirekha et al., 2024; Sivathanu & Pillai, 2020). Predictive analytics enhances the efficiency of recruitment, attrition forecasting and performance management, enabling proactive responses to talent challenges before they become costly (Palshikar et al., 2019; Sharma & Sharma, 2017). Evidence-based management serves as the mediating mechanism through which analytics converts raw data into implementable decisions (Thapliyal, 2024). Researchers caution, however, that exclusive reliance on predictive outputs without contextual interpretation may generate systematic errors, underscoring the importance of hybrid human–AI decision-making models (Hourani, 2025).

Critical perspectives, contradictory findings and employee voice

A substantive body of evidence challenges optimistic narratives about HRA's transformative potential. The first significant controversy concerns whether HRA is truly transformative or primarily rhetorical. While early scholarship positioned analytics as a strategic game-changer (Lal, 2015; Marler & Boudreau, 2017), subsequent empirical research has complicated this narrative. Angrave et al. (2016) argued that the big data challenge is structurally ill-suited to HR because of the profession's epistemological traditions and skills positioning. Cayrat and Boxall (2022), in a study of 40 large organisations, found persistent implementation gaps between analytics investment and the realisation of strategic value. Dahake et al. (2024) warn that the performance of predictive analytics remains unstable and context-dependent in high-stakes business decisions.

The second critical issue concerns algorithmic bias and fairness. As HRA increasingly employs machine learning for candidate screening, attrition prediction and performance assessment, the risk of entrenching and amplifying existing workforce biases becomes material. Hamja et al. (2025) propose explainable machine learning as a mechanism for transparency, while Kulikowski (2024) argues that standardised analytical skills training must be accompanied by ethical reasoning and bias-identification competencies. Empirical evidence on how algorithmic bias manifests across varied cultural and organisational contexts remains, however, a major gap in the literature.

Third, the use of digital data to quantify workforce behaviours through gamified attendance tracking (Herdiansyah et al., 2025) and digital measures of proactivity (Ontrup et al., 2022) raises under-researched concerns about employee privacy, autonomy and the psychological contract. The literature provides mixed evidence on whether analytics-intensive environments bolster or undermine employee trust. Bechter et al. (2022) found that employees' responses to analytics-driven performance monitoring are mediated by market and country context, indicating that reactions are not universal.

Fourth, the relationship between HRA and performance is not uniformly positive. While several studies report strong positive associations between analytics capability and organisational performance (Arora & Mittal, 2024; Mushtaq et al., 2024; Vadithe et al., 2025), others find that these relationships depend heavily on contextual moderators. Bechter et al. (2022) show that capability, opportunity and motivation interact in complex, non-linear ways, and Ekka and Singh (2022) demonstrate that behavioural and motivational factors among HR professionals moderate the use of analytics tools, regardless of organisational investment levels.

Importantly, no included study in this review directly investigated employee voice, defined as the degree to which employees actively participate in, resist, or negotiate analytics-driven HR practices, representing a substantive and under-theorised gap in the literature. Future research should examine how employees perceive, resist or negotiate analytics-driven HR practices, particularly in cross-cultural and developing-country contexts where power dynamics and institutional frameworks differ markedly from those in the Western organisational settings that dominate the current evidence base.

Cross-cutting insights

The synthesis indicates that analytics competence, decision-making quality and data governance and ethics collectively constitute the effectiveness architecture of HR analytics. Analytics capability is necessary but not sufficient: its effect manifests only when insights are channelled into decisions that are more accurate, less biased and proactively oriented toward talent outcomes (Arora & Mittal, 2024; McCartney & Fu, 2021). Data governance and ethics shape the trust, transparency and institutional legitimacy without which analytics systems cannot sustain value creation over time (Hamja et al., 2025; Kulikowski, 2024). Together, these forces constitute a positive-reinforcement mechanism: capability generates insights, governance legitimises action, and decision quality converts insights into measurable organisational outcomes (Durai et al., 2019; Durai & Manoharan, 2025; Jiang & Akdere, 2021; Kok & Akbari, 2024; Koy et al., 2025; Mishra et al., 2018; Mishra et al., 2019; Muhammad & Naz, 2022; Opatha et al., 2025; Pareek, 2025; Ratnesh et al., 2025; Shaikh et al., 2025; Singh et al., 2025; Sohu et al., 2024; Vadithe & Kesari, 2025).

Proposed multi-level human resource analytics impact model

The proposed model conceptualises HRA as a cascading system in which organisational outcomes emerge from the interaction of analytics inputs, processing capabilities, decision mechanisms and contextual moderators (Figure 5):

- **Level 1: HR analytics inputs** constitute the infrastructure that makes analytics work possible, including diverse HR data sources, integrated HRIS solutions, AI-driven analytics tools, analytics talent and leadership investment.
- **Level 2: Analytics processing and capability** captures the conversion of raw data into actionable intelligence through descriptive, diagnostic, predictive and prescriptive analytics. Higher levels of analytics maturity generate greater interpretive richness, accuracy and strategic value.
- **Level 3: Decision-making mechanisms** describe how analytics supports HR and managerial decisions. When appropriately integrated into recruitment, performance

management, engagement, workforce planning and retention processes, HRA raises the speed, transparency and precision of decisions and minimises reliance on intuition or subjective judgement.
- **Level 4: Organisational performance outcomes** capture the aggregate effects of analytics-informed decisions, including talent optimisation, cost reduction, productivity improvement, strategic agility and long-term competitive advantage.

Relationships across these four levels are moderated by four contextual factors: organisational culture (receptiveness to evidence-based decision-making), data privacy climate and ethical governance (shaping trust and legitimacy), digital capability (systems integration and analytics scalability) and employee trust in analytics (predetermining acceptance of data-driven HR practices).

Formal propositions

The following propositions are advanced to accompany the multi-level model and guide future empirical testing:

- **Proposition 1 (P1):** HR analytics capability positively affects the quality of HR and managerial decision-making, and this relationship is mediated by the quality of data infrastructure. Organisations with mature analytics capabilities but poor data integration will experience attenuated improvements in decision-making compared to those with aligned capabilities and infrastructure (Arora & Mittal, 2024; Bagiyam et al., 2024).
- **Proposition 2 (P2):** The relationship between analytics-informed decision quality and organisational performance outcomes is moderated by organisational culture. Specifically, organisations with evidence-based management cultures will exhibit stronger translation of improved decisions into measurable performance gains than those where intuition-based decision norms prevail (Bechter et al., 2022; McCartney & Fu, 2021).
- **Proposition 3 (P3):** Ethical data governance and algorithmic transparency positively moderate the relationship between HRA inputs and employee trust. In the absence of transparent governance, increased analytics intensity may erode employee trust and reduce acceptance of data-driven HR practices (Hamja et al., 2025; Kulikowski, 2024).
- **Proposition 4 (P4):** HR-business partnership quality mediates the relationship between analytics processing capability and strategic performance outcomes. Analytics insights that are not communicated through effective cross-functional partnerships will fail to influence strategic decision-making regardless of their technical sophistication (Cayrat & Boxall, 2022; Gupta & Sharma, 2023).
- **Proposition 5a (P5a):** The relationships specified in P1 and P2 are moderated by infrastructure and skills constraints in the developing-country context, such that organisations facing digital infrastructure limitations and analytics skills shortages will experience significantly attenuated performance benefits from HRA capability investment relative to counterparts in resource-sufficient environments (Oladipupo & Falola, 2020; Siddiqua et al., 2023).
- **Proposition 5b (P5b):** The relationships specified in P3 and P4 are moderated by cultural distance from data-driven norms and regulatory uncertainty in the developing-country context, such that collectivist cultural dynamics and ambiguous data protection environments will weaken the trust-building and partnership mechanisms through which analytics generates strategic value (Alexandro, 2025; Herdiansyah et al., 2025).

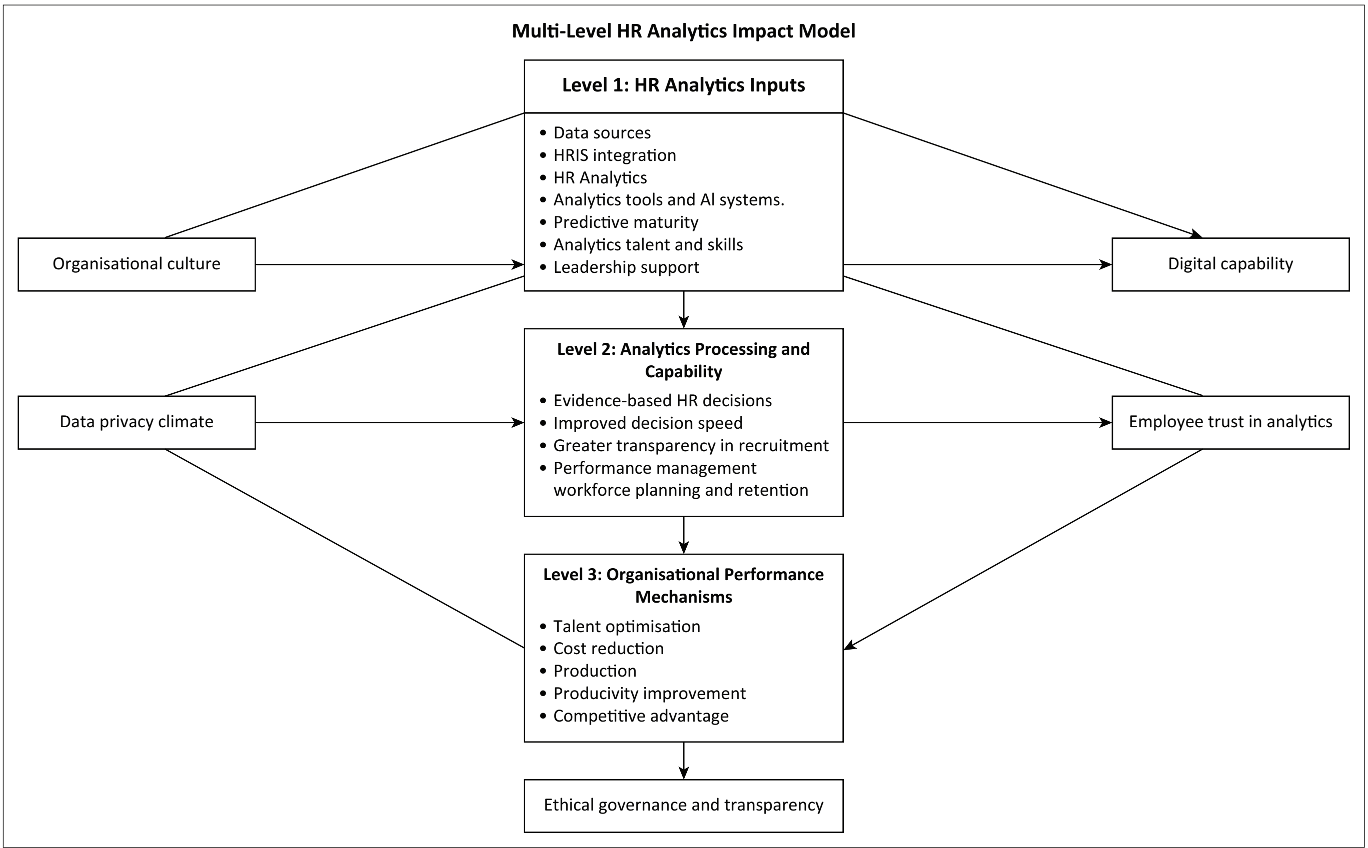
Notably, the moderating role of employee trust is qualified by contradictory findings documented in critical perspectives contradictory findings and employee voice. While ethical governance appears to strengthen trust in analytics systems under some conditions, Bechter et al. (2022) demonstrate that employees' responses to data-driven HR practices vary significantly across market and country contexts. Accordingly, P3 and P5b are advanced as tentative propositions that require longitudinal empirical testing before causal claims can be established with confidence.

TABLE 1: Evidence mapping: Themes, supporting studies and weight of evidence.

Themes	Support studies	Key findings	Weight of evidence
HR analytics capability	Arora and Mittal (2024), Bechter et al. (2022), Shet (2025), Marler and Martin (2024), Kaur and Gupta (2024), Angrave et al. (2016), Kiran et al. (2024)	Capability is multifaceted; structural enablers matter as much as individual skill	Strong: 8 studies across multiple contexts
Data quality and technology	Bagiyam et al. (2024), Wang et al. (2025), Dahake et al. (2024), Hamja et al. (2025), Kulikowski (2024)	Data errors undermine decision confidence; explainable AI enhances acceptance	Moderate-Strong: 7 studies; mixed on consistent outcome improvement
HR-business partnership	McCartney and Fu (2021), Gupta and Sharma (2022, 2023), Cayrat and Boxall (2022), Mushtaq et al. (2024)	Analytics generates value only through close HR-business collaboration	Moderate: 6 studies; limited quantitative evidence on mechanisms
Decision-making quality	Sasirekha et al. (2024), Sivathanu and Pillai (2020), Palshikar et al. (2019), Thapliyal (2024), Hourani (2025)	Analytics reduces bias and improves precision; hybrid models are recommended	Strong: 7 studies with consistent positive findings
Critical perspectives	Angrave et al. (2016), Cayrat and Boxall (2022), Dahake et al. (2024), Bechter et al. (2022), Ekka and Singh (2022)	Implementation gap persists; algorithmic bias under-researched; employee voice absent	Moderate: 8 studies; contradictory on capability-to-outcome translation
Developing country contexts	Oladipupo and Falola (2020), Siddiqua et al. (2023), Alexandro (2025), Kiran et al. (2022), Herdiansyah et al. (2025)	Infrastructure, skills shortages, and the digital divide moderate HRA effectiveness	Limited: 6 studies; primarily descriptive; insufficient comparative evidence

Note: Please see the full reference list of this article Siby, S.S., & Patel, J. (2026). The role of human resource analytics in enhancing organisational performance and decision-making: A systematic literature review. *SA Journal of Human Resource Management/SA Tydskrif vir Menslikehulpbronbestuur*, *24*(0), a3636. https://doi.org/10.4102/sajhrm.v24i0.3636 for more information

HR, human resource; HRA, human resource analytics; AI, artificial intelligence.



HR, human resource; HRIS, human resource information systems; AI, artificial intelligence.

FIGURE 5: Multi-level human resource analytics impact model.

TABLE 2: Triangulation and future research directions.

Conceptual cluster	Linked themes	Future research directions
HRA capability development	Analytics maturity, skills, infrastructure and leadership support	Develop longitudinal maturity models capturing how capabilities evolve and their impact on value creation over time
Decision-making quality	Evidence-based HRM, bias reduction, predictive accuracy	Examine how analytics reshapes managerial cognition, judgement processes and strategic reasoning
Ethical AI and fairness	Algorithmic transparency, explainability and data governance	Design governance frameworks addressing algorithmic fairness, ethical oversight and responsible AI adoption in people analytics
Cross-cultural differences	Digital adoption, institutional context, workforce norms	Conduct multi-country analyses, especially in India, Africa and South America, to explore contextual variations in HRA outcomes
Impact measurement challenges	Performance metrics, data validity, attribution issues	Develop robust metrics linking HRA to financial, productivity and innovation outcomes using rigorous causal designs
Technology-human-culture interaction	AI-driven HRM, psychological contract shifts and leadership styles	Study how AI transforms leadership behaviour, employee expectations and organisational culture dynamics
Employee trust and acceptance	Perceived fairness, transparency and behavioural adoption	Undertake micro-level studies on employee reactions, trust-building mechanisms and behavioural acceptance of analytics-driven HRM

Note: These directions collectively underscore the need for deeper theorisation, methodological innovation and cross-contextual analysis to advance the field.
HRM, human resource management; HRA, human resource analytics; AI, artificial intelligence.

These propositions specify the expected direction and contingencies of relationships within the model and are intended to guide future quantitative and mixed-methods research. Relationships are expected to be recursive rather than strictly linear: improved decision quality generates performance feedback that may further enhance analytics capability and organisational willingness to invest in data infrastructure, creating a self-reinforcing cycle of analytics-driven improvement.

Triangulation and future research directions

Thematic synthesis, conceptual clustering and triangulation of methodological patterns across the 68 studies reveal seven predominant research streams that characterise the current state of HRA scholarship. Future research opportunities arising from these streams are summarised in Table 1.

To consolidate the findings of the thematic synthesis, Table 1 presents an evidence mapping of the principal HR analytics themes identified in the literature, together with their supporting studies, key findings, and relative weight of evidence.

Theoretical contributions and integration

The RBV, the AMO framework and theories of decision-making can explain how HR analytics capabilities are transformed into organisational performance.

The RBV provides the rationale for why HRA constitutes a source of competitive advantage. Within an RBV framework, HRA is a firm-specific, knowledge-intensive capability that is valuable (enabling high-quality workforce decisions), rare (analytics maturity is unevenly distributed across organisations), imperfectly imitable (embedded in tacit organisational knowledge, data ecosystems and interpretive culture), and non-substitutable (no equivalent mechanism generates comparable strategic insight into human capital). The RBV addresses why organisations with developed analytics capabilities outperform those without, but it does not explain how those capabilities are activated and translated into decisions.

The AMO framework fills this explanatory gap by specifying the conditions under which analytics capability can be effectively deployed. The ability dimension encompasses analytical skills, data literacy and interpretive competencies among HR professionals and managers (Angrave et al., 2016; Kulikowski, 2024). The motivation dimension includes leadership commitment, perceived usefulness and professional motivations that drive analytics adoption (Bechter et al., 2022; Ekka & Singh, 2022). The opportunity dimension comprises structural enablers, data infrastructure, governance frameworks, cross-functional collaboration mechanisms and organisational culture that create the conditions within which analytics can shape decisions (Gupta & Sharma, 2023; Kaur & Gupta, 2024).

Decision-making theories, particularly bounded rationality and evidence-based management perspectives, explain how analytics enhances decision quality. Analytics reduces information asymmetry, broadens the decision-maker's consideration set, and enables systematic assessment of options through scenario modelling and predictive forecasting (McCartney & Fu, 2021; Thapliyal, 2024). The multi-level model proposed in this review advances this theoretical contribution by specifying that the decision quality mechanism operates simultaneously at strategic, tactical and operational levels, and that decision quality mediates the relationship between analytics capability and performance outcomes, a theorised but insufficiently tested pathway in prior literature.

Two additional theoretical perspectives merit integration in future extensions of this model. Dynamic Capabilities Theory would clarify how organisations sense, seize and reconfigure their analytics capabilities in response to environmental change, a process evident in the HRA literature's documented evolution from descriptive to prescriptive analytics during 2010–2025. Institutional Theory could illuminate how regulatory settings, professional standards and mimetic isomorphism shape patterns of analytics adoption across countries and industries, accounting for the institutional and geographic variation documented in geographic distribution of studies section and industry and methodology trends.

Practical and managerial implications

The findings carry several concrete implications for HR executives, line managers and organisational leaders. Firstly, organisations should invest in data literacy and the development of analytical skills before deploying predictive or prescriptive analytics, ensuring that HR professionals can translate model outputs into strategically meaningful decisions. These sequencing skills, prior to technology, are the most consistent finding across the capability literature (Angrave et al., 2016; Kulikowski, 2024; Mangla, 2023; Murray et al., 2025; Shet, 2025).

Secondly, HR functions should prioritise the quality and integration of underlying data infrastructure before investing in advanced analytical tools. The evidence consistently shows that sophisticated tools applied to fragmented or inconsistent data produce unreliable insights that erode managerial confidence in analytics outputs (Bagiyam et al., 2024; Dahake et al., 2024).

Thirdly, organisations should formalise HR-business partnership mechanisms through regular cross-functional analytics review sessions, embedded analytics roles within business units, and shared performance dashboards to ensure that insights are communicated effectively to decision-makers who can act on them.

Fourthly, leaders should implement data governance frameworks that specify the ethical boundaries of analytics use, establish algorithmic transparency requirements, and create mechanisms for employees to understand and contest data-driven decisions affecting their working conditions. These governance investments are particularly critical for maintaining employee trust in analytics-intensive environments.

For organisations operating in South Africa and comparable developing-country contexts, the practical sequence is notably different. Before investing in predictive analytics capabilities, such organisations should focus on three foundational priorities: (1) baseline data infrastructure development and HRIS standardisation; (2) targeted data literacy programmes for HR professionals in non-IT industries; and (3) culturally sensitive change management that acknowledges the role of relational trust and participatory decision-making norms in shaping employee receptiveness to data-driven HR practices.

Policy implications

At the policy level, this review highlights the urgent need for national data ethics frameworks that regulate AI-based HR practices, ensuring that algorithmic decision-making in employment contexts meets minimum standards of fairness, transparency and accountability. South Africa's existing regulatory architecture for employment equity and skills development presents a distinctive opportunity to develop HRA-aligned policy instruments that promote equitable, analytics-driven workforce planning while protecting employee data rights. Globally, the adoption of harmonised professional standards for people analytics equivalent to those emerging in clinical research and financial services would substantially reduce the risks of algorithmic bias and data misuse across organisational contexts.

Conclusion

Human resource analytics has emerged as a driving force in modern organisations, but its capacity to create value is not inherent; it is contingent on alignment with organisational culture, ethical governance, data infrastructure quality and evidence-based decision-making practice. This review demonstrates that analytics creates value only when the full chain of insights → decisions → actions → outcomes operates effectively and is supported by a trust-based, governance-enabled organisational environment.

The review contributes a theoretically integrated multi-level model that explains this chain and identifies four primary enablers: analytics capability, data quality, HR-business partnership and decision quality as the foundations upon which effective HRA rests. Five formal propositions (P1 through P5b) translate this model into testable hypotheses for future research. As HRA continues to evolve amid AI-driven digital acceleration, future scholarship should prioritise questions of causality, algorithmic fairness, cross-cultural integration, employee voice and the long-term development of analytics maturity in developing-economy contexts. Advancing these research streams will not only deepen theoretical understanding but will also ensure that analytics-driven HRM contributes to organisational success in a responsible, equitable and sustainable manner.

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CRediT authorship contribution

Shinu S. Siby: Conceptualisation, Formal analysis, Methodology, Project administration. Jayesh Patel: Conceptualisation, Writing – review & editing. All authors reviewed the article, contributed to the discussion of results, approved the final version for submission and publication, and take responsibility for the integrity of its findings.

Ethical considerations

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Appendix 1

TABLE 1-A1: Critical Appraisal Skills Programme quality appraisal summary (15 core studies).

Study	Design	CASP score	Rating
Bechter et al. (2022)	Multi-level quantitative survey	9/10	Strong
Cayrat and Boxall (2022)	Qualitative case study (n = 40)	8/10	Strong
Angrave et al. (2016)	Conceptual/theoretical	7/10	Moderate
Marler and Boudreau (2017)	Evidence-based review	8/10	Strong
McCartney and Fu (2021)	Quantitative survey/SEM	9/10	Strong
Arora and Mittal (2024)	Quantitative survey/SEM	9/10	Strong
Hamja et al. (2025)	Machine learning/archival data	8/10	Strong
Shet (2025)	Conceptual/Delphi	7/10	Moderate
Peeters et al. (2020)	Framework development	7/10	Moderate
Dahlbom et al. (2020)	Quantitative survey	8/10	Strong
Ekka and Singh (2022)	Quantitative/UTAUT model	8/10	Strong
Mushtaq et al. (2024)	Quantitative/empirical	8/10	Strong
Oladipupo and Falola (2020)	Conceptual review	6/10	Moderate
Kulikowski (2024)	Conceptual/systematic analysis	7/10	Moderate
Thapliyal (2024)	Quantitative/mediation analysis	7/10	Moderate

Note: The Table 1-A1 summarises the post-hoc quality appraisal of the 15 most-cited studies included in the review, assessed using the Critical Appraisal Skills Programme (CASP) Systematic Review Checklist (adapted for empirical and conceptual studies). Studies are rated as Strong (8–10 criteria met), Moderate (5–7 criteria met), or Limited (below 5 criteria met). *Scores reflect the number of 10 quality criteria met. No included study was rated as Limited (below 5/10)*. Please see the full reference list of this article, Siby, S.S., & Patel, J. (2026). The role of human resource analytics in enhancing organisational performance and decision-making: A systematic literature review. *SA Journal of Human Resource Management/SA Tydskrif vir Menslikehulpbronbestuur, 24*(0), a3636. https://doi.org/10.4102/sajhrm.v24i0.3636, for more information.

CASP, Critical Appraisal Skills Programme; SEM, structural equation modelling; UTAUT, Unified Theory of Acceptance and Use of Technology.