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Human Resource Analytics: A Systematic Literature Review of Its Adoption and Impact On Organisational Performance Over the Past Decade

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Abstract
The human resource analytics (HRA) market is experiencing robust growth, with a compound annual growth rate of 12.9 per cent. It is projected to attain a global market value of USD 9 billion by 2030. This paper presents a systematic literature review tracing the evolution of HRA adoption over the past decade, critically assessing the value HRA has generated, the increase in organisational investments in HRA during this period, and its impact on human capital. The findings reveal several salient implications for the implementation of human resource analytics (HRA), organisational effectiveness and the future of the workplace. In general, current HRA practices tend to focus on individual-level analyses at the expense of comprehensive organisational assessment, thereby limiting the broader strategic value of these initiatives. Moreover, the successful deployment of HRA is contingent upon three principal factors: the integrity and quality of the data, the sophistication of the analytical capability, and, finally, the adoption of a well-articulated strategic implementation framework. Additionally, the findings highlight substantial ethical concerns, including issues of algorithmic transparency and workplace datafication. Some of the gaps that continue to evolve are how to manage remote workers, addressing contextual factors such as technology and big data, and addressing environmental implications. This paper is relevant to understanding the gaps that persist in HRA adoption in today's business context. The Topic becomes more relevant with the emphasis on organisations using data to develop insights and interventions that can create a competitive advantage for the business from a resource-based view. This research works to provide an accessible summary of how HRA has evolved, studies done, applications, opportunities and risks, trade-offs as HRA transitions into a framework where data is being used to create automated models for decision-making. The topic remains highly relevant in today's context, as HRA systems have evolved, and there are still gaps in data quality, in the contextualization of how data is used, and in the ability to combine data with non-measurable factors to facilitate unbiased decision-making. Even with the advanced new applications that use AI and ML technology, the foundational layer of how data analytics applications form the base for these advanced tools makes this literature review relevant to the current business context.

Key Words: Human Resource Analytics, Future of Work, Workplace Analytics, Strategic

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Implementation

Introduction

In today's organisational competence concept, data has become "the new oil" (Thorp, 2021), with increasingly sophisticated extraction and monetisation algorithms used to identify trends and make decisions. In a study, over 85% of organisations surveyed reported increased adoption of emerging technologies such as AI and information processing technologies (Futures of Jobs, World Economic Forum, 2025). Analytical thinking remains the most sought-after core skill among employers, with seven out of 10 companies considering it as essential in 2025.[1] Organisations capture large amounts of data about people, processes and outcomes to create metrics and dashboards to manage their employees. The human resources function continues to evolve its analytical acumen and its ability to drive value for the organisation through insights that decision-makers can implement, which impacts the employee (Margherita A., 2022). According to a recent study by Gartner, by 2025, 80% of analytics initiatives will be focused on driving business outcomes rather than just standard data reporting and will be considered essential for building business capability. The urgency for organisations to adopt data-driven practices across all functional areas is no longer optional; it is essential for sustained growth (Raju, 2024). The growing emphasis on leveraging analytics in HRM signals a shift towards more informed, strategic decision-making (Solihin, 2024). A study by McCartney and Fu (2022) highlighted that HRA enables organisations to make informed choices regarding recruitment, talent management, and employee engagement. HR managers use data to anticipate employee-related challenges, thereby enhancing overall workforce management (Patil and Priya, 2024). Even with all these functional applications of HRA, barriers persist, including limited analytical capabilities, poor data quality, resource constraints, and resistance to adoption (Yadav *et al*., 2023). This challenge is compounded by fragmented systems within the organisation that operate on distinct datasets, leading to isolated analyses that hinder informed decision-making at the organisational level (Belizón and Kieran 2021).
The current SLR addresses these limitations by systematically synthesising a decade of research, critically evaluating adoption challenges, implementation mechanisms, and organisational performance outcomes to provide comprehensive insights and guide future investigations.

The study aims to address these research questions:
RQ1: What are the trending themes in existing literature concerning human resource analytics (HRA)?
RQ2: What future research directions should be pursued in this field?
The study employed a systematic literature review (SLR) using the Preferred Reporting Items for Systematic Reviews and Meta-analysis (PRISMA) model, selecting scholarly articles published between 2013 and 2024 across various disciplines. Our initial search yielded 1189 results from Scopus and Web of Science, which were refined to a final selection of 66 relevant studies.

The review of previous studies presented in **Table 1** includes details on contributing authors, research objectives, findings, methodologies, and the research gaps identified by each included study. As evident in the table and stated by Alvarez-Gutierrez et al. (2022), the HRA literature increasingly focuses on its utility rather than on strategic challenges for organisational performance. This lack of depth necessitated a systematic review to synthesise existing

[1] reports.weforum.org/docs/WEF_Future_of_Jobs_Report_2025.pdf

knowledge and provide a critical perspective on HRA's role in creating impact through these applications.

***Table 1**: Summary of recent review studies on HRA*

Author	**Objective**	**Findings**	**Metho dology**	**Research Gap**
Itam and Warrier (2023)	This paper aims to provide a review of studies on remote work.	This study argues that remote and flexible work arrangements, facilitated by technology, are now essential for businesses and will likely persist post-pandemic, reshaping the future of work.	SLR	Future research should focus on optimising remote working, promoting employee well-being, and addressing environmental implications.
Ballas et al. (2024)	This study explores how to make a psychological contract (PC) between employees and employers. It investigates how individual perceptions of mutual obligations influence work relationships in the digital age.	Highlights the nascent stage of research on psychological contracts in the digital age. The heterogeneity in addressed themes and mechanisms makes generalisation challenging	SLR	A research gap exists in understanding the impact of digitalisation on specific PC elements and cooperation mechanisms.
Wang et al. (2023)	Key factors that contribute to the successful implementation of HR analytics in organisations	Advances in HR analytics research by focusing on the implementation stage and providing a dynamic perspective. It identifies key determinants of successful implementation, explores social action mechanisms, and builds on the AST theory	SLR	A notable research gap exists in the empirical examination of determinant influences, the creation of robust measurement tools, the exploration of determinant interactions, and the integration of contextual variables, such as structural features and

				individual traits.
Xiao et al. (2023)	The possibility of HR outsourcing (HRO) to enhance organisational competitiveness and strategic capability	Proposes a comprehensive HR process model considering multiple stakeholders and contextual factors. It highlights the need for a dynamic and multi-stakeholder perspective to understand the impact of HRO on organisational performance.	SLR	A research gap persists in exploring the contextual factors, such as technology and big data, that influence HRO outcomes.
Coolen et al. (2023)	This review explores the factors driving the adoption and institutionalisation of workforce analytics, considering both human resource management and contextual factors.	This review focuses on the institutionalisation of workforce analytics. It provides insight to help organisations effectively adopt and implement workforce analytics.	SLR	Identifies the need for further research to incorporate contextual factors, investigate the interplay among various factors, and explore ways to improve the maturity of individual and organisational resources for workforce analytics. Additionally, it suggests clarifying the concept of institutionalisation in future research.

Margherita (2021)	This research deconstructs the concept of HR analytics, identifying 106 key research topics related to its enablers, applications, and value.	The study emphasises the importance of integrating ethical, privacy, and acceptance considerations into the technological and process aspects of HR analytics.	SLR	Focusing on the integration of exponential technologies, the strategic positioning of HR analytics projects, and the impact of HR analytics on employee experience and organisational performance.
Tursunbayeva et al. (2021)	This research analyses the existing literature on people analytics to understand how ethical considerations are being discussed and to identify gaps in ethical practices.	This research examines ethical issues in people analytics and highlights gaps in current practices. It emphasises the need for transparency, privacy, fairness, and ethical culture in implementing people analytics solutions.	Scoping Review	Despite its growing practical application, significant academic research on ethical considerations in people analytics is lacking. While there is some discussion in industry and grey literature, a more rigorous academic approach is needed to address the ethical implications of data-driven HR practices.
Cheng and Hackett (2019)	This research aims to clarify the definition of algorithms in HRM, identify key research topics in algorithmic HRM, and explore the differences between research-oriented and application-oriented databases in this field.	This research distinguishes HRM algorithms from traditional statistical methods, highlighting their heuristic nature. It also notes a growing gap between academic research and practitioner interest in HRM algorithms.	SLR	A significant research gap exists in addressing the ethical implications of algorithm use in HRM, particularly regarding bias and privacy, as well as in leveraging unstructured data sources to improve HRM decision-making.

Ben-Gal (2019)	This paper aims to provide a comprehensive review of HR analytics, with a focus on its return on investment (ROI). It offers practical insights for decision-makers to implement HR analytics effectively and identify potential ROI areas.	This study found that empirical and conceptual HR analytics studies offer the highest return on investment, particularly in workforce planning and recruitment.	Review paper	This review concludes that there is a need for more scientific, empirical research in HR analytics, with a primary focus on an ROI-based approach to inform future research and practice.
Safarishahrbijari (2018)	This paper evaluates workforce modelling and prediction methods, identifying their strengths and weaknesses. It compares different forecasting methods to determine their accuracy and reliability.	Emphasises the importance of incorporating feedback loops, considering uncertainties, and using more advanced techniques to improve the accuracy and reliability of these models.	SLR	integration of multiple interdependent models

From the systematic review of the articles studied, it was found that 30% articles were written with data collected for HR analytic study through surveys; the qualitative studies done are mainly single organisation case-studies/ interviews (Elimer and Reichel, 2021), while there is still scope to do some mixed-method studies on the topic of the findings either empirically or studies cross-industry groups. A detailed SLR aims to provide practitioners with an overview of HRA's theoretical, practical, and methodological aspects, as widely used in the management literature (Behl et al., 2021; Xiao and Watson, 2019). The PRISMA Model was employed to ensure consistency and a scientifically sound approach. The PRISMA guidelines provide a standardised 27-item checklist to uphold transparency and quality throughout the review process (Page et al., 2020). Furthermore, a review protocol was developed to systematically shortlist relevant research articles.

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2 Developing a Protocol for Review

A systematic search strategy was implemented to address research questions.

- Online databases: Scopus and Web of Science were included to shortlist studies published from 2013 onwards, given their status as leading abstract and index databases (Burnham, 2006). These databases are widely used by researchers in HRM and related fields (Martín-Martín et al., 2018).
- Search strings: Various search strings were employed to gather relevant research publications from 2013 to April 2024 (Table 2). The advanced search category, which included Boolean operators ('OR', 'AND'), ensured that pertinent research articles were retrieved. Occasionally, terms such as "HR Analytics," "People Analytics," or "Workforce Analytics" are used interchangeably in the literature by Zeidan & Itani (2020).

Table 2 – Table of Search Strings used

Search Topic	Search String
Analytics	"hr *analytics" OR "human resource *analytics*" OR "workforce *analytics*" OR "people analytics" OR "talent analytics" OR "human capital analytics"
AND	AND
Processes	"artificial intelligence in HR" OR "big data in HR" OR "machine learning in HR" OR "AI in HR" OR "BDA in HR" OR "deep learning in HR
AND	AND
Integration	"adoption" OR "implementation"

- Journal articles: To ensure methodological rigour and quality in the included research articles, only those published in English-language journals ranked within the Australian Business Deans Council (ABDC) list were considered. These journals undergo a rigorous selection process before publication, thereby maintaining high standards for quality research that employs robust methodologies. The journal list selected A/A* and FT50 articles for the study, given their robust methodological approach in business management and decision sciences.

2.1. Inclusion and exclusion strategy

An inclusion and exclusion strategy was developed based on the study's research questions to shortlist the most relevant research articles. A three-step methodical approach was employed, as commonly used by scholars (Bhardwaj et al., 2023; Xiao and Watson, 2019).

Step 1: After extracting all relevant articles from the database, a systematic coherence check between keywords and titles was performed. Articles that were non-coherent or inconsistent were excluded. From an initial pool of 5,712 articles, this process narrowed down to 2007 articles.

Step 2: Following the shortlisting of articles, both authors conducted a simultaneous in-depth review of abstracts for the 2007 selected articles. This detailed examination led to the exclusion of articles based on two criteria: first, when the core theme of the shortlisted article did not align with the objective of the current study, and second, when HR analytics was addressed only peripherally in the shortlisted articles. Conversely, articles whose central themes clearly aligned with the research topic were included. At this stage, 1189 remained.

Step 3: A final review of excluded articles was conducted to reassess decisions made up to this point. Both authors independently evaluated these excluded articles, followed by collaborative

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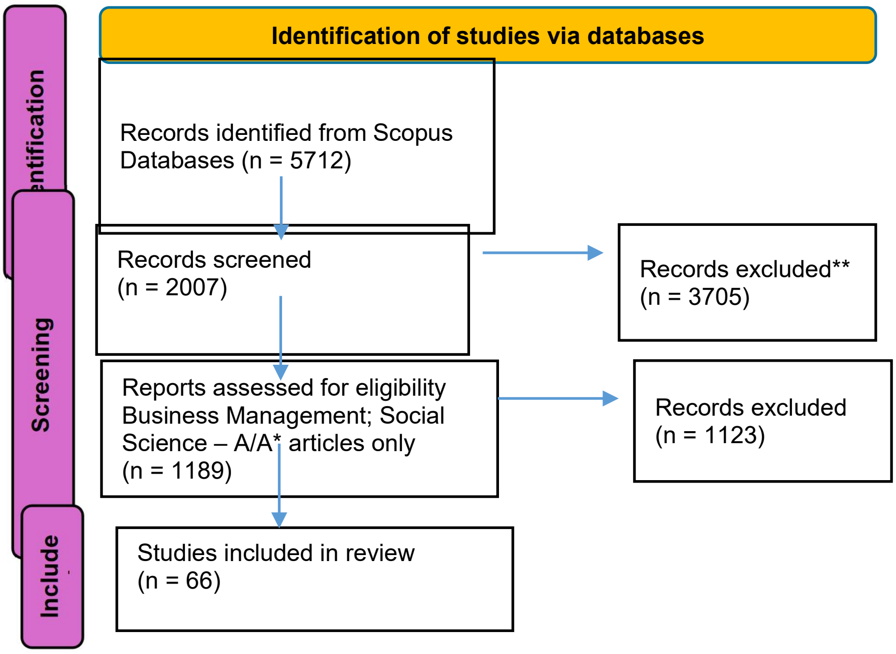
discussions to reach a consensus on their relevance. Articles that were not accessible through open-source databases or library repositories were excluded. Additionally, any articles published in languages other than English or incomplete versions were eliminated. Expert opinions were sought before proceeding with the exclusion list to gain validity of the process followed. At this stage, 66 research articles were selected for further analysis.

2.2. Final selection

Each of the 66 shortlisted research articles underwent thorough full-text reviews during this phase. To confirm that each article was suitable for inclusion, its full text was meticulously examined based on two criteria: first, HRA was the core of the study, and second, the sample article was coherent with the research objective of the current study. The results validated the incorporation of 66 research articles. A consensus among authors regarding excluded articles was reached and verified by an expert. Through an exhaustive procedure culminating in final data selection, a total of 66 scholarly articles were chosen for investigation (as illustrated in Figure 1)

Fig 1: PRISMA model of reporting



3. Findings and Discussion

After completing the data extraction process, a detailed content analysis was conducted, and coherent themes were systematically clustered in today's context of developing the workplace of the future into three themes: 1) HRA adoption and firm performance, 2) HRA implementation at the functional level, and 3) Ethical considerations in HRA.

3.1 HRA adoption and firm performance

In an empirical study by Shahbaz et al. (2020) on the adoption of big data analytics in the workplace, self-efficacy was found to strongly predict perceived usefulness, ease of use, and intention to use big data analytics. As systems start capturing real-time data, it's expected that the analytics provided will enhance managerial clarity, reducing ambiguity in complex operations (Angrave et al., 2016). At the same time, access to information facilitates team-level coordination, enabling managers and coworkers to identify when and how to assist each other (Cantor, 2016). Kryscynski et al. (2017), while examining HR professionals' analytical capabilities, provide strong empirical evidence supporting a positive relationship between data interpretation skills and performance ratings, indicating that effective analytical insights are largely contingent upon the individual HR practitioner possessing the requisite competencies (Angrave et al., 2016).

Similarly, an empirical investigation of Major League Baseball teams from 2009 to 2014 by Kim et al. (2021) demonstrated that data analytics helped identify that players positively influence organisational performance. However, the findings further suggest that in highly competitive and specialised industries, widespread access to analytical information may result in knowledge replication or depletion over time, potentially undermining sustained performance advantages (Kim et al., 2021).

Levenson's (2017) study on using workforce analytics for strategic execution found that current practices overemphasise individual-level analyses and incremental improvements rather than a holistic view of organisational effectiveness. The research demonstrated that effective workforce analytics requires prioritising strategic capability development over process optimisation, integrating multi-level analyses, and establishing clear linkages to strategy execution. Di Prima et al., (2024) study highlighted that HRA does not significantly impact the relationship between rewards and incentives and creativity, which reiterates the need for strategic alignment and context-specific application of HR practices. (Lismont et al., 2017).

While firms adopted HRA in their workplaces, there is a reliance on data quality, analytical ability, and the strategic use of data for action (Minbaeva, 2017). As systems have evolved over the decade, with attention now to how artificial intelligence (AI) can enhance the management of human resources, the progress of AI in the workplace is very slow[2] , largely due to leaders' decision-making to implement, while also citing reasons for employees' readiness, talent gap, privacy concerns, integration capabilities while the systems are still evolving. The challenge for HR professionals is to enhance their analytical capabilities and engage more strategically; otherwise, HR practices may marginalise HR's influence within the organisation, provide limited firm benefit, and become a fad (Rasmussen and Ulrich, 2015).

3.2 HRA application at the functional level
Studies examining the functional aspects of HRA primarily focus on employee turnover, recruitment, performance management, and employee well-being. This emphasis is partly due to the availability of easily quantifiable data at each stage of HR processes, such as applicant information, interview assessments, compensation, and performance ratings (Di Prima et al., 2024), which enables the organisation to make informed decisions. Google's approach to using analytics to manage their tech talent and understand their management styles helped them measure "soft" leadership skills among managers and identify what makes some managers effective (Gavin D, 2013).

Workforce planning and recruitment/selection are other functions that have achieved the highest ROI due to their reliance on predictive analytics (Chaltuz Ben-Ga H, 2019). In the build-up for creating talent for the future, HR analytics can help organisations in designing

[2] https://www.mckinsey.com/capabilities/tech-and-ai/our-insights/superagency-in-the-workplace-empowering-people-to-unlock-ais-full-potential-at-work#/

optimal work experience paths, balancing internal promotions and external hires, and aligning the sequence of work experiences has a significant impact on an employee's readiness for executive roles, building a robust pipeline (Zhu et al., 2023). Understanding this could optimise executive selection, development, and retention strategies within organisations. The central enabler for obtaining these insights was a robust data infrastructure created to model and capture employee data, and analyse it in relation to business requirements for resource allocation (eSilva and Costa, 2013; Rombaut and Guerry, 2020).

The use of HRA can enable training needs analysis by analysing unstructured datasets to gain deeper insights into performance gaps, moving away from traditional one-size-fits-all approaches and subjective inputs from employee surveys (Cotes & Ugarte, 2019). The integration of HRA optimises training resources, validates their impact on organisational objectives, reduces waste, and increases managerial accountability, while creating a workforce ready for the future.

A study on the HRA application to the effectiveness of collecting and analysing employees' mental health (Lathabhavan, 2023) highlighted how insights into mental health can guide the design and adjustment of organisational support services. As technology has improved, automated systems can flag cases of mental breakdowns, prompting HR to refer them to health specialists for support. Arora et al. (2022) discussed enhancing employees' intrinsic motivation through HR analytics, creating complementarities among analytics, rewards, and promotions. This shows that HRA can support managers in making data-driven decisions, improving workforce skills and motivation, and reducing absenteeism and administrative burdens for senior personnel (Cavanagh et al., 2022; Heidemann et al., 2024). Xiao et al. (2023) explain how AI-enabled HRA positively impact employee resilience, particularly when combined with job crafting and a robust HRM system. Hastuti and Timming (2022) highlight that HR data, like employment gaps and absences, can potentially identify employees at risk of mental health breakdowns.

A functional study on employee retention revealed that younger employees prioritised recognition and compensation, whereas older employees valued training and flexibility. Gender differences significantly impact adoption: male employees show stronger relationships with technology acceptance factors. At the same time, females demonstrate greater resistance to change, indicating an individual's internal coping behaviour in the face of the unknown (Shahbaz et al., 2020). Organisations are developing models capable of predicting employee turnover intentions and implementing interventions tailored to individual needs, while also examining psychological factors such as job security, employee privacy, and environmental influences that contribute to turnover (Tursunbayeva et al., 2018; Marler & Boudreau, 2016). The models used to study wage gaps have been used to link factors such as job role, educational qualifications, and years of experience, and to provide benchmarks that managers can utilise (Jafari et al., 2020).

The HRA models that can predict employee turnover intentions and develop interventions based on the outcomes help organisations plan the workforce through predictive analytics, enabling them to balance hiring externally with internal savings on both hiring costs and time to fill. By identifying performance gaps, individual development plans can be created to be more effective than a one-size-fits-all approach. The ability of the HRA systems to create outcomes that have an impact on organisational bottom line. This ability to create effective

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models creates a compelling case for organisations to continue investing in HRA and work to align employees for adoption.

As HRA matures to enhance employees' analytical capabilities, organisations are expected to invest in infrastructure and provide training and workshops to support effective HRA management. Verma et al. (2023), in their study on enablers of HR analytics, suggest that organisations should prioritise continuous learning and accelerate change management processes to ensure the successful digitalisation and adoption of HR analytics. However, Loscher and Bader (2023) emphasise the profound social impact of HRA, highlighting a shift from a traditional HR guardian role to a decision-enabling function, fostered by a culture of accountability. This transformation is reflected in the growing focus on data-driven decision-making and the assumptions underlying organisational practices.

3.3 Ethical Issues in HR Analytics

While HRA as a tool helps the firm achieve its objective of building a database to manage its workforce more effectively, as these applications evolve, there is a need for a governance mechanism that establishes regulatory standards and ethical frameworks (Leicht-Deobald et al., 2019). A key ethical insight is that the conceptualisation and implementation of HRA profoundly influence employees' capacity to develop psychological trust within the workplace. Three primary ethical challenges have been highlighted: algorithmic opacity, workplace datafication, and nudging to incentivise specific behaviours (Giermindi et al., 2021). These challenges can create a vicious cycle that limits employees' capacity to pursue internal goods, develop practical wisdom, and act voluntarily, all of which are essential for cultivating virtue and human flourishing. Personnel decisions made by algorithms are consistently perceived as less fair than identical decisions made by humans, even when outcomes are comparable (Newman et al., 2020).

As analytical capabilities advance, mature organisations face challenges such as managing sensitive personal data, ensuring fair and non-discriminatory outcomes, and maintaining accountability for automated decisions. Advanced analytics introduce risks stemming from opaque algorithms (e.g., neural networks) and incomplete documentation, which can undermine fairness and employee trust (Lismont et al., 2017). A central ethical concern in HRA involves ensuring that those responsible for interpreting and applying analytical outcomes possess both the required technical competence and a solid understanding of ethical practice (Marler & Boudreau, 2016). Insufficient analytical expertise within HR functions may lead to the misinterpretation of data and flawed decision-making.

In distributed work environments, capturing real-time location data poses surveillance risks when using analytical tools (Giermindi et al., 2021). The illusion of control and reductionism, in which organisations place excessive reliance on algorithmic decision-making while oversimplifying human complexity (Giermindi et al., 2021), poses a significant risk that organisations must address as part of ethical decision-making. Algorithmic management practices, such as monitoring platform workers, raise ethical concerns regarding employee autonomy and control, thereby realigning the employee-employer relationship (Ballas et al., 2024). As HRA develops, the transition to Industry 4.0 raises concerns about job stability, necessitating measures to mitigate displacement caused by automation. Ensuring equal access to digital skills training is crucial for creating fair workplace opportunities, while organisational culture must be adapted to support and encourage technological change (Ozkan-Ozen & Kazancoglu, 2021).

While organisations use store-level data to identify profitable stores in relation to employee turnover and managerial capability (Simón and Ferreiro, 2017), there is a limited understanding of how employees are informed of these analytical insights. The challenge of reconciling rigorous academic methodologies with practical organisational needs underscores the importance of unbiased analysis and critical reflection on the assumptions underlying workforce analytics. This challenge continues to plague organisations' over-reliance on quantitative metrics, which risks reducing complex human experiences to simplified numbers (Greasley and Thomas, 2020). Strong leadership support for data security is necessary to encourage employees, including those with disabilities, to share information, alongside appropriate governance for data usage and storage (Gupta et al., 2021; Chatterjee et al., 2021).

When HR initiatives are tailored to individual goals and preferences, employees are more likely to perceive their work as meaningful and supportive. (Simón & Ferreiro, 2017; Ozkan-Ozen & Kazancoglu, 2021). Conversely, uniform practices that fail to account for workforce diversity may inadvertently create disparities or reduce employee satisfaction. Therefore, promoting equity, inclusiveness, and employee-centred support within HR systems is essential for fostering both ethical and effective organisational outcomes (Lin et al., 2019).

4. Future Research Directions

Most studies provide limited investigation of industry-specific applications, and variations in HRA practices across industries remain underexplored. Investigating longitudinal and multi-source research designs to mitigate survey bias and offer comprehensive evidence for the strategic impact of HRA, including objective as well as perceptual measures of performance.
As HRA systems are now considered central to making employee decisions, they play an important role. Future research can focus on extending social exchange theory, with the HRA system serving as a mediator between the employer and employee, especially from the perspective of job satisfaction, turnover intentions, and talent management. Issues concerning employee engagement and employee trust, closely related to the AMO (ability-motivation-opportunity) theory, can be further studied as HRA systems are increasingly used in advanced systems such as chatbots and sentiment analysis tools to engage employees throughout their journey within the organisation. Using HRA to develop further competitive positioning for the resource-based view, where talent insights can drive higher value for organisational offerings.

Furthermore, research from an organisation context will benefit from systematically distinguishing between rhetorical alignment with HRA and meaningful integration into organisational processes. There is a pressing need for unified models that map the entire lifecycle of HRA adoption, encompassing early-stage experimentation, widespread dissemination, varying levels of embeddedness, and eventual adaptation or decline (Piazza & Abrahamson, 2020). Within the organisational setup, future research can examine personality differences, team structure and dynamics, environmental and cultural influences, and the alignment of business intelligence tools across settings that impact HRA adoption in the workplace. Field studies and experiments can empirically validate propositions about worker motivation and productivity using the monitoring tools organisations use to manage workers across different work practices. Taking the practitioners' view of which data points are critical for building an effective HRA model that decision-makers can use needs to be further studied,

as current models are based on an academic approach to data capture and analysis. With the evolution of analytics to big data, where the volume, velocity, and variety of data are high, building an analytical culture is an essential factor that can help drive outcomes that impact the customer, the organisation's bottom line, and market value. (Tursunbayeva et al., 2018).
Scholars are encouraged to integrate decision techniques and system modelling languages to align organisational information with analytical priorities. There is a need to consider the operational costs of data collection, validation, and maintenance, particularly as organisations transition to more advanced, resource-intensive analytics practices (Pepe T, 2016). In the age of AI-based HRA models, organisations have also started skill-based learning to build an agile workforce. Future researchers may highlight how contemporary workforce dynamics interact with HRA, especially the new gig workforce and talent-on-demand. As new AI and Machine Learning (ML) systems are able to perform and automate various HR deliverables, it will become important to study the impact of how employees experience these transactions in the workplace and the data governance policies.

5. Conclusion

This systematic literature review highlights that HRA is not merely a technological tool but a transformative force in human resource management in the current dynamic business environment. Its effective implementation requires a holistic approach combining technical expertise, strategic insight, and careful consideration of ethical implications to maintain employee trust. The future of HRA lies in its capacity to generate meaningful insights while respecting human complexity and organisational dynamics. While there are various empirical studies done in HRA, there is little attention that has been paid to how factors like workplace culture, HR Information Systems, technology infrastructure and organisation's strategy moderate HRA effectiveness (Bahuguna et al., 2023). Based on a review of 66 research articles, the study finds that HRA improves firm performance through data-driven decision-making but also necessitates ethical considerations and functional applications across organisational levels, highlighting the multifaceted impact of analytics on modern HRM practices (Thakur et al., 2024). Additionally, the evolving nature of HRA, with the integration of Big Data, machine learning (ML), blockchain, and artificial intelligence (AI), underscores the need for systematic reviews to incorporate subject-matter expertise and provide richer, more practical insights into contemporary HRA practices**.** This study makes a unique contribution by conducting an exhaustive review of HRA from a business and management perspective and presenting broad themes evident in the existing literature. Further, it offers future directions for research by advancing the HRA domain and its interdisciplinary impact on business as a whole

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