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Unleashing Organisational Potential: Exploring the Transformative Power of Cutting-Edge HR Analytics - A Systematic Review

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Abstract

Due to globalization, organizations have integrated human resource (HR) analytics into their operations. The study employs Paul's Theory-Context-Construct-Methodology (TCCM) theory, context, construct, and methods framework and integrates data from Scopus and Web of Science databases, with 64 relevant publications after filtering articles. Findings comprise theories, contexts, industries, participants, constructs, research techniques, and annual publication trends. The identified theories include the resource-based view (RBV), technology environment organization (TOE) paradigm, diffusion of innovation, social exchange theory, and more. India leads in contextual studies, but manufacturing and service industries dominate. HR Professionals are the major population, and performance expectancy is a commonly studied construct. The majority of studies use the questionnaire method to conduct studies on HR Analytics. The study investigates the cultural disparities, longitudinal surveys, the influence of artificial intelligence (AI) on human resource functions, and challenges encountered by machine learning technology. The study emphasizes human resource management system (HRMS) models, comparative analytics, leadership tactics, and the impact of HR Analytics during crises. Leading journals include "The Journal of Organizational Effectiveness" and "The International Journal of Organizational Analysis," The study addresses gaps in the literature groups into four frameworks and provides a critical analysis of identified research gaps thereby offering insights for HR practitioners, experts, and stakeholders in HR Analytics.

Keywords: Adoption, HR Analytics, Organizational Performance, Systematic Review.

Introduction

The rapid advancement of digital technologies has impacted some major HR practices in today's corporate world. HR Analytics has become an essential tool that helps businesses turn traditional human resource management into strategic division which makes a major contribution to an organization's success. In a study, Mellam *et al.,* (1) identified that modern HR practices resulted in a major performance improvement observed in state-owned enterprises. HR Analytics is referred to as quantitative and qualitative data and information management which seeks to gain insight and support decision-making processes for managing people in organizations (2). HR analytics assists workforce planning, career transitions, and upgrading ways by integrating both the data and strategic perspectives thereby improving the competitive edge of organizations (3). By improving decision-making, increasing return on investment, optimizing workforce planning, assisting strategic management of human resources, and fostering competitive agility HR analytics offers a strategic edge (4). Theories lay the necessary foundations for HR analytics. In the lens of a resource-based view, HR procedures can be strategically enhanced with HR analytics, creating a long-lasting competitive edge. The dynamic capability theory implies that organizations adapt their HR strategy dynamically with the help of HR analytics. The technology, organization, and environment framework guarantees that HR analytics is applied strategically and that anticipated results can be utilized to obtain a competitive advantage. The socio-technical theory states that with the integration of HR analytics, a balanced approach is

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attained whereby technology and human factors are optimized.

Although HR is becoming increasingly strategic and occupying a central place in an organization, its adoption rate is only up to 16%. Organizations that have reaped the benefits of HR analytics are Google, Best Buy, Jet Blue, Dow Chemical, and Sysco. As Diverse adoption trends evolve; small organizations rely on basic measures, whereas large organizations use effective statistical models and wearable Internet of Things (IoT) devices when handling workforce data (5). In a study, Kiran *et al.,* (6) states that the monitoring and improvement of human capital management using HR analytics contributes to the overall performance improvement of the organization. It has been observed that integrating HR analytics with human capital management techniques improves important performance metrics such as profitability, efficiency, and productivity which aids in data-driven decision making facilitating evidence-based management. The effectiveness of HR Analytics is also seen in banking industries, which benefit from enhanced recruitment and performance measures, thereby boosting consumer satisfaction (7). The functions of Human Resource Management and Talent Management have undergone massive changes with the advent of Machine Learning, Digitalization, and Artificial Intelligence (8). Globalization is driving firms to incorporate HR Analytics, integrating competencies and resource-based approaches for gaining a competitive edge Machine learning, which is an extension of descriptive analytics, aids in tackling big data difficulties, assisting predictive and diagnostic analytics (9, 10). Despite the initial advantages from decreasing administrative expenses to facilitating data-driven decisions, its usefulness is still in its infancy stage (11). The future may enable HR analytics to advance into a strategic function, going beyond standalone HR practices to affect decision-making in finance and marketing (12). The application traverses beyond recruitment, incorporating engagement, attendance tracking, accidents, and productivity. Failure to adapt to the latest technology could risk competitive advantage due to data security and privacy issues (13). The main aim of this paper is to systematically review HR analytics literature with a specific focus on the “Implementation” OR “adoption” OR “application” of HR analytics in organizations to get a holistic view of HR analytics. The study highlights the benefits arising from HR analytics such as workforce productivity, mid-course correction, improved leadership performance, and return generated for the company. It also deals with the obstacles associated with the adoption of HR analytics, such as resistance to change, lack of skilled personnel, and enabling IT infrastructure. By addressing these challenges, organizations can better integrate HR analytics into their operations, unlocking its full potential and overcoming barriers to adoption.

The study provides an overview of countries, industries that have successfully adopted HR analytics, and key populations for HR analytics which is useful to HR practitioners. The major constructs and theories discussed in the study can draw useful insights related to HR analytics literature. The research methods addressed in the study provide the most common methods used in a variety of studies. The critical analysis of research gaps provides directions for future research which is beneficial to HR professionals and future researchers. The study contributes to the development of new theories, inter-country analysis, robust technologies in data analysis, industry comparison, existing participants in HR analytics usage, and presenting research gaps by employing the SPAR-4 method of literature review entailing the CCTM (Context, Construct, Theory, and Methods) approach, which adds to scholarly literature and evolving human resource management.

The flow of the paper encompasses the research methodology emphasizing inclusion and exclusion criteria, source list of journals, theories adopted, methodologies used, most common country names, industry types, population addressed, and the future research avenues categorized in the form of Context, Construct, Theory, and Methods.

Methodology

The adopted review in the study is a framework-based review using Paul’s TCCM framework which is structured scientifically and specifically focused on widely used methods, theories, and constructs in the form of tables and figures. The selection of databases included “Scopus “and “Web of Science” since Scopus and Web of Science are the greatest

comprehensive databases of peer-reviewed literature for social science research and are often used by advanced systematic reviews (14).

In Table 1, the search involved keywords such as ("Human Resource Analytics" OR "HR analytics" OR "Human Capital Analytics" OR "HRM Analytics" OR "Manpower Analytics" OR "Workforce Analytics" OR "Talent Analytics" OR "People Analytics" OR "Human Resource Predictive Analytics") in line with the previous studies in human resource analytics literature (6). Along with added fields such as ("Application" OR "Adoption" OR "Implementation") since HR analytics literature is still evolving and many organizations are yet to implement and integrate HR analytics fully into their functions.

Table 1: Search Inclusion and Exclusion Criteria by Authors

Criteria	**Scopus**	**Web of Science**	**Criteria**	**Scopus**
	Inclusion	Exclusion	Inclusion	Exclusion
Date: 22nd August 2023 Source: Scopus and Web of Science Databases Search Term: TITLE-ABS-KEY ("Human Resource Analytics" OR "HR Analytics" OR "Human Capital Analytics" OR "HRM Analytics" OR "Manpower Analytics" OR "Workforce Analytics" OR "Talent Analytics" OR "People Analytics" OR "Human Resource Predictive Analytics") Add Fields: ("Application" OR "Adoption" OR "Implementation")	173		65	
Subject Area: Business, Management and Accounting	98	75	27	38
Document Type: Articles	65	10	20	18
Language: English	64	1	20	-
Duplicates			17	
			67	
Removed irrelevant articles (2 not found, 1 irrelevant)			64	

The PRISMA flowchart is used for reporting systematic reviews and meta-analyses and also aids in the critical evaluation of published reviews. It acts as an evidence-based document and thus PRISMA flowchart is given in the study (15). We filtered the search terms by limiting the subject area to business, management, and accounting since the study was purely focused on management streams. After filtering the subject area, document types are further limited to articles excluding book chapters, conference papers, books, editorials, issue papers, and other non-referred publications to ensure the inclusion of double peer-reviewed articles to maintain quality protocols of a systematic literature review (16). The articles are then filtered to the English language. By following the above criteria, the search criteria combining both Scopus and Web of Science reached up to 84 documents. The merged data is then transferred to R Studio and after applying commands for removing duplicates, 17 duplicate documents were removed. After screening the articles based on the Title, abstract, and findings the authors identified three irrelevant documents, and thus 64 documents were finalized for the study.

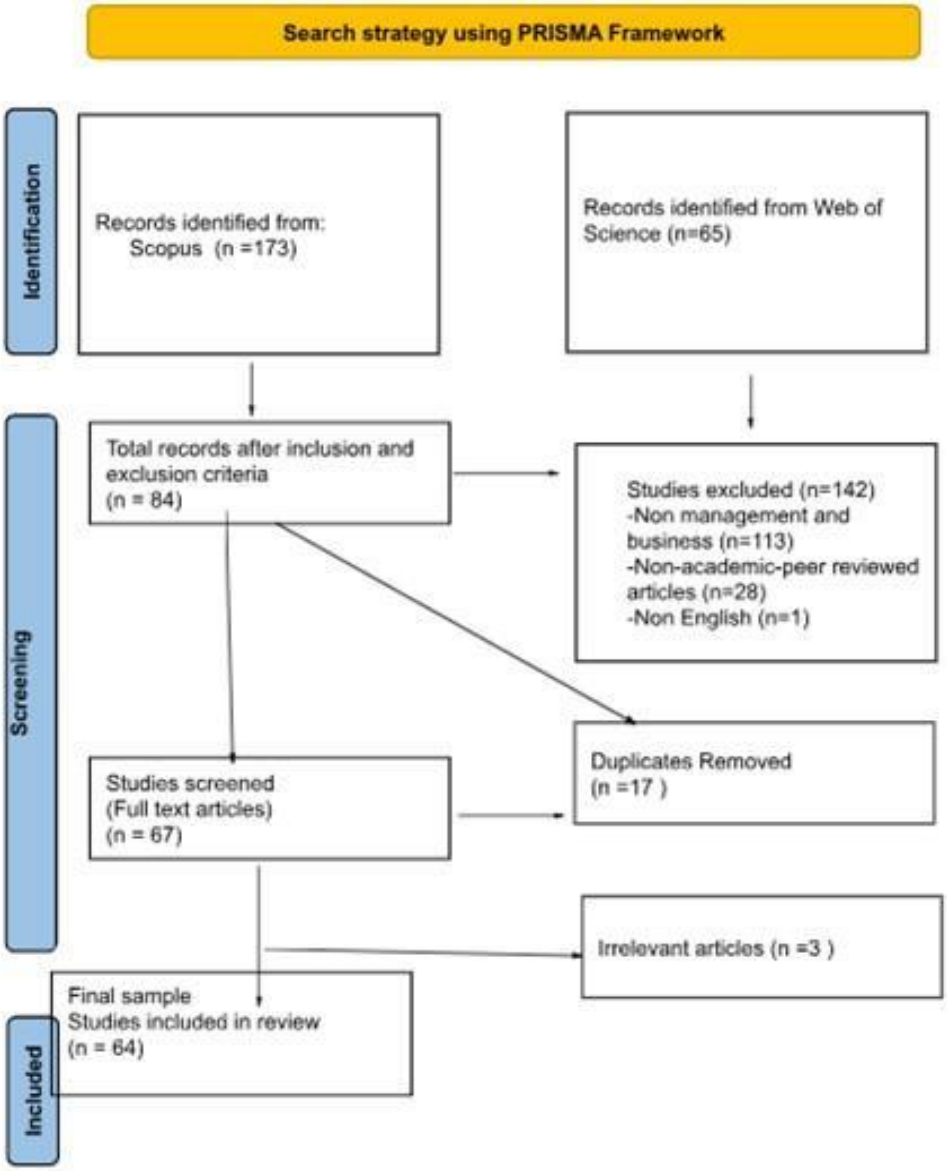

Figure 1: A Detailed Article Selection and Search Process Based on PRISMA

Results and Discussion

The results not only provide an insight into the number of studies pertaining to HR analytics but also groups them into various categories such as theories, country type, industry types, constructs (variables), population groups, various methodologies adopted, recent articles, publication trends, top journals, classification of research gaps on the basis of theory, context, construct and methods. The discussion part under each table and figures below provides critical analysis of significant results obtained as a result of systematic review.

In the study literature related to HR analytics adoption was gathered and (Table 2) denotes the Resource-based view theory used by three authors. The rest of the theories were used in isolation by independent authors. Person-environment fit theory ensures the quality of recruiting and proper fit in workgroups, while career construction theory harnesses employees' adaptivity and adaptability for HR analytics adoption (17, 18).

Table 2: Theories in HR Analytics Adoption Studies

Theory	Author
Career Construction Theory	Dhankhar and Singh (17)
Person-Environment Fit Theory	Shet and Nair (18)
Resource Based View	Böhmer and Schinnenburg (19), Mccartney and Fu (20), Gurusinghe *et al.,* (21)
Social Exchange Theory	Chatterjee *et al.,* (13)
Privacy Calculus Theory	Chatterjee *et al.,* (13)
Dynamic Capability Theory	Mccartney and Fu (20)
Social Technical System Theory	Wirges and Neyer (22)
Theory of Planned Behaviour	Vargas *et al.,* (23)
Technology Organization Environment Theory	Gurusinghe *et al.,* (21)

HR Analytics, viewed in the context of artificial intelligence, generates a rare, non-imitable resource for competitive advantage, in alignment with the Resource-Based Theory (RBV) (19). Integrating RBV and dynamic capability theories, HR Analytics is seen as a rare resource derived from data, scientific insights, and managerial experience, facilitating fact-based decision-making (20). The Technology-organization-environment (TOE) paradigm, combined with RBV, promotes predictive HR Analytics adoption, employing external elements for a competitive edge (21). The social-technical theory combines employees' qualifications and technological features for effective HR Analytics (22). The theory of Planned Behavior delves into individual attitudes, supporting HR analytics adoption organization-wide (23).

Table 3 depicts the majority of HR Analytics implementation studies conducted in India (n=9), the USA which stands at second position with three studies (n=3) followed by Germany and Thailand with two studies (n=2) conducted. The rest of the countries have one study each.

Table 3: Countries Represented in HR Analytics Studies

Country	Author
India	Chatterjee *et al.,*(13), Vargas *et al.,* (23), Ekka and Singh (24), Anam and Haque (25), Arora *et al.,* (26), Alamelu *et al.,* (27), Ameer and Garg (28), Verma *et al.,* (29)
Bangladesh	Islam *et al.,* (30)
USA	Marler and Boudreau (5) Buttner and Tullar (31), Hickman *et al.,* (32)
Italy	Conte and Siano (33)
Pakistan	Muhammad and Naz (34)
Germany	Böhmer and Schinnenburg (19), Brandt and Herzberg (35)
Ireland	Mccartney and Fu (36)
Europe	Tijssen R (37)
Thailand	Vorapah Mahasamsan and Surarak (38), Penpokai *et al.,* (39)
Belgium	Rombaut and Guerry (40)
Finland	Dahlbom *et al.,* (41)

In India, building strong relationships among HR professionals is vital for Human resource Analytics (HRA) adoption, conveying the need for cultural changes (24). In the study, Anam and Haque (25) making use of UTAUT and UTAUT 2 models, identified a lag in HR Analytics adoption, necessitating workshops to strengthen personnel and overcome resistance. In a study, Arora *et al.,* (26) focus on obstacles at various organizational levels in people analytics adoption, providing solutions underscores the monetary benefit of HR analytics in tracking recruiting and developmental

costs. In a study, Alamelu *et al.,* (27) focus on obstacles at various organizational levels in People Analytics adoption, providing solutions for the same.

In a study, Ameer and Garg (28) underscore the monetary benefits of HR analytics in tracking recruiting and development costs. Facilitators for HR Analytics adoption include learning programs, training, development measures, and human resource transformation strategies (29). These Indian studies deeply discuss the difficulties, facilitators, and obstacles of HR Analytics implementation.

Table 4 shows Manufacturing and service firms with the highest number of studies made (n=3) followed by banking and universities with two studies each (n=2) and the remaining industries having one study each. In a study, Islam *et al.,* (30) from medium and large manufacturing firms reveals that artificial intelligence-enabled technologies can enhance the talent acquisition process by replacing traditional recruitment and selection methods. The studies reveal social influence and perceived credibility to be moderating the relationships between behavioral intention to use and actual use of HR Analytics.

Table 4: Industries in HR Analytics Adoption Studies

Industry Type	**Author**
Banking	Arora *et al.,* (26), Muhammad and Naz (34)
Manufacturing and Service Firms	Islam *et al.,* (30), Vorapah Mahasamsan and Surarak (38), Dhiman *et al.,* (42)
Chinese Education market	Percy and Dow (43)
ABC Govt Agency	Buttner and Tullar (31)
Retail Supply Chain	Brau *et al.,* (44)
Legal Industry	Brandt and Herzberg (35)
Universities	Hickman *et al.,* (32), Tijssen R (37)

Table 5: Constructs in HR Analytics

Constructs	**Author**
Performance Expectancy/ Effort Expectancy/Social Influence	Vargas R*et al.,* (23), Anam and Haque (25), Arora *et al.,* (26), Ameer and Garg (28), Islam *et al.,* (30), Buttner and Tullar (31), Conte and Siano (33)
Quantitative Self Efficacy	Arora *et al.,* (26), Alamelu *et al.,* (27), Hickman *et al.,* (32)
Data Security	Chatterjee *et al.,* (13), Böhmer and Schinnenburg (19), Alamelu *et al.,* (27), Frederiksen A (45).
Employee Turnover	Ekka and Singh (24), Frederiksen (45)
HR Analytics and Organizational Performance	Kiran *et al.,* (6), Muhammad and Naz (34), Mccartney and Fu (36).
Employee Engagement	Chatterjee *et al.,* (13), Muhammad and Naz (34)

According to Table 5, the constructs (Performance Expectancy/ Effort Expectancy/Social Influence) are widely used in a large number of studies since these are individual measures (n=7) followed by Data security (privacy) with four studies each (n=5), Quantitative self-efficacy and Organizational performance with three studies each (n=3). The remaining variables have two studies conducted. Studies reveal varied views on HR Analytics adoption factors. In a study, Buttner and Tullar (31) indicate that performance expectancy favorably increases behavioral intention, however, social influence has little impact. In the study, Hickman *et al.,* (32) the advantages of technology, attitudes, and social influence on adoption are addressed. Studies by Conte and Siano (33), and Muhammad and Naz (34) highlight the favorable outcomes of performance expectancy, effort expectancy, and social influence on adoption intention and actual usage. In a study, Brandt and Herzberg (35) signifies the positive effect of hedonic motivation and performance expectancy on behavioral intention, which is offset by negative influences from effort expectancy and social influence. In a study, McCartney and Fu (36) consolidate these

findings, highlighting a strong link between HR professionals' behavioral intention and actual usage, including variables such as quantitative self-efficacy and facilitating environments.

Table 6: Population Groups in HR Analytics

Population Type	Author
HR Professionals	Vargas *et al.,* (23), Ekka and Singh (24), Anam and Haque (25), Arora *et al.,* (26), Ameer and Garg (28), Islam *et al.,* (30), Muhammad and Naz (34), Tijssen R (37)
HR Executives	Arora *et al.,* (26), Penpokai *et al.,* (39), Brau *et al.,* (44), Rombaut and Guerry (40)
Communication and marketing managers	Conte and Siano (33)
Key Officials	Alamelu *et al.,* (27), Verma *et al.,* (29), Dahlbom *et al.,* (41).
Employees	Avrahami *et al.,* (8), Chatterjee *et al.,* (13), Buttner and Tullar (31), Vorapah Mahasamsan and Surarak (38), Dhiman and Kumar (42), Percy and Dow (43), Birnbaum and Somers (46), Arena *et al.,* (47).
UG Psychology Students	Hickman L *et al.,* (32)
HRA Experts	Wirges F and Neyer (22)

From Table 6, it is evident that HR Professionals are the widely used population group in HR analytics adoption studies (n=8) followed by employees (n=7) and the third group consists of HR executives with three studies and key officials with two studies each. The rest of the sample groups have one study conducted. The capacity of HR Professionals to use HR analytics lies heavily in company culture (37). Employee resistance is common, compelling firms to provide suitable training programs and readily available data for analysis (38). Reported problems for HR practitioners include the lack of human aspect, changing data, IT infrastructure, and a shortage of top management support hampering HR Analytics adoption (39). User-friendly AI-enabled technology and adequate help propels HR Professionals to use analytics effectively (40). Utilizing HR Analytics, organizations can track HR Professionals' performance, devise retention strategies, and utilize employee engagement for enhanced organizational performance (41). To promote Human resource innovation through technology, firms attempt to positively influence HR Professionals' intention to use analytics by addressing the performance levels and social elements (42). HR Professionals' resistance, triggered by limiting ideas, requires proper training programs and job-role modifications to reduce stressors in employing current technologies (43).

Table 7: Methodologies Used in HR Analytics

Research Methods	Authors
Questionnaire Method	Van Den Heuvel and Bondarouk (12), Chatterjee *et al.,* (13), Dhankhar and Singh (17), Mccartney and Fu (20), Ekka and Singh (24), Anam and Haque (25), Arora *et al.,* (26), Alamelu *et al.,* (27), Ameer and Garg(28), Islam *et al.,* (30), Conte and Siano (33), Muhammad and Naz (34), Tijssen R (37), Penpokai *et al.,* (39)
Interview Method	Wirges and Neyer (22), Hickman *et al.,* (32), Dahlbom *et al.,* (41), Brau *et al.,* (44), Ananpalasak (48), Ontrup *et al.,* (49), Michelotti et al (50), Fernández and Gallardo (51), Kashive and Khanna (52).
Experiment Method	Buttner EH and Tullar (31).
Case Study Method	Tijssen R (37), Dahlbom *et al.,* (41), Percy and Dow (43), Brau *et al.,* (44), Saputra *et al.,* (53)

Data source (Company databases/Job Websites/Longitudinal Data)	Avrahami *et al.,* (8), Brandt and Herzberg (35), Rombaut and Guerry (40), Frederiksen A (45), Arena *et al.,* (47), Kashive and Khanna (52), Kapoor and Kabra (54), Aral *et al.,* (55) Avrahami *et al.,* (56).

Table 7 shows the maximum number of studies conducted using the Questionnaire (survey) method (n=14) to collect data related to HR analytics adoption. The second widely used research method is data generated through pre-established databases such as company websites, and job portals and data collected over a period (n=8) followed by data extracted using the interview method with eight studies conducted (n=7) and case studies with four studies conducted (n=5) leaving experimental method with only one study.

Several research studies utilize multiple strategies to examine the adoption and impact of Human Resource Analytics (HRA). In a study, Brau *et al.,* (44) utilizes a questionnaire and PLS-SEM to identify the positive effects of performance expectancy, effort expectancy, social influence, and facilitating conditions on HRA behavioral intention, while displaying the adverse impact of organizational culture on the relationship between adoption intention and actual behavior. In a study, Frederiksen A (45) non-random sampling, hierarchical regression, and SEM are applied, showing factors impacting HRA adoption intention and actual usage. Other studies apply technologies like SEM, artificial neural networks, PLS-SEM, and SPSS to reveal insights into HRA adoption, its potential in operative and strategic roles, and its impact on organizational results, shedding light on obstacles, benefits, and influence.

Table 8: Recent Articles Related to HR Analytics Studies

Author	Purpose	Methodology	Findings
Chatterjee *et al.,* (13)	To investigate negative aspects of HR analytics applications.	Survey from 315 employees using PLS-SEM.	Real-time decision and employee engagement significantly impact the perceived benefits of using HR analytics.
Dhankhar and Singh (17)	Aims to propose and test mediating roles of technology readiness, adoption of HRA, and organizational career development.	A survey from 347 HR professionals using the SPSS process Macro.	Provided evidence of technology readiness to facilitate HRA adoption and improve organizational growth.
Wirges and Neyer (22)	To examine the obstacles that firms face in deploying HR analytics effectively.	Semi-structured interview, 17HR analytics experts using Atlas software.	Need for good communication and cooperation among HR business partners, and departments to enable smooth HR analytics adoption.
Ekka and Singh (24)	To explore the factors affecting HR professionals' intention to adopt HRA, using the Unified Theory of Acceptance and Use of Technology (UTAUT) as a conceptual framework.	Questionnaire method, 270 HR professionals from India using PLS-SEM.	Performance expectancy, effort expectancy, social influence, and facilitating conditions have a positive effect on behavioral intention to use HRA.
Anam and Haque (25)	To decode factors influencing behavioral	Questionnaire from HR professionals in India.	Performance expectancy and effort expectancy have a

	intention to adopt HR analytics among HR professionals using the UTAUT model.		significant impact on behavioral intention to use HRA.
Arora *et al.,* (26)	To assess an individual's decision to adopt HRA and extend UTAUT model 2 to identify lag in HRA adoption.	Data from 387 HR professionals using hierarchal regression.	Performance expectancy, hedonic motivation, and data availability were positively influenced by HRA adoption intention.
Conte and Siano (33)	To examine the usage of 4.0 technology in HR and talent management focusing on the use of big data analytics for communication.	Web survey from 90 Italian organizations.	Growth of HR analytics is hindered by short-term perspective, lack of analytical abilities, and data quality issues.
Penpokai *et al.,* (39)	To explore the organizational factors influencing HR Analytics across large-size organizations in Thailand.	Questionnaire from 429 employees using SPSS ver 23.	Technology Adoption mediates the relationship between HR Competencies and HR Analytics adoption.
Dhiman *et al.,* (42)	To recognize the factors that affect employees' willingness to adopt HR analytics technology.	Data from 345 employees using PLS-SEM.	Social influence and job relevance have a substantial impact on the perceived usefulness of adopting HR analytics.
Arora *et al.,* (57)	To explore reasons behind the slow acceptance of HR analytics in banking and and financial services industry.	An online survey from 376 HR executives using artificial neural network.	Hedonic motivation, data availability, and performance expectancy positive impact on behavioral intention.

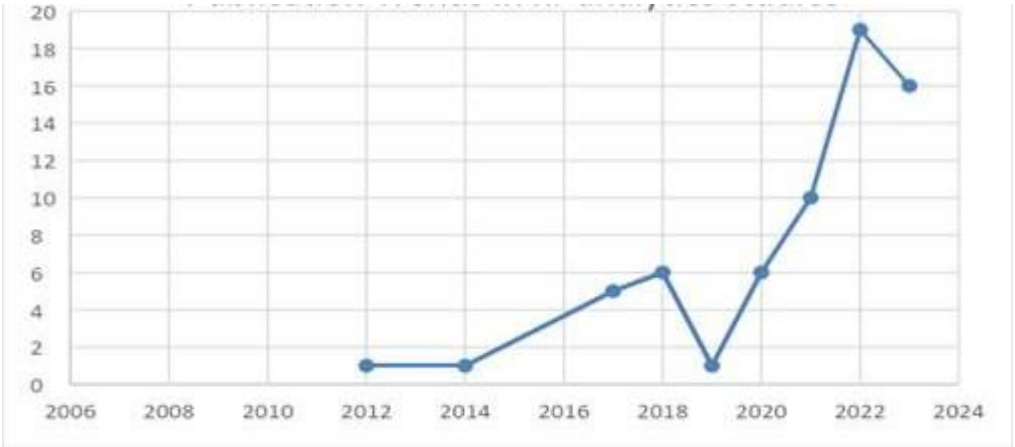

Figure 2: Graphical Representation of Publication Trends

The publication trends in Figure 2 reveal the number of articles related to HR analytics published over the years. Up until 2012, there were no publications, in the years 2012 and 2014 there has been one article in each published. Since 2017, there is a surge in HR Analytics studies having five publications. In 2018 there are six articles published whereas in 2019, the total number of articles falls to one. From 2020 up until 2023 the number of articles kept flourishing with a sum of

41 articles which may be due to COVID-19 that the interest of HR Analytics has spiked up among HR professionals and industrialists due to changing working conditions. The above publication trend arrived by merging databases from Scopus and Web of Science.

Future Research Prospects

The term "HR Analytics" is a broad term linking machine learning, artificial intelligence, and data science. There is more scope for exploring various aspects of HR Analytics apart from adopting a systematic literature review in the study for identifying research gaps and future studies. Regardless, the study identified and classified future research in terms of theory, context (industry and country type), and constructs (variables) highlighting key factors that are currently influencing HR analytics adoption and methodology with tools, and research methods to be adopted in the present state of HR Analytics.

Table 9: Representation of Research Gaps

Theory	● Conduct a study of technology adoption and HR using the UTAUT 2 model. ● Adopt other HR management fashion theories such as gamification in recruitment and social network-based real-time performance feedback. ● Expand HR adoption by employing institutional theory and resource dependence Theory. ● Apply theoretical framework related to innovation adoption, macro-organizational theory, and strategic human resource management theories.
Methods	● Case study comparing firms with AI systems and non-AI-enabled firms. ● Employ objective performance data such as ROI, Revenue Growth. ● Conduct descriptive studies on present trends in HR analytics. ● Adopt advanced methodological approaches such as cluster and factor analysis. ● Conduct qualitative methods such as interviews to gain a better understanding of learning tools for employees.
Construct	● Conduct a longitudinal Study examining present staff competencies. ● Analyse the impact of a diverse workforce on organizational performance metrics and employee outcomes. ● Examine the ethical, privacy, and legal issues amid HR analytics execution. ● Impact of personalized human resource management on global human resource management and labor relation issues. ● People analytics adverse effects on organizational outcomes. ● Moderating the impact of organizational learning on predictive HR analytics capability. ● Influence of Covid 19 on the adoption of digital technologies and people analytics. ● Explore relationships between perceived self-efficacy and maturity levels of HR analytics. ● Conduct longitudinal research on KSAOs (Knowledge, skills, abilities, others).
Context	● Smart HR analytics for happy management in the context of Industry 5.0. ● Research on organizations successfully practicing hr analytics such as nestle or Unilever. ● Comparative studies of HR analytics adoption in regulatory markets such as India and USA. ● Data protection norms in various organizational settings across regions. ● Comparative analysis of analytics implementation across industries.

Critical Analysis of Research Gaps

The following information provides a critical analysis of the identified research gaps in Table 9. In the study, Birnbaum and Somers (46) emphasize the need for understanding the stakeholder and governmental issues affecting people analytics. The proposed model offers empirical and exploratory analyses to identify the connections among enabling resources, goods, stakeholders, and governance structures.

While the focus on stakeholders and governance is essential future research should explore the dynamic nature of these interactions across time. Additionally, studying the impact of various regulatory constraints on HR analytics techniques would help to provide a better picture.

In the study, Mellam *et al.,* (1) bring out the present inconsistencies and poor maturity levels in HR analytics, stressing the requirement for evidence-based studies and clarified concepts. Addressing ambiguities in concept requires a theoretical framework that includes the diverse nature of HR Analytics. Future research should strive to establish or refine such frameworks, reflecting the dynamic nature of HR analytics in practice. In the study, Arena *et al.,* (47) suggest longitudinal surveys to assess cultural disparities in HR Analytics adoption. They also advise studying moderating factors past the conventional ones to assess the proposed model in other cultural scenarios. Cultural variations substantially affect HR procedures. Future studies should focus on the adaptation of HR Analytics approaches to varied cultural contexts. This involves understanding how cultural factors impact the customization of analytics tools and frameworks. In the study, Ananpalasak (48) promotes examining HR analytics from the viewpoint of IT specialists, undertaking industry-focused studies, and exploring the future state of HR analytics qualitatively. While recognizing the information technology (IT) viewpoint is crucial, research should also include the relationship between HR and IT departments. Furthermore, exploring the technology developments impacting HR analytics, such as AI and machine learning, is vital for holding at the forefront of innovation.

In the study, Ontrup *et al.,* (49) promote studies examining sectors beyond construction and engineering and studying social groups beyond HR experts. The generalizability of findings across sectors is crucial. Future studies should dive into individual industry difficulties and possibilities, ensuring that recommendations correspond to the unique characteristics of each area. In the study, Michelotti *et al.,* (50) suggest the usage of UTAUT 2 and other models in varied regions, performing longitudinal investigations with larger and demographically diverse samples. The adoption of models like UTAUT 2 provides a framework, yet a modification based on geography and demographics is vital. Future studies could study how geographical variations impact the acceptance and use of HR analytics models. In the study, Fernández and Gallardo (51) stress the need to define effective coaching strategies, create data-driven firms, and explore reasons leading to coaching process failures. Explore coaching strategies that match the human-centric part of HR Analytics. Future research should look into the ethical considerations of data-driven coaching and identify potential problems and obstacles in applying data-driven organizational initiatives. In the study, Neerja and Vandana (52) suggest examining variables beyond HR Analytics to derive new findings. While expanding the scope of variables is valuable, further research requires choosing additional variables based on theoretical frameworks. A methodical approach to adding variables will strengthen the validity of the research findings. In the study, Saputra *et al.,* (53) identified that clustering employees based on performance is a fine strategy, but studies ought to explore the ethical implications of categorization. Additionally, identifying the contextual aspects driving talent development and team functioning is crucial for effective HR interventions. In the study, Kapoor and Kabra (54) suggests a study on the influence of a diverse workforce on organizational performance measures. The recommendation aligns with the increasing role of diversity and inclusion. Future studies should address the way various characteristics of diversity (e.g., cultural, gender, age) impact organizational metrics and employee outcomes. In the study, Aral *et al.,* (55) suggest exploring the influence of artificial intelligence (AI) technology on the future abilities of line managers, HR Professionals, and employees. Understanding the talents required in the era of AI is crucial. Research

should not only focus on skill development but also on the potential barriers and ethical issues related to the adoption of AI tools in HR practice. In the study, Avrahami *et al.,* (56) advise studying an organization's ability to predict vital human-related processes utilizing HR analytics technologies. While predictive analytics is strong, research should address the potential biases and constraints associated with predictive modeling. Additionally, learning how firms apply predictive insights for decision-making is vital for real-world implications.

Incorporating data from various disciplines promotes the analysis, but it involves an in-depth examination of the relevance and applicability of multifaceted measures in the HR Analytics environment**.** In the study, Kiran *et al.,* (6) suggest studying factors leading to HR analytics adoption, understanding diffusion across national settings, and exploring the causes for the low diffusion of HR Analytics. Recognizing the circumstances impacting adoption is crucial. Research should consider the organizational culture, leadership support, and particular industry demands. Additionally, studying the diffusion process across diverse contexts needs a detailed understanding of the variables contributing to success or failure. In the study, Karwehl and Kauffeld (9) advise studying an organization's ability to predict vital human-related processes utilizing HR analytics technologies. While predictive analytics is strong, research should address the potential biases and constraints associated with predictive modeling. Additionally, learning how firms apply predictive insights for decision-making is vital for real-world implications. In the study, Jain and Jain (11) advocate studying organizations that have effectively executed HR analytics and undertaking comparison studies among nations with varying laws. Learning from best practices is crucial, but research should also explore the contextual variables that lead to effective HR analytics adoption. Comparative research must consider changes in organizational structures, industry demands, and cultural settings. In the study, Chatterjee *et al.,* (13) encourage exploring effective methods internationally, understanding the causes behind delayed adoption, and focusing on cost-efficient solutions for HR analytics. The global approach is crucial, but studies should also dive into the micro-level characteristics inside specific regions that contribute to delayed acceptance. Additionally, addressing the financial impacts and effectiveness of technologies is crucial for firms with varying budget constraints.

In the study, McCartney and Fu (36) recommends a comparative study of human and machine transcribing methods and evaluates the reliability of language-based algorithms. The reliability of algorithms and transcribing processes is vital in ensuring the accuracy of HR Analytics. Future studies should address the ethical problems of relying on automated technologies for decision-making in HR operations. In the study, Tijssen R (37) encourages more study on comparative analytics among European firms and eradicates identified hurdles to HR analytics execution. The cross-cultural perspective is crucial, and future studies should analyze how regulatory environments and cultural variations impact HR Analytics methods. Additionally, overcoming recognized barriers involves a complete understanding of their organizational and environmental origins. Table 10 denotes the journal name and total number of articles pertaining to HR Analytics adoption research published in the mentioned journals. As per (Table 10), "Journal of Organizational Effectiveness" (n=4) has the highest number of publications followed by "International Journal of Organizational Analysis", "International Journal of Manpower", and" Human Resource Management" (n=3) each having 3 articles. The subsequent eight articles have two publications each. The remaining (n=31) articles have one publication.

Table 10: Most Impactful Journals in HR Analytics Studies

Journal Name	TP	Journal Name	TP
Journal of Organizational Effectiveness	4	Managerial science	1
International Journal of Organizational Analysis	3	Electronic hrm in Smart Era	1

International Journal of Manpower	3	International journal of Indian culture and business management	1
Human Resource Management	3	TQM Journal	1
Competitiveness review	2	Journal of Management Development	1
South Asian journal of human resource management	2	Journal of risk and financial management	1
Journal of management information and decision sciences	2	International journal of business environment	1
Human Resource Management Journal	2	Quality access to success	1
Vision	2	Equality, diversity and inclusion	1
International Journal of Professional Business Review	2	Human Resource Development International	1
International Journal of Human Resource Management	2	Employee relations	1
Evidence-based hrm	2	Journal of Cases on Information technology	1
Corporate communication	2	International journal of economic research	1
Human resource management review	2	FIIB Business Review	1
International journal of emerging technologies	2	German journal of human resource management	1
Industrial and Commercial training	1	Management decisions	1
Administrative Sciences	1	Review of managerial science	1
Engineering, construction, and architectural management	1	Organizational dynamics	1
Gruppe	1	Transnational marketing journal	1
Journal of Business Research	1	Organizacija	1
Journal of Business Logistics	1	Journal of Management Analytics	1
Journal of Workplace Learning	1	Journal of Chinese Human Resource Management	1
Baltic journal of management	1	Asian Pacific Management review	1

Research Implications

The systematic review of HR Analytics adoption literature indicates numerous critical findings and patterns. The introduction presents an extensive overview of the HR Analytics landscape, highlighting its strategic importance, the problems faced, and the possible benefits for enterprises. The study methods section details the rigorous strategy followed, combining two main databases, Scopus, and Web of Science, to ensure a full evaluation of the literature. The selection criteria, including keywords, subject area, document kinds, and language, add to the quality and relevance of the reviewed articles. The results section includes valuable findings across multiple dimensions, such as theories applied, the context (country, industry, population type), variables explored, research methodologies employed, annual publishing trends, and key journals in the field. The utilization of RBV theory, contextualized inside the AI-driven environment, stands out, showcasing HR Analytics as a rare and non-imitable resource contributing to competitive advantage. The contextual analysis uncovers a concentration of HR Analytics adoption studies in India, illustrating the relevance of cultural factors and relationships among HR Practitioners. The industry-wise distribution reveals a prevalence of studies across manufacturing and service sectors, underlining the potential for technology-driven innovation in talent acquisition procedures. The concentration on HR Professionals as the major population category aligns with the broader narrative of HR analytics being a tool for increasing HR Practitioners' performance and decision-making. The emphasis on individual traits, particularly performance expectancy, effort expectancy, and social influence, implies a detailed investigation of factors driving HR Analytics adoption. Additionally, the prevalence of the questionnaire method in data collecting suggests a dependence

on survey-based approaches, bringing insights on perceptions and attitudes about HR Analytics adoption. The annual publishing trend reveals a considerable spike in HR Analytics studies from 2017 onwards, probably inspired by the altering workplace dynamics and the COVID-19 pandemic.

The future research possibilities section recommends numerous routes for additional inquiry, extending stakeholder challenges, governance frameworks, cultural disparities, and the impact of developing technology on HR Analytics. The critical study of future research proposals highlights the necessity for a balanced view, considering industry-specific dynamics, regulatory constraints, and ethical consequences. The diversity of suggested research subjects, ranging from the influence of AI technology to the examination of coaching tactics and the long-term benefits of retention approaches, demonstrates the varied nature of HR Analytics adoption.

Conclusion

The systematic review of HR analytics adoption literature provided in the paper provides a complete and insightful overview of the current state of research in this field. The study uses a robust methodology, utilizing the TCCM framework and combining data from Scopus and Web of Science, resulting in 64 relevant articles. The results are presented systematically, encompassing theories, context (country, industry, population), constructs, research methods, yearly publication trends, and future research prospects. The review highlights the dominant use of the resource-based view (RBV) theory in understanding HR Analytics as a rare, non-imitable resource that adds to competitive advantage. The contextual analysis shows a concentration of studies in India, with a growing interest in the USA, Germany, and Thailand. The industry emphasis on manufacturing and service companies suggests a practical application of HR Analytics in diverse organizational settings.

The population study highlights the central role of HR professionals in HR Analytics adoption, stressing the importance of organizational culture, training, and technology in overcoming resistance. Constructs such as performance expectancy, effort expectancy, and social influence originate as important forces influencing adoption, representing different perspectives. The research methods section (Table 7) shows a preference for the questionnaire method, aligning with the survey-based nature of HR Analytics research. The annual publication trend (Figure 2) highlights a significant uptick in interest from 2017 onwards, possibly driven by the dynamic changes in the workplace environment, including the impact of COVID-19. The future research possibilities section (Table 9) provides valuable insights into the directions that HR Analytics research should take. From understanding the impact of people analytics on organizational outcomes to exploring stakeholder and governmental issues, these recommendations correspond with the evolving nature of HR Analytics in practice. This paper makes a significant contribution to the HR Analytics literature by giving a detailed review of existing research. The thorough analysis of theories, contexts, constructs, and methods provides a solid basis for future scholars, HR Practitioners, and key players interested in advancing the understanding and application of HR Analytics. The critical analysis of future research possibilities adds depth and nuance to guide future investigations in this evolving field.

While the review presents a detailed and analytical analysis, it is crucial to identify some limitations. The review relies primarily on publications available in the Scopus and Web of Science databases, ignoring significant literature from alternative sources. The geographical concentration of studies in India can limit the generalizability of findings to a global context. Moreover, the fast-paced advancement of HR analytics and technology may render some conclusions outdated, necessitating constant updates and reviews. In conclusion, the systematic review adds useful insights into HR Analytics adoption literature, identifying trends, obstacles, and future research objectives. The critical study underlines the need for a detailed and context-specific approach to ensure the relevance and applicability of findings in the evolving landscape of HR Analytics.

Abbreviations

HR: Human Resource

TCCM: Theory-Context-Characteristics-Methodology

RBV: Resource Based View

TOE: Technology Environment Organization

AI: Artificial Intelligence
HRMS: Human Resource Management System
IoT: Internet of Things
SPAR-4: Source, Population, Area, Results - 4 Steps
CCTM: Context, Construct, Theory, and Methods
PRISMA:- Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RBV: Resource-Based View
TOE: Technology-Organization-Environment
UTAUT: Unified Theory of Acceptance and Use of Technology
HRA: Human Resource Analytics
UG: Undergraduate
SPSS: Statistical Package for the Social Sciences
SEM: Structural Equation Modeling
PLS-SEM: Partial Least Squares Structural Equation Modeling
IT: Information Technology
ROI: Return on Investment
KSAOs: Knowledge, Skills, Abilities, Other
CARG: Critical Analysis of Research Gaps
COVID-19: Coronavirus Disease 2019
UTAUT 2: Unified Theory of Acceptance and Use of Technology 2
TP: Total Publications

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Authors Contributions

Sindhuja conducted the research and analysis for the study. Dunstan Rajkumar supervised the project and provided critical revisions to the manuscript. Both authors contributed to the writing and approval of the final manuscript.

Conflict of Interest

The authors declare no conflict of interest regarding the research content of this article.

Ethics Approval

The study involves a systematic review of existing literature and does not include any human or animal subjects.

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