Analysing Past to Prepare for Future: A Systematic Literature Review of Research on Human Resource Analytics in the last Decade

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Abstract

Since its inception in the previous forms of traditional measurement sources for distinct sub-functions, human resource analytics (HRA) has come a long way. With the growing importance of analytics in human resource management, research in this area has gained traction. The vast majority of this research remains unexplored. This study conducted a comprehensive literature evaluation of 62 peer-reviewed published research publications to offer a narrative overview of HRA research during the previous decade and highlight research gaps. HRA research is divided into six primary research categories in order to provide an overview of the major contributions of current HRA research and to identify research needs. Concrete directions for further empirical research are suggested as a result of the identified deficiencies.

The Systematics Literature Review (SLR) yielded major themes that included Evolution and Conceptualization, Antecedent, Process, Facilitators and Inhibitors of HRA, Technology as Enabler, Impact of HRA, and Other Themes such as HR Strategy, employee effort and collaboration, Human Resource Management Information System (HRMIS), Organization Work Environment, Employee Learning Activity, Enhancing the Impact of People Analytics, Talent Retention, Decision Support System (DSS), Evidenced based HR. The paper uses resource Based View (RBV) to describe the notion of HRA, integrating a number of definitions of HRA.

Keywords: Human resource analytics (HRA); Systematic literature review; Workforce analytics; Human resource information system (HRIS); HR Metrics

1. Introduction

Interest in using statistics to make people-based decisions grew after Lewis' book "Moneyball: The Art of Winning an Unfair Game" was published in 2004. Oakland A, the iconic baseball team of the United States, discovered a more advanced and complete application of metrics in 2002, when Billy Beane, the organization's general manager, used sabermetrics extensively to pick club members. (Lewis, 2004). The ‘Moneyball' concept has been applied to the business world on a big scale since 2006 when Google launched ‘Project Oxygen' to discover the characteristics of effective managers. However, it wasn't until 2010 when HRA became well-known in the business sector (Davenport, Harris, and Shapiro, 2010). Soon after, a slew of research papers was published highlighting the advantages of using analytics in workforce management. (Devenport, Harris, and Shapiro,2010; Garvin, Wagonfel and Kind,2013). Finally, businesses have new hope of discovering the "right people" by employing a data-driven approach to workforce management known as "HR Analytics," "People Analytics," or "Workforce Analytics." These analytics claimed to go beyond metrics and into predictive analysis employing algorithms to make data-driven personnel management decisions.

Human resource analytics (HRA) is a relatively new intervention in the larger domain of human resource management, and it relates to the application of statistical tools, metrics, and methods for employing and recognizing the most effective people decisions. It can be defined as “An information technology-enabled HR approach that uses descriptive, visual, and statistical analyses of data related to HR processes, human capital, organisational performance, and external economic benchmarks to determine business impact and enable data-driven decision-making.” (Marler & Boudreau ,2017). HRA is more credible since it provides statistically valid data and proof that can be used not only in the development of new HR strategies but also in the implementation of current HR policies.

The scholarly literature defines Human Resource Analytics (HRA) as a framework for assessing and evaluating the causal relationship between HR practices and organisational performance outcomes, as well as providing legitimate and dependable foundations for human resource decisions aimed at influencing corporate strategy and performance, using statistical techniques and experimental approaches based on efficiency, effectiveness, and impact metrics (Lawler, Levenson & Boudreau, 2004; Boudreau & Ramstad, 2006). Many scholars have looked at the statistical effects of HRM systems on company performance in the literature. (Agdelen, 2003; Becker and Huselid, 1998; Huselid, 1995). However, demonstrating the link between HR, company strategy, and performance using data proved difficult. In his paper "The measuring imperative," Jac Fitz-enz (1978) advocated that human resource operations and their influence on the bottom line could be assessed.

From the foregoing explanation, it is evident that HR Analytics is deeply entrenched, primarily attributable to HR professionals' constant desire to quantify the impact of HR activities on organisational efficiency. Over time, scholarly interest has grown, leading to a better understanding of its significance. In most organisations, HRA and data-driven HRM are still in their infancy. As can be seen, a rising number of articles on HRA have been published in the last decade, resulting in a large body of knowledge to review and opportunities to think on how to move this topic forward. To present a comprehensive picture of HRA research over time, a variety of review studies were created. Relevant material from past reviews was compiled to better comprehend the principles and phenomena of HRA, and to highlight key voids in review articles, as stated by Low and MacMillan (1988). For performing in-depth research of recent literature review studies, the following factors were considered: study objective, analytical tool, study period, and study scope. The majority of previous studies focused on HRA's impact (Ben-Gal, 2019; Lunsford, 2019; King, 2016) and process (Safarishahrbijari, 2018; Nair, 2018; Marler, & Boudreau, 2017). Some of the review studies also looked at the research on HRA Challenges (Levenson & Fink,2017; Cheng, 2017).

Table 1: Overview of Previous Literature Reviews on HRA

Author	**Diagnostic Tool**	**Study Objective**	**Study Duration**	**No. of articles reviewed/ Cases**
Ziebell et.al, (2019)	Systematic LR	Digital transformation of HR	1974-2018	365
Hila Chalutz Ben-Gal (2019)	Systematic LR	Implementation tools for expected ROI	2000-2016	80
Dale L. Lunsford (2019)	Integrative LR	develop an analytics system model	Not mentioned	50
Arroyo &Osca (2019)	Systematic LR	main clusters of HR practice systems	2000-2019	41
Safarishahrbijari (2018)	Systematic LR	workforce modelling and prediction methods	1980-2015	275
Nair (2018)	Evidence based LR	HRA implementation	Not mentioned	Not mentioned
Levenson & Fink (2017)	Literature and conceptual review	Barriers in HRA implementation	Not mentioned	Not mentioned
Marler& Boudreau (2017)	evidence-based review using an integrative synthesis	Conceptualization	2003-2011	14

Cheng (2017)	Case Studies	underlying disconnect between practitioners and scholars	Not mentioned	8
King (2016)	Case Studies	Role of academics in HRA	Not mentioned	2

An examination of current review studies indicated a scarcity of studies categorising HRA research into main search themes, synthesising their findings, and analysing each theme on key features like conceptualization, theoretical frameworks, and research gaps. The authors aimed to review recent HRA research on defined aspects to suggest an appropriate approach and directions for future research. Considering the limitations cited in the existing literature and the mounting interest of researchers; the current study aims to further advance the knowledge about human resource analytics. This study will categorise contemporary HR analytics research into core research themes and describe the academic research within each theme. The objectives of the study are twofold:

- To classify the HRA Scholarly research in main themes
- To identify the research gap and provide directions for future research
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By knowing the previous research on a certain area, this review study will also be valuable in offering answers to practical questions. Simultaneously, the explanation of recent HRA research will assist HRD professionals, enterprises, and researchers in comprehending recent breakthroughs in the HR analytics arena.

The research article is organised as follows: Section 2 provides an outline of research methodology; Section 3 presents main research themes highlighting key academic contributions. Section 4 delves into the details of the studies that have been examined needed to make concrete recommendations for further study. Section 5 brings the review to a close and makes recommendations for theory and practice application.

2. Review Methodology

The study involved identification, cleaning, critical appraisal, and synthesis of relevant studies in the area of HRA leading to the portrayal of the current state of HRA research (Linnenlueckeet. al, 2020). The study uses a replicable, systematic, and tranparent process thus categorized under systematic literature review (Tranfield et al., 2003; Denyer, D., & Tranfield, 2009). In the first step, the authors identified the available literature (2010 to 2020) for inclusion and categorized them into six central themes. Following the original procedure given by Kitchenham (2004), the authors further synthesized the researches categorized under each theme. The study follows the suggested methodology starting with developing the protocol and culminating in the production of results. This is further explained below.

2.1 Protocol Development and Selection of Relevant Articles

The study generated the research paper from online English language research databases SCOPUS, EBSCO, Google Scholar, and Proquest. The referred databases with appx. 12,000 publishers and 35,000 peer-reviewed journals provide a comprehensive picture of academic researches. Intending to minimize the probability of missing important papers and articles, the researchers used search strings “HR”, “HRM”, “Talent”, “Human Resource”, “Workforce”, “Human Capital” and “Analytics”, “Scorecard”, “Metrics” with boolean “and” operator. Further, the strings “Human Resource Analytics”, Work Force Analytics”, “Talent Analytics” were used with boolean “or” operator as they are being used interchangeably by the practitioners and researchers.

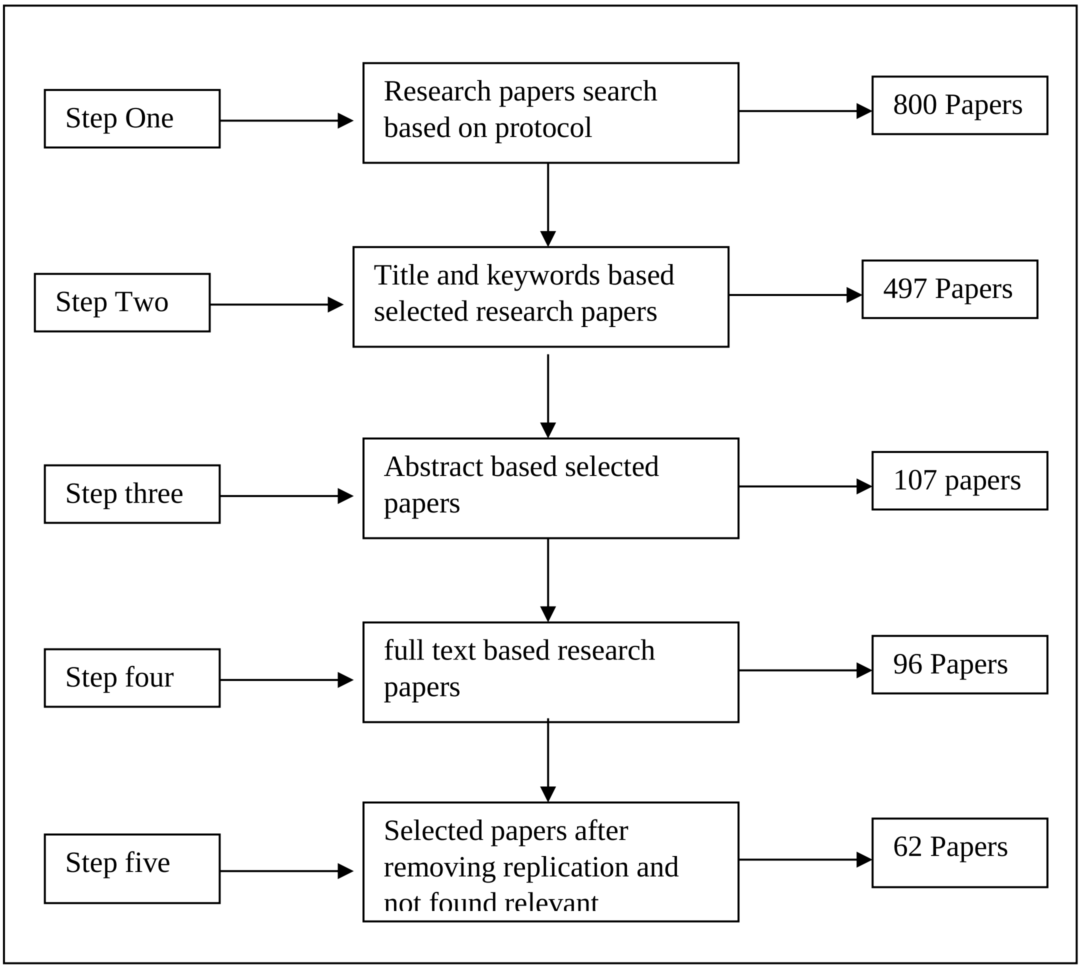
To ensure the inclusion of every important contribution; researchers have included interdisciplinary journals (Linnenluecke et.al, 2020). The emphasis has been placed on peer-reviewed journals without missing out on the important contributions from non-peer-reviewed publications like McKinsey Quarterly, Conference proceedings, Conference papers, Dissertation thesis(Adams et al., 2017; Linnenlueckeet. al, 2020). The peer-reviewed publications ensured that highly credible, high-quality research papers are being considered for the review providing the methodological and scientific rigor and quality control of the study (Light and Pillemer, 1984; Kelly et.al, 2014; Gupta et.al, 2020). The researchers collected 800 articles after this step.

A four-step process (Table 1) was followed to further screen the relevant papers out of 800 collected in stage 1. intending to maintain strict selection criteria, two authors independently worked on the exclusion criteria and to make it more robust and stringent, the third author rechecked the excluded studies to ensure inclusion of important research studies. The strategy was followed at each step of selecting the final papers for review to narrow down the list. The authors further screened the papers based on the title and keywords and excluded the irrelevant studies. While doing so the articles and papers having scope to be included based on the text were retained with discussion amongst the authors (Brereton et al., 2007; Gupta et al., 2019; Linnenlueckeet. al, 2020). The number of articles and papers after stage 2 stood at 497. This was followed by thorough screening of the papers based on the abstracts with an objective of further refining the sample and removing the false positives (Linnenlueckeet. al, 2020). Stage 3 gave 107 papers for further process. After the abstracts; the inclusion criteria shifted to the full-text review with excluding the studies which did not have a core research theme of HRA and the main objectives of the study were different from HRA (Gupta et.al, 2020). This step had the output of 96 studies. To avoid recurrence and reject studies that had even a remote probability of being irrelevant, the studies were read again and the irrelevant ones were screened out. This gave the authors a final figure of 62 studies to be considered for the research. At every step, two authors independently performed exclusion exercises and the third author screened the excluded studies independently to ensure that an important study is not accidentally eliminated.

2.2 Data Extraction

The systematic literature reviews with a small number of studies are better presented with a review matrix citing the research objectives, variables studied, analytical tools, and major findings (Gupta et. Al, 2020; Linnenlueckeet. al, 2020). Following the approach, the authors presented the review matrix (Table 1) with extracted data in the form of an excel sheet. In the later phase, the matrix was refined with discussion and reaching a consensus (Gupta et.al, 2019).

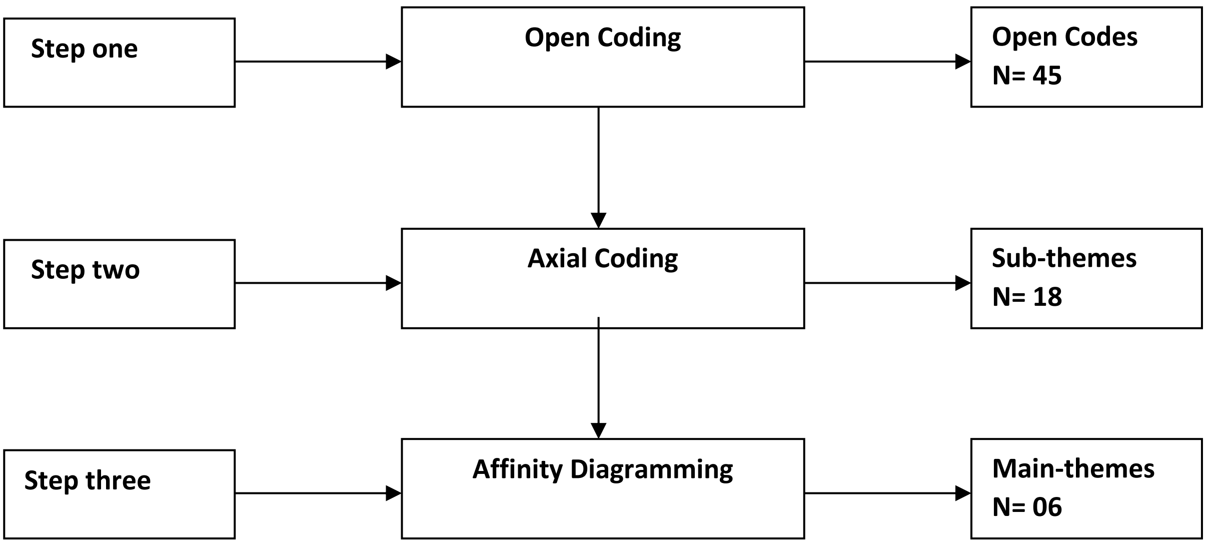
Figure 1: Selection of Sample Papers



2.3 Research Theme Classification

SLRs are more commonly presented in the form of theme centric reviews which gives thorough reviews of past studies contribution in development of the themes (Linnenlueckeet. al, 2020). To systematically present the findings of the studies, the authors developed a classification scheme based on the data extracted in the form of research objectives and main findings. The “bottom-up” was used for a thorough and rigorous literature review (Wolfswinkel et al. 2013). The final studies were analyzed for specific sub-themes to be clubbed under more generic themes (Figure 2). The open coding technique widely used in contemporary SLRs resulted in 45 codes (Gupta et al., 2019, 2020) recording the research objectives, major findings, and results of the studies. Further examining the relationship under open codes, the process of axial coding resulted in 18 sub-themes (Gupta et.al, 2019,20 20). The last stage of affinity diagramming suggested by Kawakita (1982) synthesized the sub-themes into major six themes (Table 1). For example, organization performance, talent management, employee retention, performance management, etc were clubbed in one of the themes “Impact of HRA”. The authors were involved in the discussion and brainstormed the final categorization of six themes which also resulted in few hybrid themes. Few studies came into the purview of more than one theme making the themes mutually inclusive. The authors further validated the themes with cross-examination.

Figure 2: Theme Classification Process



3. Scholarly Research on HRA in the Last Decade – An Overview

HRA is rapidly progressing towards gaining the attention and be the focal point of researchers and on the top priorities in business agendas. An early decade of 2010 to 2015 witnessed the researchers exploring the foundations of HRA with the shift to evidence-based HR wherein analytical skills and adoption resulted in enhanced organizational performance along with HR core functional areas like HR planning, talent management, etc. (Bourne & Haddon, 2010; Harris et. al,2010; Aral et.al, 2012; Romree et.al, 2012). Moving to the second half-decade, researchers shifted their attention towards the development of HRA and analysing the sustenance value of the concept and challenges attached (Romree et.al, 2016; Heuvel &Bondarouk, 2017; Green, 2017; Anderson, 2017; Boudreau & Cascio, 2017). The trend to study the impact of HRA on HR practices was on the rise (Sharma & Sharma, 2017; Arellano et.al, 2017). Towards the end of the decade, the focus of researchers shifted to analyzing the association between IT deployment, innovation resulting in agility, and competitive advantage (Mishra et.al, 2018; Vargas et.al, 2018; Mclever et.al, 2018; Levenson, 2018). HRA research gained momentum with special attention to people analytic instrumental role in strategy execution thereby causing the disruption (Simon &Ferreio, 2018; Sivathanu& Pillai, 2018), the cognitive, behavioural, and contextual factors with the role of HRA in HR metrics, strategic HRM, strategy execution and very important ethical concerns leading to a resilient organization system (Al Ayed, 2019; Manley &Willimas, 2019; Singh & Malhotra; 2020; Ziebell et.al, 2019).

The researchers develop the conceptualization of the term 'HRA' as exhibited in Table 2 'Summary Statistics'. Table 2a lists the total number of 62 papers referred to in the review ranges from 2010 to 2020 keeping in line with the time recent developments and adoption of HRA by the organizations. The number of a paper published at the beginning of study period is less owing to the apprehensions revolving around the concept of HRA. As the disruption happens in the environment and with the advent of technology-dominated evidence-based management, the application vis-a-vis interest in HRA increased with each passing year.

The transition and progression in defining HRA are studied by dividing the study period into three categories. Initial years under study i.e. 2010-14 did not have much of the elaborate focus on defining HRA. Authors during the stated period were confined to the basic aspect of data collection and its analysis for better-informed decisions. 2014-18 witnessed the major shift into defining HRA; focusing on logical analysis, strategic approach with the addition of new forms of databases. System thinking is emphasized along with advanced analytics and the use of modeling tools. Post-2018, authors have highlighted the leveraging of the Internet of Things (IoT) for improving business decisions, making it an indispensable part of defining HRA. The unification of data from various sources is considered for matching employee and organization needs.

Along with the breadth of the terminology used, table 2b shows the range of definitions used for HRA and synonymous terms for the same in the literature reviewed. One-third of the papers have used the term ‘Human Resource Analytics and define it in terms of statistical techniques, experimental approaches, HR practice enabled by information technology, application of existing scientific knowledge, tracking HR investments, HR data analysis, usage of various modeling tools in HR decision making, a methodology to understand the relationship between HR practices and organization performance, integration of HR data from different but relevant sources, the capability of organizations to design evidence-based solutions; to give the data a predictive ability by organizing it more logically giving the result in terms of more logical, rational decisions for better organization performance. Jeble et.al., 2019 used the term ‘Big Data and Predictive Analytics (BDPA) defining in terms of amalgamation of knowledge, skills, and techniques. Cheng and Heckitt, 2021 go with the term ‘HR algorithm’ defining in terms of computer programmes of heuristics nature. Few reviewed papers used the term ‘Human Capital Analytics’ defining it on the similar lines of HRA as the analytical technique with visual, statistical, and descriptive analysis of the tremendous amount of data pertaining to HR processes to reach decision making with organization performance as the focal point. The review papers used ‘Talent analytics’ as synonymous with HRA with special emphasis on extraction, examination, and assimilation of data pertaining to identifying, attracting, and retaining the talent in the organization to build a sustainable competitive advantage. A fair number of papers have used ‘People analytics’ and ‘Workforce analytics’ interchangeably defining the terms as quantification of personal and qualification details of the workforce to enable the managers more infirmed and evidence-based decisions for finer organization performance with the help of information technology.

The major constructs used as independent variables are in the basic building blocks of HRA like skills and capabilities, technology and automation, and core HR operations (table 2c). The variables taken under study majorly impact the adoption of HRA by the organizations resulting in enhanced employee and organization performance. The research in HRA is majorly driven with a focus on the conceptual and theoretical approach, validating the fact that HRA is still in contemplation phase with most organizations are still struggling to put HRA in place (Table 2d and 2e.) Nearly half of the papers use qualitative measurements with 12% using a quantitative approach of measurement. This brings to the fact that researchers are mostly in consensus with using the qualitative approach while researching HRA with not much of a difference in primary and secondary sources emphasis in data collection methods. The empirical papers gathered data from industrialized countries with one-ninth of these papers take data from developing countries (table 2f). The researchers are categorically not in the favor of geographical specific studies but the global application of HRA in the age of global each where business can’t be confined into national boundaries.

Table 2: HRA research – an Overview

2a. Year-wise distribution of papers

Year	N
2020	3
2019	20
2018	15
2017	9
2016	4
2015	3
2014	1
2013	1
2012	3
2011	1
2010	2
Total	62

2b. Definitions

Time Period	**Definition**	**Authors**
2010-14	"the application of a methodology and integrated process for improving the quality of people-related decisions for the purpose of improving individual and/or organizational performance"- *Bassi (2012)* "the integration of relevant HR data from different sources, the performing of organizational and workforce analysis on this captured data, and ultimately the gleaning of insights from the findings to shape decisions for better organization performance. *Kapoor &Kabra (2014)*	Kapoor &Kabra (2014); Dulebohn& Johnson (2013); Aral et.al, (2012); Bassi (2012)

2014-18	"analytics involves both traditional relational database and spreadsheet-based analysis, new forms of database software that allow very large quantities of data to be stored and organised more efficiently and new techniques for representing and understanding data through visualisation." *Angrave et.al, (2016)* "a methodology for understanding and evaluating the causal relationship between HR practices and organizational performance outcomes (such as customer satisfaction, sales or profit), and for providing legitimate and reliable foundations for human capital decisions for the purpose of influencing the business strategy and performance, by applying statistical techniques and experimental approaches based on metrics of efficiency, effectiveness, and impact." *Patre (2016)* "an HR practice enabled by information technology that uses descriptive, visual, and statistical analyses of data related to HR processes, human capital, organizational performance, and external economic benchmarks to establish business impact and enable data-driven decision-making". *Sousa (2018)* They involve the analysis of HR-related data, but also the integration of data from different internal functions and even data external to the firm. Information technology enables the collection, manipulation, and reporting of diverse types of both structured and unstructured data. *Mclever (2018)*	Vargas et.al, (2018); Schiemann et.al, (2018); McIver et.al, (2018); Levenson (2018); Simón &Ferreiro (2018); Kryscynski et.al, (2018); Minbaeva (2018); Shrivastava et.al, (2018); Nagdev& Rajesh (2018); Sousa (2018); Hicks (2018); Rombaut&Guerry (2018); Togt& Rasmussen (2017); Heuvel &Bondarouk (2017); Green (2017); Andersen (2017); Boudreau & Cascio (2017); Rios et.al, (2017); Sharma & Sharma (2017); Arellano et.al, (2017); Pate (2016); Khan & Tang (2016); Angrave et.al, (2016); Romrée et.al, (2016); Lal (2015); Rasmussen & Ulrich (2015); Lippens et.al, (2015)
2018-20	"People analytics is leveraging the Internet of Things (IoT) for improving business decisions related to acquisition, motivation, utilization, and retention of talented employees in the organizations" *Shukla et.al, (2019)* "People Analytics refers to the unification of Human Resource data from various, different but relevant sources, analyses on the occupied data, and further the complete understanding and discernment from the analyses to bring stronger decisions into shape for finer organizational performance." *Singh & Malhotra (2020)*	Singh and Malhotra (2020);Dahlbom et.al, (2019); Meena &Parimalarani (2019); Claus (2019); Wang &Katsamakas (2019); Shukla et.al, (2019); Hamilton &Sodeman (2019); Kakkar&Kaushik (2019); Shiya (2019); Stoian &Tohanean (2019); Ayed S.I.(2019)

2c. Constructs

Construct	**Few Examples**	**Independent Variable (IV)/ Dependent Variable (DV)**
Business Intelligence	Sousa& Dias (2020)	IV
Skills and Capabilities	Dahlbom et.al, (2019); Mishra et.al, (2018)Kryscynski et.al, (2018); Khan & Tang (2016)	IV
Technology/ Automation	Iwamoto (2019); Bhattacharyya & Nair (2019); Kakkar& Kaushik (2019); Shiyaa (2019); Stoian, &Tohanean (2019); Heuvel &Bondarouk (2017)	IV

HRM Functions/ Operations	Prakash et.al, (2019); Sousa (2018); Arellano et.al, (2017); Aral et.al, (2012)	IV and DV
Decision Making	Sousa& Dias (2020); Meena &Parimalarani (2019)	DV
HRA Adoption	Dahlbom et.al, (2019); Bhattacharyya & Nair (2019)	DV
Organization Performance	Mishra et.al, (2018); Iwamoto (2019); Sivathanu& Pillai (2019); Hamilton &Sodeman (2019); Shiyaa (2019); Green (2017)	DV
Employee Performance	Manley &Williams (2019); Kryscynskiet.al, (2018); Green (2017)	DV

2d. Research Methods

Type	N
Quantitative	8
Qualitative	16
Theoretical and Conceptual	35
Qualitative and Quantitative	3
Total	62

2e. Sources of Data Collection

Data	N
Primary	20
Secondary	12
Not Applicable	30
Total	62

2f. Geographical Reach

Geographic Context	N
Developed	13
Developing	9
Combination	4
Not Mentioned	36
Total	62

4. Discussion on Main Themes

In this section, we provide an overview of major findings and contributions of scholarly research under each main theme (Table 3).

Table 3: Themes and sub-themes mapped with their contributors

Sub Themes	Main Themes	Contributors
Dimensions of HR Analytics, Future of HR analytics, Mastering the art and science of HR analytics	Evolution and Conceptualization	Cheng & Hackett (2019); Sousa (2018); Heuvel & Bondarouk (2017); Bassi (2012);
Industrial Organizational Psychology, HR Analytics, Design Thinking, Behavioural Economics, human capital analytics as enabler of competitive advantage, HR Infrastructural support, HRIS	Antecedent	Frederick et.al. (2020); Claus (2019); Minbaeva (2018); Vargas (2015); Angrave et.al. (2016);
building an organizations' analytical capability, Agility, competitive advantage analytics and enterprise analytics, Impact of workforce analytics on strategy execution and organizational effectiveness.	Process	Shahbaz et.al. (2019); Mclver et.al. (2018); Levenson (2018); Simón & Ferreiro (2018); Harris et.al. (2010)
Big data and HR Operations, Recruitment Innovation adoption and use, development of human capital analytics, Obstacles in greater use of human capital analytics commitment, Effective use of people analytics, Information for Decision Making, Challenges of improving HR's contributions to business performance.	Facilitators and Inhibitors of HRA	Dahlbom et.al. (2019); Hamilton & Sodeman (2019); Vargas (2018); Andersen (2017); Boudreau & Cascio (2017); Khan & Tang (2016); De Romrée (2016); Rasmussen & Ulrich (2015); Harris et.al. (2011);
IT Deployment and HR, Human Capital Management HR Metrics, Job Flexibility with Tech Advancements, privacy, and ethical issue, SHRM, Artificial Intelligence, PMS as enabler of dynamic aspects and digitalization, Data Analytics	Technology as Enabler	Mishra et.al. (2018); Iwamoto (2019); Sahta & Ashley (2019); Bhattacharyya &Nair (2019); shukla et.al. (2019); Kakkar & Kaushik (2019); Sahlin & Angelis (2019); Hitmi & Sherif (2018)

Work force analytics and Strategy execution, recruitment process and its importance of decision making in the process, Talent Management, SHRM, Developing competitive advantage, Cognitive, Behavioural and contextual aspects of organizational resilience, Disaster Management, Human capital analytics as enabler of business success, approaches to cultivating analytical skills, the role of smart HR as a catalyst in the disruption process in the human resource domain, Role of analytics and its advantages in the human resource domain, Voluntary Turnover, enhancing the impact of HRM, Performance Appraisal, Organization Performance, Transforming HR, Business value chain and organizational performance, adoption of HCM, Human resource Planning	Impact of HRA	Singh & malhotra (2020); Meena &Parimalaran (2019); Prakash et.al. (2019); Sivathanu & Pillai (2019); Stoian & Tohanean (2019); Al-Ayed S.I.(2019); Jeble et.al. (2019); Schiemann et.al. (2018); Kryscynski et.al.(2018); Sivathanu & Pillai (2018); Shrivastava et.al. (2018); Rombaut & Guerry (2018); Togt & Rasmussen (2017); Rios et.al. (2017); Sharma & Sharma (2017); Arellano et.al. (2017); Patre (2016); Lal P. (2015); Kapoor & Kabra (2014); Aral et.al. (2012); Romree et.al. (2012);
HR Strategy, employee effort and collaboration, HRMIS, Organization Work Environment, Employee Learning activity, enhancing the impact of people analytics, Talent Retention, DSS, Evidenced based HR	Other Themes	Sousa & Dias (2020); Wang & Katsamakas (2019); Shiyaa (2019); Manley & Williams (2019); Hicks (2018); Green (2017); Lippens et.al, (2015); Dulebohn & Johnson (2013); Bourne & Dale (2010)

4.1. Evolution and Conceptualisation

The first cluster of 4 studies examined how datafication of HRM activities in the last decade has evolved and diffused in routine managerial functions. The majority of the studies on this theme were carried out in the developed economies and only a hand full of the studies focused on developing economies (e.g Vargas, et. al.,2018; Dahlbom, et. al., 2019; Hamilton, & Sodeman,2020).In the increasingly challenging global competitive digital environment relying on accurate data, HR managers are under pressure to adapt rapidly to the changing market conditions. Analytics are devices that can assist in making decisions in those contexts (Sousa, 2018). HRA is an evidence-based approach to improving individual along with organisational performance adopting descriptive, pictorial, and quantitative analyses of data linked to HR procedures, human resources, organizational effectiveness, and various macroeconomic standards. (Marler, & Boudreau, 2017; Bassi et al., 2010; Aguinis, &Lengnick-Hall, 2012). In addition, the increased datafication of HRM activities draws attention to the creation and deployment of advanced HRM algorithms (Cheng, & Hackett, 2019). With the advent of technology-enabled operations within HRM, HRA's wings are expanding along with the challenges it raises. It was, therefore, felt appropriate by the scholars to examine the reasons for the increase in analytics (Bassi, 2011), HRM-related algorithmic applications (Cheng & Hackett, 2019), the different dimensions and levels of HR

Analytics (Sousa, 2018) along with its potential in future (Van Den Heuvel, &Bondarouk, 2016). It is characterized as a procedure for assessing and evaluating the causal association among Human resource activities and organisational work performance (such as customer satisfaction, revenue), as well as a valid and reliable foundation for human capital decisions to influence business strategy and results, by employing quantitative methods and research techniques efficiency, productivity, and impact metrics (Lawler et al., 2004; Boudreau & Ramstad, 2006).

HRA, workforce analytics, and people analytics terms coexist and are commonly used interchangeably, but there is a distinction between HRA and HR Metrics. HR metrics are measures of key HRM outcomes, classified as efficiency, effectiveness, or impact. HRA, by contrast, is not calculated but instead reflects statistical methods and experimental approaches that can be used to illustrate the effect of HR operations, including more advanced solutions focused on 'predictive models' and 'what-if scenarios (Lawler et al., 2004). In practice, HRA usually starts with simple measurements and reporting, which can subsequently be integrated into more advanced descriptive-analytic models (Fitz-enz, 2010; Davenport & Harris, 2007). The seven metrics for HRA proposed by Mayo (2006) and hypothesized to be associated with the process of decision making by the HR professionals, included workforce statistics, financial ratios relating to people and productivity, measures of people's values and engagement, the efficiency of the HR function, the effectiveness of people processes, investment in one-off initiatives and programs(Sousa, 2018).

For a long period, HR strived to get a seat on the table along with finance, operations, sales & marketing functions to become a strategic function in any organisation. The Resource Based View (Barney, 1991) laid the groundwork for connecting HRM to business strategy by stressing that resources could only be a source of competitive advantage if they fulfill four requirements of being valuable, rare, inimitable, and organised. Scholars subsequently stressed HR's position in policy design, maintaining a vertical and horizontal alignment, and emphasised the role of HR in designing policies, ensuring vertical and horizontal alignment (Baird &Meshoulam, 1988). It became apparent from all these claims that human capital plays a critical role in producing results for organizations.

Nevertheless, until the mid-1990s, efforts to assess HR were limited to finding the best people for the right job and who can produce high results. "Jac Fitz-enz offered a new, anti-establishment notion in 1978 in this publication wherein it was highlighted that HR operations and their influence on the bottom line may be analysed and should be," according to a report published in Workforce Management (2004) (previously the Personnel Journal). It was, however, mocked, and the response was one of apathy, dissatisfaction, and skepticism (Caudron, 2004). The deployment of data gathering for core HR processes like recruiting, pay, and employee turnover began as a result of constant efforts. As a result, in recent years, the availability of big data and related algorithms have changed the HR environment of what used to be considered one of the least data-driven business functions (Davenport, 2014; Van Den-Heuvel&Bondarouk, 2016). Developments in the tools used to manage administrative parts of people development and maintenance have broadened the spectrum of opportunities and made it possible to connect different data sources, bringing HR and tool metrics closer together (Reddy & Lakshmikeerthi, 2017). However, not much attention has been placed on tapping a balanced scorecard to reap the full benefit, the perceived probability of expected future innovations within HR analytics, ethical dilemmas that will challenge the advances in HR Analytics.

4.2. Antecedents

Scholarly literature classified the antecedents of HRA in two broad categories; pull-based and push-based factors (Ranjan &Basak, 2013). Pull factors are considered as external factors as the organization has no control over them, while push factors are within the control of an organization and hence internal (Nair et al., 2016). The various push-based variables include sophisticated data collection and storage technologies (Oswald et al., 2020), advancement in tools and technology (Claus, 2019; Sohrabi et al., 2018), integration and implementation of Human Resource Information Systems (HRIS) (Vargas, 2015), and examples of successful HR Analytics (Ranjan &Basak, 2013, Fitz-Enz, 2010). An important driver of HR metrics and analytics has been the integration and implementation of HRIS (Carlson& Kavanagh, 2011).

While pull variables include growing competition, increasing demand for resource quality, talent shortages, movement beyond intuitive decision-making, and minimal actionable insights from existing processes (Minbaeva, 2018, Ranjan &Basak, 2013, Sohrabi et al., 2018, Angrave, et. al. 2016, Vokic, 2011). With the increasing use of technologies such as artificial intelligence (AI), cloud computing, global network platforms, robotization, etc. greater attention has been paid to evidence-based decision-making (Claus, 2019). The demographic trends in the longevity pattern, the multi-cultural makeup of the workforce, and the diversity of work teams create a multi-generational workforce and generate virtually additional complexities and challenges (Grubb, 2017). Big Data technology related to work and the workplace is another example of a push factor. Sophisticated data collection and storage technologies through sophisticated algorithms can handle and analyse large and messy organizational data sets (Oswald et al., 2020).

Undoubtedly, advances in IS have intensely influenced traditional HR tasks in recent years, with nearly every HR task (i.e., compensation, recruitment, training, etc.) facing some types of reengineering of its processes due to advances in IS. This process of change has made considerable challenges for HR professionals who should rapidly get up to speed in the latest information technologies and concurrently alter traditional processes into online processes. As a parallel movement, the implementation of HRA through data science and machine learning algorithms has become a major trend (Sohrabi et al., 2018; Bassi, 2011).

HRA develops a strategic understanding of how people (human capital) contribute to the success of their organization leading to creating a unique strategy (Angrave, et. al. 2016; Boudreau & Ramstad, 2007). The availability of information, both internal as well as from an external source, in a readily usable, digital format has spurred the application of analytics (Ranjan &Basak, 2013). Several business firms have used HRA to address prolonged profitability problems, identify cost-effective locations, improve operations, and major HR challenges such as Staffing and retention (Fitz-Enz, 2010). Furthermore, HRA can help organisations predict employees' behaviour by tracking their use of the internet, be prepared for the turnover, or avoid the turnover of high performers (Vargas, 2015). Some global companies like Google, Procter & Gamble, Royal Bank of Scotland have all established HRA groups to get deeper insights into their people practices (Davenport et al., 2010) to facilitate better understanding and usage of very large data by enabling the storage and, for data representation through visualization (Angrave, et. al. 2016).

Data-driven decision-making following careful empirical analysis using advanced statistical and econometric techniques that move beyond the analysis of the correlation between variables in experiments and quasi-experiments to identify how human capital inputs affect the organizational performance (Angrave, et.al.,2016; Bassi, 2011). Human Capital Analytics (HCA) is the need of businesses to consistently gain a competitive edge. HCA as an organizational capability in turn is rooted in three micro-level categories (individuals, processes, and structure) and comprises three dimensions (data quality, analytical competencies, and strategic ability to act) (Minbaeva, 2018). When closely linked to an organization's business strategy (Huselid, 2015), the effective use of HCA may be "the most important future contributor to the creation of strong, long-lasting organisations" (Beatty, 2015). HR professionals understand that hiring and retaining the right talent is an integral part of a company's success. At the time of recruitment, promotion, etc., the use of HCA enables them to reduce both, apparent and hidden biases in an objective manner. This further reduces costs for the organisation in hiring, performance management, and promotions and eliminating any unnecessary legal issues regarding the aforementioned (Vokic, 2011). For companies to be successful in today's global environment, the pursuit of innovation, in general, must be accepted to gain a competitive advantage (Bersin, 2013; Gardner et al., 2011; Giuffrida, 2013).

4.3. Process

5 Studies contributing to this theme primarily discuss the process of HRA in the context of multinational companies (Simón, &Ferreiro, 2018, Harris, et. al., 2010) using cloud-based complex, dynamic, and often knowledge-intensive systems. (Shahbaz, et. al., 2018). This group of studies focused on the systems approach to HRA (Levenson, 2018), the process of developing agile workforce analytics (McIver, et. al., 2018), building key talent management capabilities (Harris, et. al., 2010), and initiating workforce analytics through collaboration between scholars and practitioners (Simón, &Ferreiro, 2018).

Workforce analytics is a methodology emphasizing prioritisation of potential critical organizational performance factors to support corporate decision-making by enhancing problem solving through sound assessment, effective testing techniques, comprehensive data analysis, and technology (McIver et. al., 2018). Scholars argue that before workforce analytics, practitioners should use systems diagnostics to understand the role of competitive advantage analytics and enterprise analytics primarily to address two critical issues; to recognise the important business issues that are the greatest problems for senior business executives, and to decide whether there are systemic problems that arise from the architecture and culture of the company(Levenson, 2018). Strategy maps (Kaplan & Norton, 2004), SWOT (strengths, weaknesses, opportunities, threats) analysis, value chain analysis, and models of product maturity are basic methods that can be applied for recognising and prioritizing strategic issues. The competitive advantage analytics is followed by analytics at the team/group, unit, and/or organisational level to explore the complexities of implementing the plan arising from the job design. The final step is a human capital analysis involving diagnostics at the level of the position, person, and/or HR process (Levenson, 2018). Gaker (2015) proposed that prioritization must be driven by two dimensions; market effect and, organisational preparation. Workforce data must be constantly verified, analysed, cleaned up, added (e.g. new data collection), and converted into dependable metrics as part of a data and measurement strategy. Another primary workforce analytics activity is demonstrated by translating information into action; measuring and analysing results to determine whether the action was successful (Lengnick-Hall &Lengnick- Hall, 2018).

Another set of studies in this cluster emphasized on application of HRA in developing and managing talent. Four main talent management skills include; defining analytical talent needs, discovering new sources of analytical talent, developing analytical talent, deploying analytical talent (Cheese et. al., 2007). Scholars argue that four types of analytical individuals are required to be an effective analytical organisation viz' champions (who rely on comprehensive data and analysis), professionals (the chief analytical technology architects responsible for designing the mathematical models and algorithms), semi-professionals (for implementing professional-developed models and algorithms) and, amateurs (to use Microsoft Excel spreadsheets and other simple information management software to enter and manipulate data) (Davenport & Harris, 2007; Harris, et. al., 2010). The creation of a viable workforce analytics infrastructure goes beyond the implementation of statistical techniques using assumptions as well as the development and testing of hypotheses to solve practical management problems (Simón, &Ferreiro, 2018). Additionally, it requires expert knowledge sets on market research methods and robust analytical skills, and the development of a questioning mindset that fuels data design, collection, assessment, and further interpretation (Angrave et. al., 2016)

4.4. Facilitators and Inhibitors of HR Analytics Adoption

Another cluster of 4 studies uncovered the facilitators and inhibitors of HRA adoption by business firms. HRA provides various business opportunities as it forecasts workforce demands, allows HR to accomplish corporate goals, and enhances organisational performance that helps companies succeed. Despite the achievement, the organizations face multiple challenges in implementing and using the HRA tools in business (Tomar& Gaur, 2020)resulting in minimal investment in HRA and only marginal effectiveness in analytics (Lawler & Boudreau, 2015). In smaller organisations, which recruit the significant majority of the workers, this is likely to be especially true (Cascio & Boudreau, 2014). This set of studies focused on challenges of HR Analytics implementation were conducted in European and Asian countries and responses were sought from people in the HR domain. In an endeavour to understand the different challenges affecting the adoption of HRA, we classified them as being attributable to individual and organisational factors.

The numerous different individual factors include lack of required skills (Dahlbom, et. al, 2019; Andersen, 2017), lack of knowledge of appropriate research and statistical methods (Hamilton &Sodeman, 2020), individuals' perception and attributes (Vargas et. al. 2018; Khan & Tang, 2016). Individual level characteristics/features affecting the adoption of HRA are individual's perception that he/she is able of doing the analytics (attitude and self-efficacy) (Vargas et. al. 2018). Internal motivation thus guides the individual adoption process, and the low quantitative self-efficacy level observed in post-organizational adoption is consistent is found to be an obstacle to HRA adoption. (Rogers, 2003). Additionally, employees' attributions of organisational motives behind its use have a significant impact on their affective commitment. For example; employee attributions that indicate cost reduction in HRA activities and employee manipulation strategy adversely affect their affective commitment; while employee attributions that HRA activities represent quality and employee improvement techniques have a positive effect on affective commitment (Khan & Tang, 2016). The paucity of varied competencies at hand is one of the reasons why HRA is not yet there and has been slow to advance (Dahlbom, et. al, 2019). For the organisation to extract the most value from data and metrics, analytical skills must be developed and used throughout HR (Harris et. al., 2011), such as excellent statistics and numbers skills, strong data management skills, captivating storyteller, visualization techniques (Anderson, 2017). While many HR managers face a problem even in examining big data (Angrave et al., 2016; McIver et. al, 2018), another set of chronic issues with machine learning are accuracy, overfit, and algorithmic bias, which reinforces the need for senior HR managers to be aware of appropriate research and statistical methods and to properly train the algorithm (Hamilton &Sodeman, 2020).

On the other hand, the various diverse organisational factors affecting HRA adoption are; poor data quality (Boudreau & Cascio 2017), unorganised data (Andersen, 2017), poor strategic mindset (Rasmussen, & Ulrich, 2015), absence of C-Suite support (Harris et. al., 2011) lack of stakeholder collaboration (Hamilton &Sodeman, 2020) and non-conducive organizational culture (Vargas et. al. 2018). HRA is mostly concerned with doing things right with an "inside-out" HR perspective, although it can generate disproportionately more value when it applies an outside-in" perspective and doing the right thing" (Rasmussen & Ulrich, 2015). Poor inaccurate, incorrect, and unreliable data prevents organizations from recognising the benefits of their HRA and also results in HR departments conducting time-consuming data clean-ups (Dahlbom et. al, 2019). At best, these types of data reflect very basic organisational or advanced reporting, and not advanced information for strategic or statistical analyses(Armstrong, 2016) rather than on strategic issues. The question of mindset is about a lack of strategic thinking (Andersen, 2017). While these data may be insightful, they may also contribute to a focus on HR activities rather than the influence of HR decisions and expenditures on organisational outcomes (Boudreau & Cascio, 2017). Too often, HR has several systems that produce incomparable metrics based on idiosyncratic calculations (Harris et. al., 2011). Many HRA functions have been transferred to HR divisions in re-organization programmes as organisations have sought to recognise where HRA is better suited to HR (Angrave et al., 2016; Marler& Boudreau, 2017). Considering that the data is distributed through different areas of the organisation, navigating the data collected, deciding where specific data sets are stored, whether the databases are compatible, or whether the data is available for use or review may be challenging in certain cases. (Waters et al., 2018).

Companies that lack support from the C-suite are likely to face greater practical and bureaucratic obstacles to effective analyses (Hamilton &Sodeman, 2020). Sadly, compared to roles that are seen to have a more direct effect on profitability, HR has been consigned to insignificant status (Anderson, 2014; Benko & Volini, 2014). A strategic alliance with key stakeholders becomes difficult for productive HR big data analytics consequent to stakeholder cooperation (Hamilton &Sodeman, 2020). Ultimately, line managers handle main data and directly affect competitiveness and firm efficiency (Armstrong, 2016; Sikora & Ferris, 2014).

Besides all these factors, analytics culture is necessary to motivate an individual’s innovation-decision process (Davenport,2006; LaValle et al.,2011; Davenport,2013), but can only be done if the business adopts complex technologies across the organisation.

4.5. Technology as Enabler

The role of technology has been relatively subdued in the past, but this will be far more seriously reflected in the future. By using technology and giving HR its place as a strategic partner, the discipline of HRA has gained traction (Kakkar& Kaushik, 2019). Scholars in the last decade have attempted to understand the theme of technology as an enabler by identifying technologies that shape the future of work (Bhattacharyya & Nair, 2019), IT capabilities (Mishra et.al, 2018), the role of wearable IoT devices in providing unbiased and transparent results (Shukla & Verma, 2019) and monitoring performance (Al-

Hitmi&Sherif, 2018), the use of technology tools (Kakkar& Kaushik, 2019) and the role of technology in performance management (Sahlin& Angelis, 2019).

IT capabilities are considered as high-performance organisational processes, such as technical and human assets, that obtain, apply and optimize IT assets (Pavlou& El Sawy, 2006; Bingham et al.2007; Tian et al., 2010) to improve performance. Kim et al. (2011) highlighted in their study on IT capabilities that there is a positive relationship between IT capability and company efficiency, business process, and financial performance. Technology in HR began with the Human Resource Information System (HRIS), an integrated forum for the link between human resources and information technology (Bagga, 2012, Srivastava &Bagga, 2014). While sound management concepts of the past mostly relied on more "soft skills" style metrics: intuition, gut instincts, a sense of people, the management of the future, combined with Artificial Intelligence (AI), would combine big data analytics to quantitatively analyse business achievements and failures (Sahota & Ashley, 2019). Three independent components consist of IT implementation capabilities: strategic IT versatility, business-big data, and predictive analytics(BDPA) collaboration, and business-BDPA alignment (Mishra et.al, 2018). Technology has been used in almost all HR sub-functions, such as electronic work analysis, e-recruitment, use of crowdsourcing, and social media for recruitment, to name a few (Kakkar&Kaushik, 2019). Most businesses agree that the use of HRA supports business strategy assessment as data-driven decisions are more reliable and much more valuable in the service age, as HR has a significant role to play in the service sector as it serves as the only differentiator. (Kakkar& Kaushik, 2019). Technology also helps to monitor employee performance through Performance Management Systems (PMS), which offers a more systematic way of conducting activities through assessing performance and providing information that supports informed decisions (Neely,1997). Digitalization helps Decision Support Systems to automate processes using data, information, and analytics capabilities (Delen&Demirkan, 2013). Algorithms are built that play the role of decision-making and action based on a set of performance metrics, such as Algorithmic Management (AM), to adapt to changing circumstances (Schildt,2017).

Addressing emerging requirements of applying advanced technologies, especially data science-related technologies such as big data analytics, many businesses are making the transition to algorithmic-influenced decision making, to streamline the often chaotic process of handling people and their everyday activities (Iwamoto, 2019; Sahota & Ashley, 2019). For example, The Internet of Things (IoT) is an evolving array of technologies connecting devices to the Internet to track and manage performance remotely (Kaupins& Coco, 2017). The perceptions of employees towards IoT-enabled monitoring have been reshaped by three significant factors: a culture driven by productivity and strongly adhering to policies and standards to achieve set goals; a highly competitive job market; and a paradoxical leadership that balances competition with lucrative rewards (Al-Hitmi&Sherif, 2018). Supported wristband wearable IOT technology can provide a very concealed insight into an employee.

With the aid of the IoT-enabled wearable band, critical data from each of these departments can be obtained from an employee in real-time (Shukla & Verma, 2019).

The scholarly researchers have emphasized the fact that "Technology cannot be held back. It can be regulated and controlled to a limited extent based on some ethical principles, but never be excised from the world" (Gandhi, 2018). There is, however, a need to incorporate quantitative and qualitative research to better understand the future of HRA in organisations in global and cultural contexts (Hitami&Sherif, 2018; Bhattacharya & Nair, 2019; Sahlin& Ashley, 2019). Scholars need to pay attention to employee sentiment analysis and its effect on the perceived fairness of workers at work (Kakkar& Kaushik, 2019; Sahlin& Ashley, 2019). The creation of internal protocols, a field understudied in human analytics, involves privacy and ethical concerns surrounding technological advances (Sahlin& Ashley, 2019).

4.6. Impact of HRA

The scholarly work on the impact of HRA contributed by 21 studies can be divided into two broad categories; first, research focusing on the impact of HRA on various HRM functions such as acquisition, training, and growth, etc. (DeCenzo et al., 2016; Shrivastava et. al, 2018; Meena M.R. &Parimalarani, 2019, etc.) and second, its role and influence on building competitive advantage and, organizational efficiency (de Romree et. al, 2016; Kapoor &Kabra, 2014; Lal, 2015; etc.). Emphasizing the role of workforce analytics in improving the efficiency of various HRM functions, scholars argued that strategic intent required to make critical business decisions is also something that comes out as one of the advantages provided by workforce analytics. If used strategically, HRA is a powerful tool for organizations in optimizing their workforce decisions for best business results. By evaluating and interpreting trends throughout an employee's career, as well as anticipating the future, proper workforce planning will lead to a thorough assessment of HR's abilities, resulting in a productive way of using those abilities. (Hota & Ghosh, 2013; Schiemannet.al., 2018; Singh & Malhotra, 2020; Lal, 2015). By addressing the subjectivity bias of performance appraisal, HRA wins the trust of employees on performance appraisal systems leading to a strong desire to improve their performance. (Sharma & Sharma, 2017). Moreover, it aids in defining the skills required and cultivating potential leaders, and, developing a stable and productive human capital. (Momin, & Mishra, 2015). The outcome of talent analytics assists in monitoring the efficiency of the talent pool that leads to organizational success (Sivathanu& Pillai, 2019).

HRA facilitates synchronization of recruitment trends with the workforce needed and the workforce already in place (Fred, 2017), the recruitment process that is talent and behavior focused (Kapoor &Kabra, 2014) and, optimum utilization of the recruiting channels (Stoian & Tohanean, 2019). With the aid of HCA and its algorithms, useful information about current and future employees can be gathered such as; comprehensive data on skills, credentials, and years of experience, allowing for the prediction of actions and suitability of the candidate for the appropriate position and specific tasks (Meena M.R. &Parimalarani, 2019; Stoian &Tohanean, 2019). This helps the organizations avoiding arbitrary hiring and retention decisions (Shrivastava et.al, 2018). Another important facet of HRM functions is training and development. Numerous studies have found that HRA assists in identifying and evaluating the interventions that can be beneficial for an employee with a particular level of expertise in the training and development arena and, selection of potential employees for leadership positions (Stoian &Tohanean, 2019; Prakash et.al. 2019).

One of the most important advantages of HRA is employee sentiment analysis, assessing how an employee feels about his status and reasonableness in the organization. annual survey data and tracking an employee's opinion on different areas by following his/her data on contribution level in the organization provides inputs for sentiments analysis (Meena M.R. &Parimalarani, 2019). HR administrators may use predictive analytics to detect early warning signs of employee turnover (Arellano et. al., 2017; Kaplan and Haenlein, 2019). Highly valuable workers who are at high risk of turnover can be recognized, counselled, and offered persuasive value propositions through various internal opportunities to keep them in the company (Jalali & Singh, 2018; Sivathanu& Pillai, 2018). Since it secures data and offers solutions to talent-related problems such as recruiting and retaining talent, talent analytics software gives the business a competitive advantage. Organizations use talent analytics to create staffing strategies, engage workers, map talent, monitor employee performance, assess training effects, recruit and retain top talent contributes, manage talent mobility, forecast recruiting, retention, and attrition, plan employee welfare, outline company benefits, and evaluate employee sentiment (Grillo, 2015; Kaur & Fink,2017; Rana et al., 2019; Harpur, 2014; Lal, 2015).

According to a new survey conducted by MIT Sloan Management Review, businesses that have used analytics before have a strategic advantage over those that have yet to embrace what analytics has to offer (Kiron & Shockley, 2011). Companies using HRA can survive in the most turbulent competitive environment due to organizational resilience developed by the efficient use of available information. They demonstrate the ability to design and incorporate positive adaptive behaviors that react quickly to the circumstances it faces with minimal stress (Mallak, 1998; de Romree et. al, 2016). Big data analytics offer the possibility of evaluating which HR metrics and drivers are the most efficient, true, and accurate predictors of organizational outcomes (Rios et. al, 2017). It is especially significant in the industries that engage a large pool of human resources such as; hospitality industry since large hotel chains hire a large number of people. (Harris &Mongiello, 2001; Graham & Harris, 1999; Togt& Rasmussen, 2017). HR departments will be better able to provide value to the enterprise through their analytical efforts as HR practitioners become more proficient in HRA (Kryscynski et. al, 2018)

5. Analysis and Directions for Future Research

5.1 Future Directions - Conceptualization

HRA definitions span a wide range of activities, including measurements and data, as well as various views. According to Bassi (2011), HRA is the use of a methodology and an integrated process to improve the quality of people-related choices to improve individual and/or organisational performance while Fitz-enz& Mattox (2014) argue that it encompasses more than just HR metrics. Narula (2015), defines HRA from the perspective of evidence-based managerial decisions, on the other hand, Marler and Boudreau (2017) explain it in terms of information technology-enabled HR practice facilitating data-driven decision making. Our review revealed a lack of standard definitions and standards to explain HRA.

The issues posed by fragmented explanations of HRA are reflected in the previous section. Moreover, the terms HRA, human capital data, people analytics (Shrivastava, et al., 2018), human resource data, HR metrics (Liberatore & Luo, 2010), HR predictive analytics (Mishra, Lama & Pal,2016) collaboration analytics, people intelligence, labor analytics, and relationship analytics are used interchangeably. This voluminous vocabulary makes it difficult to grasp the core concept of HR Analytics. To add to the debate, some scholars have claimed that HRA is only a fad or irrational trend that may not have a long-term influence as a management tool (Angrave et al., 2016; Rasmussen & Ulrich, 2015). This issue highlights the need for scholastic research in this area as well as the development of HRA standards.

Furthermore, scholars and practitioners interested in this topic should look for similar literature outside of the HR or management literature, such as in professional sectors where HRA is used, such as financial services, security, or healthcare, and focus on real applications in addition to academic research. There is a substantial disconnect between HR practitioners' perceptions of HRA and their capacity to contribute significantly to organisational competitiveness.

5.2 Future Directions - Theoretical Models

It is critical to study theories because they serve as a crucial foundation and guide for offering reasonable explanations of how and why specific interactions may lead to certain outcomes (Baillien et al., 2017). Several studies have recently attempted to give theoretical solutions to key HRA issues. For example, the Resource Based View has been used by the studies highlighting the importance of HRA to understand how HR inputs are transformed into business outcomes (Mishra et. al., 2019; Bhattacharyya & Nair, 2019; Angrave et. al., 2016)to how to synchronize incentives and monitor employee behaviour (Aral et al., 2012), how to develop incentive systems in which both the principal and the agent are risk averse, and the agent makes a single effort decision to focus on employee performance measurement (Aral, Brynjolfsson & Wu, 2012). Innovation theory, as influenced by the Theory of Planned Behavior (TPB), has been used to investigate the individual's decision to embrace HR Analytics and uncover why the adoption rate is lagging (Vargas et. al.,2018). The Theory of Planned Behaviour states that behaviour is deliberate and so anticipates it (Ajzen, 1991). Equity theory has also been examined to better understand the impact of employees' perceptions of fairness and the function of analytics in conveying the same (Al-Hitmi, &Sherif, 2018). Employees are more prone to see monitoring as unfair when work rewards are allocated unequally concerning job inputs, according to equity theory (Niehoff&Moorman, 1993). Employee turnover, customer satisfaction, revenue, and profit may all be predicted using equity theory (Schiemann, Seibert & Blankenship, 2018). Organizational justice theory (Skarlicki&Latham, 1996) is frequently used to explain perceived discrimination in the workplace (Harris et al., 2004; Bibby, 2008; Wood et al., 2013). Employees' perceptions of accuracy and fairness will improve as a result of the usage of HRA, which will raise their willingness to improve performance (Sharma & Sharma, 2017).

By emphasising that resources can only be a source of competitive advantage if they are valued, scarce, inimitable, and organised, the Resource Based View (Barney, 1991) lay the framework for tying HRM to corporate strategy. Some research has focused on how the HR department may more successfully incorporate HRA and the importance of analytical talents, without which HR may not be "pushed" toward their audience, based on an awareness of the LAMP (Logic, Analytics, Measures, and Process) (Kryscynski et. al,2018; Boudreau & Cascio, 2017). The LAMP framework (Boudreau and Ramstad, 2007) enables HR to apply rigorous decision-making principles to engaging workforce management. The systems approach has been examined in an attempt to undertake workforce analytics that is aimed to improve strategy execution and organisational effectiveness (Levenson, 2018). All the individual-level models and techniques of conducting analyses play a key role in a systems approach since all of the pieces in an organisation are interconnected and interdependent.

Scholars have integrated established ideas to explain HRA, as evidenced by the debate above. Future research should look into how each of these steps of the analytics adoption process may be facilitated successfully and efficiently. Multiple steps of Rogers' (2003) innovation-decision process should be investigated to see if they are linear, iterative, or could be bypassed based on the discovery. To move the field forward, more study should be directed to developing new theoretical models that incorporate the distinctive qualities of HRA into surrounding academic fields.

5.3 Future Directions - Thematic Understanding and Research Methods

HR managers were able to make the most of data thanks to technological advancements. The HRA drive was aided by increased IT capabilities, HR information systems (HRIS), and big data (Dlomu & Spears, 2015; Du Plessis & De Wet Fourie, 2016; Schiemann et al., 2018). Though the role of technology in supporting HRA is undisputable, privacy and ethical considerations surrounding technological breakthroughs need the development of internal protocols, an area of people analytics that has received little attention. More research is needed to learn how practitioners, vendors, and employers are balancing the need for innovation with the need for transparency and responsibility. Though much study has been done on the rise in analytics (Bassi, 2011), HRM-related algorithmic applications (Cheng & Hackett, 2019), the numerous dimensions and degrees of HRA (Sousa, 2018), and its future potential (Sousa, 2018), there is still more to be done. Certain areas that require greater examination include making the most of a balanced scorecard, the anticipated likelihood of expected future developments in HR analytics as well as ethical concerns that will confront HR analytics advances.

Additionally, we observed that to function at three levels: personnel, processes, and structure, an organisation desiring to grow HRA must work with its three dimensions—data quality, analytical competencies, and strategic abilities. The role of the organisational context and its connection to the overall business plan, on the other hand, requires more emphasis. Individual elements such as self-efficacy and attitude toward analytics are examples of obstacles to HRA adoption (Vargas, 2015). The studies are limited to HR professionals and focus mostly on individual adoption of technology innovations. More attention to the adoption of innovation at the organisational level will aid in the identification of obstacles that organisations encounter in successfully using HR Analytics.

While examining the research methods and context, we observed that quite an encouraging number of scholars conducted the impact assessment studies (Levenson, 2018; Rombaut&Guerry, 2018; Sivathanu& Pillai, 2019; Al-Ayed, 2019; Aral et.al., 2012). A vast majority of research has been done in underdeveloped countries. Furthermore, few researchers relied on HR professional interviews and perspectives with a small sample size (Sivathanu& Pillai, 2019; Levenson, 2018). In terms of techniques for using analytics to give practical and operational proof for optimal HR management decisions, there is a void in the scholarly literature. The majority of HRA research is not empirical and does not follow traditional scientific qualitative research techniques. The literature consisted of case studies (Simón &Ferreiro, 2018; Sivathanu& Pillai, 2018; Martin-Rios, Pougnet, & Nogareda,2017) that were used to describe and conclude rather than inductively identify links between HRA characteristics and company performance, focusing on the use of HRA in a specific HR domain, such as recruiting or turnover prediction. Furthermore, we propose that future research use quasi-experimental approaches to assess the impact of organisational characteristics on HRA predictions and outcomes. Despite the fact that the commercial market for HRA tools and services is varied and offers a wide range of functional and strategic benefits, documented evidence of these outcomes is scarce. There appears to be a paucity of solid proof of HRA's favourable business outcomes.

6.Conclusion

The past decade has witnessed a steady and gradual increase in the interest shown by researchers in the field of Human Resource Analytics (HRA). The advent of digitization and the adoption of analytical-based strategic decisions have undoubtedly elevated the significance of data to an unprecedented level. As a result, research endeavors in the area of HRA have gained considerable momentum, aligning with the growing importance of analytics in the broader domain of human resource management. However, it is important to note that despite the progress made, there remains a vast and largely unexplored territory within this field.

Scholars of the past have diligently emphasized the conceptualization, importance, and practical application of HRA. Yet, there exists a critical gap that demands attention and careful structuring of this research. Sensing the need of the hour, the authors of the paper under discussion have taken on this challenge and responded admirably by categorizing the available literature reviews into six distinct and significant themes. A deeper analysis of these main themes reveals a compelling need for future studies to place an enhanced focus on the intricate 'process' of HRA rather than solely fixating on the 'results' it yields. Drawing from the methodology and flow adopted in the current study, a multitude of avenues emerge for potential future research. It is imperative to acknowledge that earlier studies conducted prior to the timeframe considered in this paper may undeniably influence the graph of themes, thus warranting a comprehensive examination of the vast body of existing literature. The authors cautiously acknowledge the plausibility of achieving improved outcomes by leveraging alternative review techniques in addition to the systematic literature review (SLR) employed in their work.

While great care was exercised in the application of exclusion and inclusion criteria for this study, it is crucial to expand our scope of consideration to encompass the interconnected areas allied to HRA, such as HR strategy, decision support systems, employee learning and development, and organizational resilience. By exploring these synergistic domains, a more comprehensive and holistic understanding of HRA may be achieved. Finally, it is important to note that the current study does not specifically address the enhancement of the inherent design and execution of the studies included in the review. This highlights an area of opportunity for future research endeavors, where greater attention could be devoted to refining the fundamental facets of the studies considered.

In conclusion, the interest in HRA shown by researchers over the last decade has exhibited a consistent and incremental growth. The emergence of digitization and analytical-based decision-making has propelled the importance of data to new heights, instigating a surge in research activities within the domain of HRA. Nevertheless, there remains a vast expanse of untapped potential within this field, revealing an exciting opportunity for further exploration and investigation. The authors of the paper have admirably responded to this clarion call by effectively categorizing the existing literature into six major themes. Yet, a careful analysis divulges the need for future studies to prioritize the 'process' of HRA rather than simply fixating solely on the 'results'. With a solid foundation established by the current study, future research directions become apparent, and the potential influence of earlier studies in shaping the thematic landscape cannot be overlooked. In addition, alternative review techniques, aside from the systematic literature review, may yield valuable insights and enhance the quality of outcomes. Moreover, considering the broader aspects of HRA, such as HR strategy, decision support systems, employee learning and development, and organizational resilience, would provide a more comprehensive understanding of this field. Finally, future studies may focus on advancing the design and execution of the studies included in the review, thereby contributing to the continual improvement of HRA research practices.

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