Examining the determinants of successful adoption of data analytics in Human Resource Management - A framework for implications

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Abstract

Data analytics has gained importance in human resource management (HRM) for its ability to provide insights based on data-driven decision-making processes. However, integrating an analytics-based approach in HRM is a complex process, and hence, many organizations are unable to adopt HR Analytics (HRA). Using a framework synthesis approach, we first identify the challenges that hinder the practice of HRA and then develop a framework to explain the different factors that impact the adoption of HRA within organizations. This study identifies the key aspects related to the technological, organizational, environmental, data governance, and individual factors that influence the adoption of HRA. In addition, this paper determines 23 sub-dimensions of these five factors as the crucial aspects for successfully implementing and practicing HRA within organizations. We also discuss the implications of the framework for HR leaders, HR Managers, CEOs, IT Managers and consulting practitioners for effective adoption of HRA in organization.

Keywords: Human resource analytics, HRM analytics, people analytics, adoption of HR analytics, challenges, implementation of HR analytics, big data, data analytics, framework synthesis

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1. Introduction

Human resource analytics (HRA) is attracting increasing interest as an innovative practice in the domain of human resource management (HRM) (Huselid, 2018; Mclver, Lengnick-Hall & Lengnick-Hall, 2018; Boudreau & Cascio, 2017; Levenson, 2017; Rasmussen & Ulrich, 2015). The emergence of disruptive technologies such as artificial intelligence, computational intelligence techniques, data mining, machine learning, and the Internet of Things has speeded up data-driven decision-making in HRM (Duan et al., 2019; Dwivedi et al., 2021; Tambe et al., 2019; Davenport, 2018; Brynjolfsson et al., 2011) such as candidate selection, employee mood, and sentiment analysis, and attrition prediction (Gelbard, Ramon-Gonen, Carmeli, Bittmann & Talyansky, 2018). Such technologies have also provided enormous opportunities for advancing data-driven workforce management. Consequently, organizations are investing in analytics infrastructure, including tools, capabilities, and other resources. However, the pace of adoption of HRA has not been as expected (Angrave et al., 2016).

The HRA is considered a future value-driver in HRM because it enables the systematic analysis of complex data that may help resolve various organizational challenges (Boudreau & Ramstad, 2007). The adoption of a scientific approach in decision-making for HR has the potential to improve decisions concerning people very much on the lines of how a scientific approach helps marketers to make informed decisions about the spending strategy of their customers and finance departments for working capital predictions (Boudreau & Ramstad, 2005). However, to reap the benefits of data-driven decision-making, HRA should be integrated with relevant products, services, and business-level indicators (Levenson, 2011; Angrave et al., 2016; Levenson, 2005; Lawler et al., 2004; Boudreau & Ramstad, 2007).

Despite the potential benefits of HRA, it has not received adequate attention from management researchers (Marler & Boudreau, 2017). This is because very little information is available about the process through which HRA influences organizations and their performance (Huselid, 2018; Schiemann, Seibert & Blankenship, 2017). In addition, it is also not completely clear how organizations should use HRA to achieve important organizational outcomes (Mclver, Lengnick-Hall & Lengnick-Hall, 2018). Therefore, more structured solutions to these issues are needed before analytics can be adopted in the HRM of an organization.

HRA adoption is defined as the process through which an organization invests in, operationalizes, and assimilates HRA into workforce's decision-making process. This includes envisioning the decisions they want to be driven by data, assessing the resources required to support the decision-making, building the case for HRA adoption and making relevant investments, prioritizing the design and delivery of such supporting resources, enabling stakeholders in their decision-making process, and driving the usage of HRA in the entire organization. However, the adoption of HRA by an organization is marred by several challenges. A major challenge that adversely influences the implementation of HRA is the varying levels of process maturity within the HR function across its subsidiary organizations and in different departments, units, and locations. At times, even basic data metrics are unavailable to the subsidiaries, and if available, they are not consistent, reliable, or standardized (Fitz-enz & Mattox, 2014). As a result, HRM has always been found to be lagging in integrating analytics into its processes (Angrave et al., 2016; LaValle, Lesser, Shockley, Hopkins & Kruschwitz, 2011). However, the multitude of processes is continuously creating more data at play in an organization, the HRM has to find ways to leverage advanced capabilities that analytics has to offer (Cheng & Hackett, 2019). For instance, digital communications and sensor technologies have resulted in novel methods for understanding and measuring employee behavior (Davenport, 2018; McAfee et al., 2012).

The HRA involves an interplay of knowledge from information science, information technology, computer science, mathematics, and statistical science to process data on a real-time basis and arrive at a data-driven decision to predict the outcomes of complex challenges. Therefore, specialized skills are needed to manage the influx of data from multiple sources (text, voice, image, and video), analyze them to extract meanings, establish causal relationships, and drive actions by influencing key decisions. However, HRM practitioners are generally not well-versed with the analytical capabilities required in HRA. In this study, we systematically analyze the factors that impact the adoption of HRA in an organization and propose a framework for value creation in an enterprise business environment. The considerable opportunities that HRA offers motivated us to investigate the adoption of HRA from an organizational perspective. We used frameworks on the theory of planned behavior (TPB; Ajzen, 2012), diffusion of innovation (DOI) model (Rogers, 2003), and technology organization environment (TOE; Tornatzky & Fleischer, 1990) as a theoretical lens to understand and contextualize HRA as an innovation in HRM for the present study.

The aim of our study is to analyze why organizations have not been able to apply analytics in HRM or derive business values from HRA. We identify the challenges that act as a deterrent in practicing HRA. We systematically analyze and categorize these challenges and propose a framework based on the factors that impact the adoption of HRA. We then discuss the implications of our proposed framework by assessing organizational readiness to create business value by practicing HRA. Moreover, we introduce framework synthesis as a methodology for conducting integrative reviews in the business management domain. We frame our research question as follows: “What are the typical challenges encountered while implementing HRA?” If the challenges are evident, then we focus on how organizations can overcome those challenges, aiming to address the question, “What are the essential factors that should be considered when adopting HRA?” Finally, we connect this aspect to the practice of HRA by focusing on, “How do organizations adopt HRA?” by discussing the implications for practitioners and researchers. This study shows the emergence of the 23 dimensions of five factors—technological, organizational, environmental, data governance, and individual—as the challenges that need to be addressed for effective implementation and practice of HRA. These factors can be contextualized to other functions in organizations such as finance, marketing, operations, and supply chain. A significant contribution of this article is the comprehensive coverage of all the factors, which are contextualized to HRM, along with their implications. This study aims to assist both researchers and practitioners in gaining a better understanding of an organization's ability to inculcate HRA into its daily operations and possibly direct their focus on the factors that impact their ability to reap the benefits of HRA.

2. Challenges in the Adoption of Data Analytics in HRM

Organizations need to overcome several challenges before they can adopt HRA in their processes. They need to review how analytics can be employed to capture, organize, and leverage the HR data to derive value. For this to happen, HRA needs to move from the existing descriptive models to the predictive ones to understand human capital's strategic impact (Boudreau & Lawler, 2015; Boudreau & Casico, 2017). The current HR platforms and applications are mainly designed to support data reporting; they rarely assist in understanding the contribution made by the human capital in an organization's success (Angrave et al., 2016). Therefore, even in today's technology-driven work environment, HR practitioners continue to rely on spreadsheets for MIS rather than on HRMS or eHRM platforms, as the existing HRMS software is incapable of providing analytical insights. Although business processes such as inventory management, finished goods, and value chain management have been extensively analyzed, the analysis of workforce contribution is limited to its cost and output. In the absence of a strategic perspective on HRA, the HRM cannot provide the desired support to the top managers and CEOs, even though they widely consider human capital as a valuable resource that offers competitive advantages. Thus, organizations should focus on building a data-driven culture for a mature HRA practice.

Other challenges that hinder HRA adoption include efficiency and effectiveness in collecting and analyzing the data (Pape, 2016; Rasmussen & Ulrich, 2015). HRA cannot be implemented without reliable data; thus, the data need to be synchronized and made usable for the HRA platform (Scullen et al., 2000). Lack of quality data and proper data are major issues affecting the implementation of HRA (Anderson, 2017). Many organizations try to make up for their deficiency in HR capabilities by outsourcing the HR functions to external vendors, which, however, may lead to data privacy issues. Thus, it is necessary for organizations to develop in-house solutions to fill in this knowledge gap (Minbaeva, 2018). Another challenge is the lack of organization-wide buy-in for HRA and the difficulty in understanding how AI-powered tools should be employed (Strohmeier & Piazza, 2013). Given a large number of AI-powered tools available, HRA professionals need continuous experimentations to determine the most appropriate tools and techniques for resolving their organization's challenges.

Some studies have also discussed whether the HRA domain should even be a part of the HR function (Rasmussen & Ulrich, 2015). It has been argued that it is better to have a centralized analytics cell within an organization because HRA requires data from other departments too, such as marketing, to address larger business challenges (Bersin, 2015). Note that data analyses alone will not serve any purpose unless they are used to extract insights, which are then used to weave a compelling story to drive decision-making (Anderson, 2017; Green, 2017). Angrave et al. (2016) questioned whether HR professionals are even capable of effectively extracting various trends and insights from big data and analytics to generate organizational benefits. Even if HR professionals were capable of conducting the relevant analyses, data collection from all sources remains a difficult task (Fitz-enz & Mattox, 2014). The non-central positioning of HR departments within organizational hierarchies and the lack of relevant skills partly explain their poor performance in this aspect (Angrave et al., 2016). Another reason for the low level of HRA adoption is that it requires the HR professionals to be able to perform mathematical and statistical analyses (Vargas et al., 2018), which they may not be familiar with.

HR practitioners need to build a strong case for leveraging data insights to attract investments; however, there is a dearth of informative literature on how to leverage such data. Resolving this issue is trickier in the case of HRA, because it is often difficult to understand the fundamental behavior and decision-making processes (Fitz-enz, Phillips & Ray, 2014). Although several HR strategists foresee an encouraging future for HRA, businesses worldwide are still struggling to take correct steps in making this a reality (Angrave et al., 2016). Many consulting organizations claim that analytics remains one of the biggest capability gaps in HR practice, while acknowledging that HRA is “under active development” in their businesses (Deloitte, 2015). They also state that most organizations, including large multinational companies, lack the requisite vision to successfully imbibe HRA tools within their processes. Despite its low adoption rates, the fact that the concept of HRA is gaining popularity in academic circles is evident from the various programs and courses being offered on the topic, which may speed up the HRA adoption rate (Greasley & Thomas, 2020). Hence, more methodological studies are required on the adoption of HRA (Marler & Boudreau, 2017). However, existing organizational dynamics are not yet mature enough to provide space for HRA both within the HRM and the organization. Thus, it is essential for organizations to implement HRA with a strategic intent for sustained value creation (Côrte-Real, Ruivo, Oliveira & Popovič, 2019).

Because of the increasing popularity of analytics, examining the factors responsible for the adoption of HRA and its impact on business performance has become a critical research topic (Aydiner et al., 2019). Although an increasing number of organizations are investing in the HRA space, the overall proportion still seems to be insignificant. This limited adoption of HRA makes it difficult for researchers to assess its importance in the success of an organization. That is why, no strong academic framework has yet been developed to understand the HRA adoption process within organizations. Despite the widespread use of HRMS and eHRM in organizations, there has been a surprising dearth of theory and research on these topics (Stone & Duleboh, 2013). In addition, existing literature on HRA provides little or no evidence on how HRA can be applied to operational business practices (Angrave et al., 2016).

More research should be carried out on information systems to illustrate the acceptance, usage, and success of information systems technologies in different management fields, although these technologies are yet to be adopted in HRA (Venkatesh, Morris, Davis & Davis, 2016). In addition, more scholarly research is needed on HRA, and its practice should be encouraged at the individual, process, and structural levels within organizations (Marler & Boudreau, 2017; Huselid, 2018; Minbaeva, 2018). It has been suggested that researchers from the management domain could provide significant support to the development of HRA as it can help build organizational competence and establish relevant infrastructure (Simon & Ferreiro, 2017, 2018).

3. Research Design: Framework Synthesis Method

We used the integrative review method to recognize the challenges in HRA adoption and to identify mature and new emerging topics in the field of HRA adoption. We used the "framework synthesis method" to uncover the challenges and propose a framework for the adoption of HRA (Figure 1). However, because HRM deals with topics and issues that vary along an age continuum from old to new, all integrative literature reviews do not fit neatly into "old" or "new" categories (Torico, 2005). The latter form of integrative literature review addresses new or emerging topics that would benefit from a holistic conceptualization and synthesis of the literature to date. Because these topics are relatively new and have not yet been comprehensively reviewed, the integrative literature review is more likely to lead to an initial or preliminary conceptualization of the topic (i.e., a new model or framework) rather than a reconceptualization of previous models (Torico, 2005).

Synthesis integrates existing ideas with new ideas to create a new formulation of the topic or issue. Synthesizing the literature means that the review weaves the research streams together to focus on core issues rather than merely reporting previous literature. Framework synthesis can be employed for conducting systematic reviews to examine the complexity of the factors involved in HRA adoption (Brunton, Olilver & Thomas, 2019; Houghton et al., 2016; Gale et al., 2013; Carroll et al., 2011). Framework synthesis originates from framework analysis, a method of analyzing primary research data developed by Ritchie and Spencer (2002) to address policy concerns. As shown in Figure 1, the stages of framework synthesis correspond to the systematic review process, albeit with some overlap between the steps and processes. Framework analysis presents an opportunity to use a "scaffold against which findings from the different components of an assessment may be brought together and organised" (Carrol et al., 2011, p. 29), which is described as a "framework synthesis" (Thomas et al., 2017; Carrol et al., 2011). We chose this method for its superior advantages over method of systematic reviews, which are generally rigid. This gives us the flexibility to focus on the research questions with an iterative process until we complete the review process.

<Fig 1: Framework Synthesis>

Framework synthesis consists of five stages: Familiarization, framework selection, indexing, charting, and mapping and interpretation. In the **familiarization** stage, reviewers first familiarize themselves with current issues and ideas about the topic by drawing iteratively on various sources to select a framework, which involves choosing an initial framework, a conceptual or policy framework, a logic model, a causal chain, or an established theory that might explain the challenges involved. After gaining familiarization with HRA and its scope, the next step involves understanding the challenges in the adoption of HRA. Given that such challenges are multifold, it may not be possible to obtain all answers from the HRM domain only. Analytics is a multidisciplinary approach involving mathematics, statistics, computer science, information science and technology (IS/IT), and management. We therefore extended the familiarization stage not only to the HRM, but also to the IS/IT domain as the evidence for the significance of addressing the challenges related to big data analytics in organizations. However, the adoption of HRA and the related challenges have not been discussed enough in the literature.

For **framework selection**, we performed background scoping of literature to identify a relevant conceptual framework for including the studies that can be covered in our research. A purposive search strategy was used to identify studies that would address our research question and scope. Key papers were identified from the databases of various publishers, including Elsevier, Wiley, Emerald, Sage, Springer, and Taylor&Francis. To be consistent and transparent in assessing all the retrieved references, each paper was screened using eligibility criteria (inclusion and exclusion) based on the research questions. First, reports screened based on the title and abstract had to specifically indicate the use of "analytics" and be relevant to HRM for inclusion in the synthesis. Full-text reports of references meeting both these criteria were retrieved and screened again. This discussion was evidenced in bits and pieces in the identified papers. We selected such papers as the base to discuss our research further. We contextualized the theories applicable to HRA by systematically identifying relevant previous research on the adoption of analytics in information system, e-commerce, information technology, and HRM technologies. To identify the relevant articles through the publishers' database, we used the following keywords as the search criteria: "HR analytics," "adoption of analytics," "analytics challenges," and "technology adoption challenges." As no HRA-related paper could be found, we chose papers on similar topics such as the application of analytics in the information management domain. We identified only those papers that have discussed the challenges of adopting analytics in their respective domains. More specifically, because our objective was to develop a framework for HRA adoption, we checked only those papers whose theoretical contributions and development could meet our standards.

At the **indexing** stage, we screened the selected papers and extracted the data using the initial conceptual framework to determine their relevance with respect to the review questions and to identify their main characteristics. We listed all the challenges that hinder HRA adoption from the identified papers and then moved to the next stage of charting to derive meaning from the collected data.

In the **charting** stage, we analyzed and classified the challenges identified in the previous stage into five categories: technological, organizational, environmental, data governance, and individual. The entire process was manually coded as the significance of each challenge was discussed before it could be included in the present study. These analytical categories were then used to synthesize the findings. For the quality assurance of the review, we adhered to the ENTRAQ standards suggested by Tong et al. (2013).

Finally, at the **mapping and interpretation** stages, the derived themes were contextualized in light of the original research questions. Findings from the review are presented in a tabular format (Annexure-Table 1) for ease of interpretation. At the synthesis stage, themes were determined based on the characteristics of the included studies. The emerging themes were then identified for the "adoption of HR analytics." The reliability of the process was established as two researchers were involved in all the phases of this process.

4. Analysis of the factors for driving HRA adoption in organizations

We used the framework synthesis method to identify the factors—technological, organizational, environmental, data governance, and individual—crucial for the effective adoption of HRA (see Annexure-Table 1). In addition, we identified 23 subfactors associated with each of these factors, some of which have been investigated previously such as the importance of analytical capabilities, data quality, strategic ability to act (Minbaeva, 2018), technology, people, and organization (Bondarouk et al., 2017), infrastructure capability Yasmin et al. (2020), followed by the management and HR capabilities. We discuss how each of these variables influences the adoption of HRA in an organization.

4.1 Technological factors

It is important to assess whether a new technology will favorably or unfavorably affect the decision-making process during its adoption (Maduku et al., 2016; Tornatzky & Fleischer, 1990). The decision for adopting HRA technologies depends on "what" is available and "how" these technologies will work with the existing technologies in the business (DePietro et al., 1990; Jeyaraj et al., 2006). By using the TOE framework, the current study analyzes the application of the DOI model to review various technological factors that impact the adoption of HRA. The decision to adopt an HRA technology generally depends on the complexity (learning an IT innovation or ease of use) and compatibility (both organizational and technical) of the technological innovation (Kapoor et al., 2014ab; Rogers, 2003). The technological infrastructure required for HRA adoption is usually part of the overall analytical strategy of an organization (which includes IT and HRM). The technology influences the HRM, particularly the way organizations gather, store, utilize, and disperse information about their employees and applicants (Stone, Deadrick, Lukaszewski & Johnson, 2015). It has been suggested that the adoption of various systemic, complex technologies such as HRA can increase the return on their adoption, that is, the initial increase in the adoption leads to a better technological experience. As a result, the rate of technological improvements and usage also increases, leading to further adoption of new technologies (Makinen, Kannianen & Dedehayir, 2013). In this study, we show that technological factors are critical for the adoption of HRA in an organization. The factors that influence the technological perspective for the adoption of HRA include the perceived usefulness of HRA in an organization, the complexity of the HRA, the quality of the HRA data, the compatibility of data-driven decision-making in the form of HRA, and access to and availability of the relevant data for HRA.

4.1.1 Complexity

Complexity is the extent to which an innovation is viewed as difficult to understand and use (Rogars, 2003, p. 257). Technological complexity increases the implementation's uncertainty; it also increases the probability of a technology not being adopted (Premkumar & Roberts, 1999). User-friendly technologies are generally more likely to be adopted. The complexity may also refer to the extent to which a business user understands how to use analytics before gaining some confidence and incorporating it in their decision-making processes. HR as a function is subjective, and the decisions made in different contexts are dynamic, while HRA is objective. Therefore, different variables that are perceived as important by HR are challenging to quantify. Even though complexity may delay or even prevent the adoption of IT in organizations, it is a significant determinant for such adoptions (Grover, 1993; Thong, 1999)." The HRA is highly technical as it involves the application of both IT and computer science. As a result, HR leaders find it challenging to assess its outcomes and implement it as an HR-driven initiative.

4.1.2 Perceived Usefulness

Perceived usefulness is considered a significant factor in the context of technology adoption (Wamba et al., 2017). This variable plays an important role in the adoption of technology in different contexts and settings (Ngai et al., 2009). The employees' (including its senior management) perception of the importance and effectiveness of HRA in an organization may help in its adoption. HRA provides insights that are used by HR practitioners to develop more objective and data-driven initiatives for HRM applications in organizations. The perceived usefulness also helps HR teams to quantify different benefits or returns on their efforts. Therefore, HRA should be able to tackle management and leadership constraints while bringing in more value. If HRA predicts that an employee is going to exit and if attrition is not a major concern in that organization, then the management will not see much value in HRA. This means that the analytics function can help HR teams to keep track of the priority areas for the HR function. Perception regarding the benefits generally depends on the failure or success in analytics adoption in an organization (Davenport, 2012).

4.1.3 Data Quality

Data quality refers to the availability and consistency of the data required for the adoption of HRA (Levenson, 2011; Rasmussen & Ulrich, 2015; Angrave et al., 2016). The HR data are diverse because they contain information from a multitude of processes under the HRM. HR decisions can be based on data metrics only if there is confidence in the accuracy of that data. There are several challenges associated with data such as wrong entries, data duplication, and issues with the absence of formal and centralized coordination of data-gathering activities (Minbaeva, 2018). As a result, it becomes impossible to integrate diverse datasets, resulting in data discrepancies because of the propagation of different metrics and time frames of longitudinal nature (Minbaeva, 2018). In addition, many information sources such as performance appraisals, feedback, and surveys are subjective, making it difficult to ascertain their accuracy (Shet et al., 2019a). Since HR is considered a soft function, numbers presented by the HR personnel are often questioned. Thus, data quality is an important aspect for helping build the credibility of the metrics shown by HR.

4.1.4 Access to Relevant Data

Access to data is a major challenge for HR because the data related to an employee is so varied that substantial efforts are required to standardize the input–output values in different processes. Because all processes in HR are not managed through technology, considerable efforts are required to collate and govern the data captured from these processes. A large number of successful organizations not only recognize the existence of data, but also prioritize their accessibility (Barrett et al., 2015). Although there are multiple stakeholders of data insights, some data are considered sensitive and thus need to be properly classified to define who within the organization can view it. In addition, information such as compensation and performance ratings are highly sensitive and even the analysts have to work under the constraints imposed by data confidentiality. It may also be possible that some of these data are outside of the scope of the HR function, making it difficult to access information. As the ownership of data can be controversial, clearly stating the ownership will help organizations with the accessibility of data (Ramaswamy, 2013; Agarwal & Dhar, 2014).

4.1.5 Compatibility

Compatibility is defined as "the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters" (Rogers, 2003, p. 240). The solutions and metrics designed by the HRA teams help change the way processes are managed, and hence, they should be in line with the values and vision of an organization. An innovation should be able to meet the technological needs and organizational values of an organization before it can be adopted (Lee, 2004). Hence, while designing solutions based on analytics, it is also necessary to define how the end-user will use it. Unlike many other best practices in HR such as recruitment, talent management, and learning, the practices in HRA are highly customized. Every organization has a different way of calculating a standard metric such an attrition or even headcount, which, in its unique way, helps in decision-making. Hence, HRA must be compatible with the stakeholders of an organization so that it is positioned as the employee data-driven decision-making process.

4.2 Organizational Factors

Factors such as innovativeness, top management (TM) support, technical expertise of employees, organizational structure, and organizational readiness influence the adoption of information technology (IT) by organizations. Chwelos et al. (2001) termed the construct "IT sophistication" consisting of TM support, expertise, and infrastructure in their empirical test of the adoption model. The organizational capabilities influence the adoption of analytics (Wamba et al., 2017). For the present paper, we selected constructs such as financial readiness, IT infrastructure and capabilities, and TM support. Training and development orientation and access to a skilled workforce were taken as specific dimensions of organizational factors. The organizational context refers to the internal factors of an organization that affect the adoption and implementation of an innovation (Tornatzky & Fleischer, 1990). The investigation culture, habit of making evidence-based decisions, and use of action-oriented tools by the TM for discussions on the HRA strategy are also part of organizational factors (Minbaeva, 2018).

4.2.1 Top Management Support

The TM support is the degree to which the TM of an organization understands the importance of HRA and the extent to which it is involved in HRA activities (Rasmussen & Ulrich, 2015; Hamilton & Sodman, 2018). The higher the support from the TM, the greater the overall HRA effectiveness (Thong et al., 1996). Analytics is a highly resource-intensive function and depends on collaboration among different departments. Therefore, TM support is necessary to help establish a friendly environment and offer sufficient resources to expedite the adoption of IT innovations (Low et al., 2011). The influence of the TM support and attitudes toward change are the key factors that determine the adoption of technology innovations (Daylami et al., 2005). However, in many organizations, the TM is not interested in investing large amounts of money in HRA, often because they are unsure of the likely benefits (Minbaeva, 2018). As a result, the adoption of HRA becomes difficult in such organizations. Thus, for such change to be effective, a leadership support drive from the TM is required (Shet, 2020c).

4.2.2 IT Infrastructure and Capabilities

Analytics is a highly resource-intensive function, including the use of technology infrastructure. HR analysts need data infrastructure to perform data analysis using different analytical techniques and computational intelligence. To implement the HRA, both intangible (human resources, experience, and skills) and tangible (physical assets) resources are required (Aral et al., 2012; Angrave et al., 2016). Well-established IT infrastructure and an efficient analytics team are needed to capture, transform, and analyze the data to automate repetitive processes and to create better products and solutions However, very few organizations make efforts to bridge such gaps while initially configuring their IT platforms. As a result, they may fall behind in this aspect and may have to make significant efforts later to develop IT infrastructure and capabilities, depending on the availability of funds, among other requirements.A positive connection between the IT infrastructure and capabilities and the adoption of IT innovation has been proved empirically (Hsu et al., 2016; Maduku et al., 2016).

4.2.3 Financial Readiness

Financial readiness is the availability of financial resources to learn and incorporate a new system (Chwelos et al., 2001). Without sufficient financial resources, it will be quite difficult for firms to afford the required talent and IT resources for analytics (Maduku et al., 2016). HRA is a fast-evolving field that needs collaboration between multiple technologies, which, however, cannot happen without adequate financial support. The adoption of HRA involves various costs such as adoption-related setup costs, training costs, and operating costs, including the costs for implementation and related potential administrative functions (Chau & Hui, 2001). There are also costs related to the implementation and maintenance of analytics and regulatory policies for data security and privacy (Esteves & Curto, 2013). Analytics takes time to deliver substantial results, especially in a domain like HR, where assessing the impact of implementing its recommendations is particularly time-consuming. Therefore, a financial sponsor is required who trusts the function and is dedicated to it over an extended period of time.

4.2.4 Training and Development of Employees

Continuous training of the employees on new tools and technology is a major challenge for any organization, which becomes even more important when it comes to the adoption of HRA (Taylor et al., 2014; Wamba et al., 2017). Analytics is a technical function and requires expertise on various technologies. However, in a support function such as HR, organizations generally do not invest much, which implies a need for capabilities across multiple technologies as well as adequate support. It may be easier to learn the analytics techniques; however, understanding its implementation is challenging. Hence, an effective and contextual training is critical for HRA adoption. Analytics training may also involve aspects such as consulting, data management, data transformation, visualization, interface designing, statistical analysis, application development, documentation, and communication. The diffusion process would be easy if on-the-job training along with hands-on experience is provided not only to the HR personnel but also to other decision-makers (Barton & Court, 2012).

4.2.5 Access to Skilled Workforce

The HRA adoption process is closely related to the accessibility of the relevant human resources in the business, in third-party organizations, or even to the outsourced expertise (Provost & Fawcett, 2013). Indeed, as a support function, HR cannot invest a large amount of resources in the analytics team. Therefore, the HR department should use the limited resources available more responsibly and develop cross-functional abilities to work on new technologies and apply them to solve a varied set of problems. Organizations need to ensure the availability of resources having capabilities such as data mining, aggregation, visualization, and data processing, all of which are necessary for the adoption of HRA (Wang & Hajli, 2017). In addition, they need to understand various statistical techniques ranging from classical statistics to machine learning to its applications such as NLP and sentiment analysis. As a result, there is a sudden boom in analytics-related educational courses (Gandomi & Haider, 2015). However, tailor-made programs for teaching HRA have still not been developed. The challenge of the absence of structured HRA teams is evident in most organizations, especially those lacking in-house organizational systems/capabilities on HRA (Minbaeva, 2018).

4.3 Environmental Factors

Successful adoption of HRA also depends on the external environment, which includes competitors and business partners of an organization. An interplay of these factors decides the adoption of HRA. Some of these factors include the ability of an organization to withstand competition, the industry type to which it belongs, and data-related factors such as data governance.

4.3.1 Competitiveness/External Pressure (EP)

Both business partners and competitors may influence an organization's decision to adopt a particular technology. For example, pressure from competitors and/or business partners is a significant factor in IT adoption (Musawa & Wahab, 2012). The HRA setups of some FMCG companies with app-based interviews definitely do have an edge over others when it comes to mass hiring and selection. Managing people is a key aspect of any business, and an organization that is better at it will certainly be able to deliver better results. Thus, if a competitor can improve their ability to manage people by being better at hiring, developing, rewarding, and retaining talent using analytics, it becomes imperative for the HR team to leverage analytics to manage their people like their competitors do. Thus, to remain competitive, HR managers might be forced to keep abreast of technological developments and follow the dominant trends.

4.3.2 Industry Type (InT)

InT becomes a moderating variable that determines the adoption intention of technology by an organization (Yeung et al., 2003). For example, several studies have proved that the industry under which an organization works influences IT adoption (Levenburg & Kelein, 2006). As analytics is a technical function and requires a favorable environment to be impactful, specific industries are better equipped to provide such an environment than others. For example, IT companies provide a better technical infrastructure to ensure credible data availability, financial firms are more data-driven and thus have more demand for analytics that they can take action upon, and services organizations have more operational data to measure productivity to design more meaningful analysis objectively. Therefore, the industry to which an organization belongs affects its information processing needs, which may influence the adoption of innovations (Goode & Stevens, 2000). The industry type also determines the type of data available for analysis, the kind of questions that the organization wants to answer using analytics, and the benefits it perceives from making data-driven decisions. HRA also enables specific organizations that operate under stringent employment laws to ensure they are compliant. Therefore, such organizations see more merit in HRA adoption.

4.4 Data Governance

The main focus of analytics is on modeling, mapping, and categorizing of the data by resolving the unstructured and complicated nature of datasets. Hence, effective data governance is necessary for guaranteeing the quality of the data extracted and examined from huge datasets (Hashem et al., 2015). Setting up systems and establishing workflows are critical not only for process-level growth, but also for enhanced data quality, linking the results of analytics projects to existing processes within an organization and supporting the experimentation and follow-up actions through HR business partners. Using poor data for smart analysis would generate little value; similarly, a higher level of dataset will not be useful if the analyses are not properly carried out (Minbaeva, 2018). Similarly, any data or data analysis would not be useful without an appropriate and well-designed research question (Deliotee, 2015). In addition, the final goal of HRA is not just to provide innovative insights; the main objective is to continuously provide “support in decision-making in the management of the workforce of an organization” (Deliotee, 2015).

4.4.1 Data Ownership

Data ownership means that the process owners are accountable to maintain the specific quality standards of the data. Data ownership can become highly complicated, depending on the size and complexity of the data (Kostkova et al., 2016). Data preparation for analysis is a time-consuming process; in addition, the delivery time increases manifold if the data quality was poor. The data that HR personnel has to work with is typically dispersed across multiple HR systems and therefore not easily accessible (Dahlbom, Siikanen & Sajasalo, 2020). The continuous mobility of HR members also poses question as to who owns the data. Generally, expectations with the process owners can only be set when the data quality issues within that process are resolved. Ownership guarantees the accuracy and monitoring of the data (Sivarajah et al., 2017). However, many times, issues arise when processes are outsourced, dispersed across different departments in-house, or shared between corporate and subsidiaries. While HRA teams work on data analysis, the ownership of the data lies with the process owners. Therefore, process owners’ commitment to maintain the expected data standards enables analytics teams to work on more value-added activities.

4.4.2 Data Security

Data security is a major issue. If the data cannot be secured, then data analytics would not gain much acceptance from the stakeholders. HRA teams manage the critical and confidential data of processes such as performance management, compensation, and succession planning. Thus, they have to be very careful about who the data is being shown to and whether they have the permission to view this data. The distributed nature of large data is one of the biggest security issues (Yi et al., 2014). Other key security issues include cyberattacks, malicious or malware applications and viruses, poor security controls (Abawajy, 2012), network threats, system events, forensics loss and intrusion (Wieringa et al., 2019), and poor data-security infrastructure (to ensure confidentiality, accountability, integrity and availability). Most of the HR data is sensitive and can be personally identifiable, which renders organizations legally compliant if it is misused or accessed by unauthorized personnel. In addition, HR's talent-related information is also very valuable and can act as a competitive advantage if accessed by competitors (Shet, 2020b).

4.4.3 Data Privacy

Use of analytics has led to privacy challenges. At the same time, it also suggests methods to maintain privacy in the digital era. With new laws such as General Data Protection Regulation (GDPR), it is high time organizations show proof of transparency while using information about their employees with their consent and by following ethical HR practices. Ethical issues are always given primacy while applying analytics to the HR data (Tursunbayevaa, Lauroc & Pagliaria, 2018). As data is now being considered the latest currency, its use is often constrained by privacy issues, leading to a common perception that data analytics and privacy are conflicting issues. Often managers and leaders feel that they should have access to all the information provided by the employees working under them, as the employees are accountable to them and the employees have provided that information. However, HR has to play a policing role here to decide which information can be accessed by whom and in what form. Nevertheless, businesses can adopt different approaches that meet various degrees of privacy and yet allow them to use diverse aspects of data analytics (Wieringa et al., 2019). For this to happen, it is necessary to appropriately classify the various data elements used by HRA teams and design policies to decide who can access what data in compliance with regulatory requirements.

4.4.4 Data Analysis and Modeling

The process of data analysis and data modeling comes into play after the collection of data followed by storing, cleaning, integrating, and organizing the data. To demonstrate the influence of the HR processes on business performance, we need experimental approaches, analytical models, and data-validity measures of both output and input variables and dimensions (Camps & Luna-Arocas 2012; Lin et al., 2016). The data modeling capabilities required depend on two factors: (i) the type of problem and (ii) the type of data that need to be analyzed to obtain the output. To resolve employee-related data problems, different types of information (such as texts, numbers, audios, and videos) and datasets in various formats need to be analyzed to explore potential complex relationships between the variables. The techniques that can be used to resolve a problem vary from forecasting and estimations to regression and classification. Hence, the data to be used can also vary from quantitative and qualitative based on employee profiles to aggregated and transactional based on the activities that an employee performs. It has also been suggested that the HRM develops its own decision science, just like marketing and accounting, in order to direct, assess, and improve the decision-making process (Boudreau & Ramstad, 2007). Hence, data analysis and data modeling can help predict the future course of action (Chen et al., 2013).

4.4.5 Data Aggregation and Integration

This step involves the process of aggregating and integrating data extracted from huge unstructured datasets. Unstructured datasets in a raw format do not provide any relevant information. However, when accessed and integrated with other enterprise platforms, such huge unstructured datasets can provide new knowledge and data-driven insights for decision-making (Karacapilidis, Tzagarakis & Christodoulou, 2013). HR departments usually manage a huge expanse of processes; sometimes, the same process might be executed in a different manner using different terminologies. Collating data from different processes, managed on different systems (online or offline), is an important aspect of designing and delivering analytics products. In addition, integrating and using a common taxonomy for the collated data also plays a key role in providing a comprehensive view of the analytics products to the senior management. Indecision and the inability to prove the origin of data are major barriers that adversely affect data aggregation and integration. In addition to HR, data from other functions are also required for creating actionable analytics, and often, this data needs to be mapped in a manner such that the HR data can be shown using aggregation taxonomy utilized by other functions and vice versa. Sharing information and data between diverse organizations and/or departments is another major challenge (Al Nuaimi et al., 2015).

4.4.6 Data Mining and Cleansing

Data mining and cleansing involve extraction and cleaning of data from a pool of large-scale asynchronous data. An effective method of extracting and cleaning data for analytics will greatly impact the overall value of the data (Chen et al., 2013). Understanding data-generating processes is critical to make correct assumptions while cleaning the data. If such assumptions can be standardized, the resulting data can be incorporated into a data warehousing process, which will make the compiled and stored data readily usable. Data mining, data cleansing, and data assessment are major challenges of data analytics because of the diverse, interrelated, and nonstable nature of data (Chen et al., 2013). Therefore, an extraction technique to draw useful information from asynchronous datasets will always be important; however, it remains a continuous challenge as an organization needs to continuously adapt to be able to use the emerging new data variables (Labrinidis & Jagadish, 2012). To facilitate more effective analysis, common measures and dimensions that are utilized during analysis need to be incorporated into the data marts so that they are readily available for analysis.

4.5 Individual Factors

To improve the data analytics capability, a coordinated effort is required to develop technical knowledge, relational knowledge, business knowledge, and knowledge about technology management (Wamba et al., 2017). Employees are crucial stakeholders in the data collation process (Minbaeva, 2018). Employee buy-in to data analytics-based decision-making is crucial for any organization. Not all employees trained in data science have knowledge about the HRM (Waters, Streets, McFarlane & Johnson-Murray, 2018), which means that only HR executives who are trained in actual data processing should be involved in all operations of HRA. HRA professionals are expected to understand how different variables should interact in the algorithms and how to avoid false conclusions (Angrave et al., 2016; Minbaeva, 2018). HR managers should have a basic understanding of research methodology, which includes data and method validity and reliability (McAfee et al., 2012). However, it has also been argued that a manager's intuition usually wins when there is a conflict in data analysis (Marler & Boudreau, 2017). In other words, HR managers need to be prepared to describe why the findings of big data are more reliable than traditional wisdom, assuming that the analytics processes have been conducted systematically. Given the prominence of algorithms in the analysis and prediction of the human behavior, many new HRM-related products will emerge, which requires different analytical skill sets for HRM (Cheng & Hackett, 2019). Hence, HR professionals should develop analytical skills that can help them devise an accurate causal model with a sufficient degree of complexity and evaluate the models through statistics (Erevelles, Fukawa & Swayne, 2016).

4.5.1 Culture

Culture is a major issue that affects the adoption and usage of analytics. UPS, a service-oriented organization, is a good example of proactively developing data-driven HRA culture for addressing their business challenges using people as an enabling factor (Davenport, 2018). There are at least five generations working together in today's organization (Haeger & Lingham, 2014). Hence, culture plays a crucial role in the adoption of analytics. A data-driven culture tends to challenge status quo and existing work practices. An open-minded culture is generally characterized by a change in decision-makers' beliefs based on data analysis. Data initiatives include benefits such as hiring people with a comprehensive technological and managerial understanding of big data and analytics, promoting a culture of corporate learning and incorporating big data decision-making into an organization's culture (Mikalef, Boura, Lekakos & Krogstie, 2019). Development of a new culture in HRM based on a data-driven approach requires the same effort as in any other change in management initiatives. Business leaders need to support the HRA demand and render it less optional for implementing data-driven decision-making.

4.5.2 Attitude Toward Analytics

The role of attitude is well examined for explaining the adoption of various technologies (Dwivedi et al., 2007; 2017; 2019). Drawing on the established literature, it can be argued that employees' attitude toward analytics is also an important factor influencing the adoption of HRA. The transition toward HRA depends on the eagerness and promptness of the employees of an organization to learn and adopt this new technique (Angrave et al., 2016). However, HR professionals who consider themselves experts on the "soft skills" of managing employees often feel uncomfortable dealing with cold database of analytics, especially when it is concerned with people's issues. Therefore, it is necessary to train HR professionals to understand the analytics, identify data sources and their significance, and know how to make adjustments with the wider strategic plan of the organization (Minbaeva, 2018). Having only analytical skills is not helpful; similarly, individuals with excellent HR and business knowledge but without analytics skills also fail to make the desired impact. Along with the HR function, the analytics team must also have deep knowledge of business (Minbaeva, 2018). Hence, HR managers should work together with their analytics teams to better conceptualize and understand the organizational problems and use this knowledge to make the analysis more actionable.

4.5.3 Quantitative Self-efficacy

Quantitative self-efficacy is a characteristic that motivates an individual to attain the highest knowledge required to succeed in a given field (Ajzen & Fishbein, 2000). Self-efficacy is a belief that every individual possesses enough skills to be successful and improve their work performance (Bandura, 1997). HRA professionals need the ability to extract and transform data to design analysis. Further, the ability to understand a problem statement and design the analysis and to apply different data analysis techniques based on the data attributes and problem statements is an important skill. Quantitative self-efficacy is influenced by mathematical literacy (Ozgen, 2013). Therefore, HR professionals' acceptance and use of HRA depend on their perception about their own individual capabilities to show acceptable levels of performance. Quantitative self-efficacy also determines the acceptance and application of HRA at the individual level whether to adopt HRA. Mathematical knowledge and thinking, considered as unique skills within HR, are the characteristics of quantitative self-efficacy (Dahlbom, Siikanen & Sajasalo, 2019).

4.5.4 Technology Self-efficacy

Analytics has greatly evolved over the last decade. Today, multiple technological platforms are used together to deliver analytics. Thus, HRA managers need to have an excellent understanding of what capabilities each platform brings to coordinate better with the experts who support the development of these analytics products. Technology self-efficacy is essential for better HR services. It is also essential for HRA because competing on analytics means competing on technology (Davenport, 2006). Hence, technology has been identified as a key challenge that determines the adoption of HRA. While technology can deliver analytics, the interpretation and understanding of output from the analysis require analytical capability. However, the possibility to use pre-existing analytical tools and available information systems is sometimes impeded by the gap in employee skills (Dahibom, Siikanen & Sajasalo, 2020). Data transformation, distribution, storage, computation, business intelligence, statistical packages, and data mining tools are some of the technologies used for data analysis. It is difficult for a single person or platform to deliver the results using all these technologies. Hence, it is necessary for the HRA manager to know what is needed and who has the required expertise to deliver the product.

4.5.5 Storytelling Ability

Analytics is a complex process that tries to explain an actual phenomenon in mathematical terms. Big data analytics as applied to HR involves storytelling, which can help everyone understand the major findings better in their own context (Lipkin, 2015). Thus, for business users to understand the underlying assumptions and the basis of the outcomes, the process needs to be explained in an easy-to-grasp manner. A business analyst should be able to break down real-life problems into quantifiable subsets and then use the output from these subsets to suggest a real-life solution for the complete problem. While this might involve multiple technicalities and techniques, the senior stakeholders should be presented with the different aspects in a manner that is simpler for them to understand. Analytics is considered a highly technical domain, and hence, all business users may not understand the related terminology and jargon. Analysts who can make complex data easily understandable can influence the final decision-making. Often, this technical ability is also aligned with the ability to create visualizations that help the audience to focus on and understand the important aspects of the analysis.

5. Discussion

We herein discuss the challenges to HRA practice using the framework synthesis method and propose a “framework for HRA adoption.” We conducted a systematic review of literature using the framework synthesis method and identified 23 variables that can be clustered under five categories as technological, organizational, environmental, data governance, and individual-level factors. We showed that successful adoption of HRA depends on many factors such as the firm’s capabilities (people, existing processes and technology, organization’s orientation), data availability, quality of data, the attitude toward data-driven decision-making, and IT infrastructure and capabilities.

(Insert Figure 2- Framework on the adoption of HRA)

Analytics is particularly useful for data-driven decision-making in HRM. Therefore, organizations that use new technologies employ their data in a better way to gain insights for decision-making. Hence, the use of various technologies, particularly HRA, should be encouraged. However, the use of HRA in itself requires the application of different technologies varying from business intelligence tools for dash boarding to specialized products to conduct studies based on network analysis. Because some technologies are highly complex to compute and understand, HR teams tend to shy away from investing in them. One of the advantages of an analytics function is that it often helps break down silos within an organization, especially when different departments use different technology products and tools. However, this is possible only if the HRA function has access to the dataset of other functions. For example, for more objective employee recognition, a company could start using customer feedback data from operations to identify the population creating an impact but not recognized for the same. To make these data connections, it is necessary to ensure that the systems used to manage them are compatible with HRA function's technology.

HR leaders may not have the required technical expertise to assess the resources they want to have in their team. It may also be difficult for them to design a development plan for leveraging newer technologies. Moreover, they need to design teams with fewer resources but with better capabilities to leverage different technology stacks that can deliver products varying from dashboards to prescriptive analytics. New technologies developed over the last decade have enabled HR teams to design and execute better strategies to provide the organizations with a competitive edge. Some industries have been at the forefront when it comes to investing in this field. Through their shared experience, companies in these industries tend to have definitive demands from the HRA teams and use the outcomes to drive their strategic talent initiatives. These industries have made a good progress in this field owing to factors such as the presence of a supporting environment, a favorable setting whereby there are resources with expertise in managing data infrastructure, investments in robust technology to manage the HR processes, and a data-driven culture. Thus, HRA teams can leverage both the key management knowledge for an analytics function from other teams and their experience in functions such as designing a data dictionary, SOP documentation, and productivity tracking.

Data-related hurdles are the most apparent constraints affecting the HRA adoption. These hurdles can be overcome by large-scale standardization of existing talent practices, creating a data governance framework, redefining the data ownership (including HR data), mitigating the privacy and security concerns, properly integrating HR data with other datasets within the organization, and adequate data analysis, management, storage, and visualization. Organizations have invested in setting up teams within their HR function and equipped them with quantitative capabilities, especially with data science skills.

Our paper makes some key recommendations to improve the HRA capability and reviews individual factors that enable HR professionals to leverage the benefits of analytics. We also derived an integrated framework for HRA adoption using the theoretical findings (Figure 2). Methodologically, our work introduces the framework synthesis method for a systematic review of literature in the business management domain. This framework shows that multiple factors determine the extent to which an organization invests in this function, designs effective products, and implements them to improve decision-making. Use of this framework may also help assess how these factors impact their investments, how to be rational with their expectations, and where they can influence to ensure that the team they invest in receives the necessary support to succeed.

5.1 Practical Implications

Multiple stakeholders are involved in the effective adoption of data analytics in an organization. This study has several implications for key stakeholders such as HR managers, IT managers, HR leaders, and consulting practitioners, and the CEOs, academia, and policymakers. As shown in Figure 2, this study discusses the managerial characteristics necessary for the adoption of HRA. Technological, organizational, environmental, data governance, and individual factors need to be considered by both HRM practitioners and HRA managers. Each variable has been discussed in length to sensitize and identify gaps from the concerned organization's perspective. Organizations that are struggling to set up and reap the benefits of HRA should assess their position on these factors and identify the focus areas that will enable them to build a stronger practice. HRA is not an IT project-driven function; instead, it needs to be embedded within the HRM function, which defines the scope and different processes and responsibilities that come with HRA adoption.

If HRA is to be used to grow business, then it should receive adequate financial support from the TM. However, other core functions of an organization such as marketing, operations, and finance receive more support and investments than the HRA. We believe our study may contribute to a better understanding of some of the key theories applicable to the adoption of analytics, not just HRA. The above mentioned factors should be assessed by an organization interested in adopting analytics (or HRA) and for removing any impediment to their efforts to reap the maximum benefits from their investments and IT systems. Organizations may decide to build some infrastructural capabilities as needed by the introduction of required software applications; however, a focus on internal factors is also necessary for a successful adoption. For example, an organization might lease a vendor application to control internal attrition using machine learning. By considering the other factors (technological, environmental, data, and individual support for this implementation), leaders and managers should restore a culture of evidence-based decision-making relying on tools and approaches that are acceptable by peers and the staff.

5.1.1 Implications for HR Leaders

The advent and scaling up of HRA have put pressure on HR leaders to invest in this technology. The adoption of analytics is trickier than the previous efforts to adopt HR technologies geared toward increased HR functions' efficiency and delivery. Analytics has a longer gestation period. In addition, instead of relying upon IT teams and external consultants, organizations have to build ownership and accountability to obtain returns from this investment. Unlike other HR initiatives that are time-bound and defined by a project cluster, HRA needs constant involvement and a better alignment of specialist teams. However, HRA's technicalities make it difficult for HR leaders to establish who is accountable for what. In fact, HR leaders themselves are often unsure of their role, apart from driving the cost and resource investment. Our framework might help them assess HRA's different aspects and facilitate a more supportive environment for its adoption.

5.1.2 Implications for CEOs

HRA helps a CEO in assessing their organization’s progress based on metrics and data-driven insights. Many CEOs assert that their people are their biggest assets, making it imperative for the HR leaders to share the key metrics on how their organization manages their employees. In addition, HR leaders are also expected to show the values they anticipate from their investments clearly. As a result, HR leaders often pitch the use of analytics as a way to enable them to meet these expectations. However, because analytics is a highly technical function, it may result in a tussle between the HR and technology support departments about taking accountability for this investment's success. With their bird’s-eye view, CEOs often find it difficult to demarcate the responsibility clearly. We believe that our framework would enable them to define who they need to engage with and track to ensure the approved investment gives them the desired results.

5.1.3 Implications for HR Managers

HR has been striving to get a seat at the table and become more strategic. Analytics has become a buzzword in the HR community, considering its opportunities to position HR as a strategic business partner. Over the past few years, HR managers have been called upon to become more analytical; however, consultants' promotional literature has not helped them enough to reach this target. Even after being provided with training to hone their quantitative abilities, including the ability to work with different tools used by data analysts, there is a lack of clarity around how to use this knowledge as part of their role within the organization.

The proposed framework examines the multiple factors that influence the adoption journey of HRA in an organization. This framework may help HR managers better focus on factors that infleunce the HRA adoption and see how the HRA can help them become more strategic and align better with their respective organizations' business plans. Moreover, our framework can help them better understand not only their role in making the analytical products more actionable, but also the importance of building a strong partnership with the dedicated analytics teams than just treating them as service providers.

5.1.4 Implications for IT Managers

Since analytical processes are highly technical, IT teams are often responsible for materializing HRA projects because of their technical know-how. They possess the required resources to accomplish tasks such as managing data and security, creating processes for extraction, and transforming and loading data. However, the IT team can only provide limited support to this journey. IT experts are expected to follow various rules and deliver output through a technology-driven interface while developing systems for certain specific tasks. Yet, the definition of such rules rather devolves upon HR partners. Besides, when they raise questions about the design of a metric or the actions to be conducted through the technology, they often do not answer because the HR partners, who are more interested in setting up the infrastructure for delivery, may consider such questions trivial. We believe our framework will show all the stakeholders concerned that the IT team can play a significant role in making the HRA function a success.

5.1.5 Implications for Consulting Practitioners

HR consultants are sometimes blamed for creating an unnecessary hype around HRA. It has been claimed that they apparently promote HRA as a solution for all the issues faced by an HR leader. This is partly owing to the lack of patience on the part of HR leaders rather than their ability to understand the complete process of HRA adoption. It has been observed that HR leaders often invest in HRA under peer pressure or when they are looking for partners for quick implementation. HRA may sometimes be likened to HR technology in terms of implementation, even though HR personnel fail to grasp the complete implications and continuous nature of HRA. The adoption of HRA is not about automating the work of reporting; it is rather a function that constantly changes the way the decisions about employees are made. As external service providers, HR consultants often find it difficult to assess the efforts that the organizations have to put in to make this investment a success. Again, there is only a limited extent to which the consultants can support the process by bringing in their expertise. Our framework should give them a basis to clearly communicate the different factors that need to be considered by any organization, together with a more transparent role in HRA adoption.

5.2 Theoretical Implications

Our research's main contribution is that it provides a framework for the adoption of analytics for HRM. We identified five factors that influence the adoption of analytics in any organization: technological, organizational, environmental, data governance, and individual. Each of these factors contains certain subfactors that are critical for a successful practice of analytics. The existing literature has discussed some of these factors that affect the adoption of HRA, such as the need for analytical competencies, data quality, and strategic ability to act (Minbaeva, 2018), technology, people, and organization (Bondarouk et al., 2017). Our study supports the findings of Yasmin et al. (2020), who reported that the data analytics capabilities are interdependent and that the infrastructure capability is the most important factor, followed by management and HR capabilities. Our study makes a unique contribution in understanding the adoption of HRA (Figure 2) in an organization by performing a detailed analysis of all the challenges and by connecting them to broader themes defined as factors. The variables within each factor are discussed in detail to emphasize their impact on the adoption journey. Theoretically, our work's contribution in the emerging domain of HRA as applied to the HRM is made by contextualizing the theory of technology adoption, the TPB, and diffusion theory. As the technology increases efficiency, we believe that HRA adoption will make HRM more effective. The proposed framework will help further studies on the implications of HRA on HRM effectiveness and business performance.

Sub-factors such as complexity, perceived usefulness, data quality, access to relevant data, and compatibility have emerged as the critical technology-based drivers of HRA adoption. The organizational sub-factors such as TM support, IT infrastructure and capabilities, financial readiness, training and development of employees, and access to a skilled workforce have been identified as critical for adopting HRA in organizations. The influence of environmental factors such as competitiveness/EP and InT, all of which are externally oriented, should also be considered in HRA practice. The most crucial factor that affects the adoption of HRA is data governance, which has subfactors such as data ownership, data security, data privacy, data analysis, and modeling, data aggregation and integration, and data mining and cleansing. The individual factors have sub-factors such as culture, attitude towards analytics, quantitative self-efficacy, technology self-efficacy, and storytelling ability. By contextualizing the discussion on HRA adoption, this paper makes an important theoretical contribution to the literature.

5.3 Limitations

The study has some limitations as well. There is a need to better explain, through systematic reviews, all the existing and accessible research studies (both conceptual and empirical) on HRA. Although we conducted a thorough and intensive literature review using the publisher database to identify all possible relevant articles, it is highly likely that we missed to include some research articles in this review, especially those from some other databases. Additionally, the analysis and synthesis of the collated data were based on the research team's interpretation of the selected articles. We attempted to avoid these issues by independently cross-checking papers to avoid the embedded bias; however, errors may still have crept in despite the robustness of our research and every effort made to mitigate the errors.

5.4 Future Research

This paper examines the challenges that need to be resolved before HRA can be adopted by an organization. The analysis of the selected articles revealed that the opportunity clearly exists to extend this research to multiple areas. Based on the results obtained, the future research on the topic should be conducted on the following lines:

- The proposed framework can be tested empirically with quantitative or qualitative studies either with all variables or a few variables to understand each of the independent variables' effect on the dependent variables in the process. The proposed dependent variables for the "adoption of HR analytics" can be operationalized with the scale development process or some proxy variables.
- The antecedents, moderators, and outcomes of HRA can be studied in detail. The HRA outcomes can be analyzed in relation toHRA outcomes can be analyzed in relation to its adoption rate to establish proximal and distal outcomes of HRA in HRM and business through the RoI value for HRA. Various moderators and mediators of the framework have been identified, including the industry type and data governance. Their in-depth analysis can help in identifying the critical factors for HRA adoption.
- Methodological studies using multicriteria decision-making techniques such as analytical hierarchy process (AHP) or analytical network process (ANP) can be used to identify which factors influence the adoption of analytics in organizations. Practitioners can better grasp such events by making a detailed case study of the adoption of HRA that closely examines the identified variables. The qualitative review studies can integrate the outcome variables for organizational performance or effectiveness.
- It will help HRM practitioners if they knew how each of these variables can be leveraged to redefine the process of HRA in an organization, including the interdynamics between the organization and the HRM structure and the interplay between the IT, external vendors (e.g., HRMS or outsourced vendors), and the overall effectiveness of the analytics practice across the organization. Such dimensions of the study are critical for reviewing the contextual factors of HRM that influence the HRA adoption.

- The existing framework can be applied to other functional areas, including marketing, supply chain management, IT, and operations. Similar challenges associated with the above functions are likely to appear in these cases as well. Therefore, the proposed framework should be investigated in other settings as well.

5.5. Conclusions

This work reviews the various factors influencing the adoption of HRA, proposes a framework to managers, IT experts, and HR specialists for this adoption, and makes an inventory of the various challenges that impact business-related decision-making. We used a framework synthesis method, systematically analyzed the challenges related to HRAHRA challenges, and proposed solutions to overcome the impediments in HRA adoption. We showed the importance of addressing the constraints related to the various determining factors (technological, organizational, environmental, and individual) to successfully adopt analytics in HRM. We substantiate the results obtained by using the HRA adoption framework with various subfactors. We examined both theoretical and practical implications and determined some avenues for future research. We believe that our work will help advance the emerging domain of HRA and its adoption across organizations to help in data-driven decision-making.

References

Abawajy, J. (2012). User preference of cyber security awareness delivery methods. Behaviour & Information Technology, 33(3), 237-248.

Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50, 179–211

Al Nuaimi, E., Al Neyadi, H., Mohamed, N., & Al-Jaroodi, J. (2015). Applications of big data to smart cities. Journal of Internet Services and Applications, 6, 25. https://doi.org/10.1186/s13174-015-0041-5

Andersen, M. K. (2017). Human capital analytics: The winding road. Journal of Organizational Effectiveness: People and Performance, 4(2), 133-136.

Angrave, D., Charlwood, A., Kirkpatrick, I., Lawrence, M., & Stuart, M. (2016). HR and analytics: Why HR is set to fail the big data challenge. Human Resource Management Journal, 26(1), 1-11.

Aral, S., Brynjolfsson, E., & Wu, L. (2012). Three-way Complementarities: Performance pay, human resource analytics, and information technology. Management Science, 58(5), 913-931.

Aydiner, A., Tatoglu, E., Bayraktar, E., Zaim, S. and Delen, D., (2019). Business analytics and firm performance: The mediating role of business process performance. Journal of Business Research, 96, 228-237.

Barrett, M., Davidson, E., Prabhu, J., & Vargo, S. L. (2015). Service innovation in the digital age: Key contributions and future directions. MIS Quarterly, 39(1), 135-154.

Barton, D & Court, D. (2012). Making Advanced Analytics Work for You. Harvard Business Review. 90. 78-83, 128.

Bassi, L. (2012). Raging debates in HR analytics. Human Resource Management International Digest, 20(2). https://doi.org/10.1108/hrmid.2012.04420baa.010

Bersin, J., Agarwal, D., Pelster, B. and Schwartz, J. (2015), “Global human capital trends 2015”, available at: www2.deloitte.com/content/dam/Deloitte/at/Documents/human-capital/hc-trends-2015.pdf (accessed January 20, 2017).

Bondarouk, T., Parry, E., & Furtmueller, E. (2016). Electronic HRM: four decades of research on adoption and consequences,The International Journal of Human Resource Management, 28(1), 98-131.

Boudreau, J. & Ramstad, P. (2005). Talentship, Talent Segmentation, and Sustainability: A New HR Decision Science Paradigm for a New Strategy Definition. Human Resource Management, 44(2), 129-136.

Boudreau, J. and Lawler, E. (2015). Making Talent Analytics and Reporting into a Decision Science. Working paper, Centre for Effective Organizations. University of Southern California.

Boudreau, J. W., & Ramstad, P. M. (2005). Talentship, talent segmentation, and sustainability: A new HR decision science paradigm for a new strategy definition. Human Resource Management, 44(2), 129-136.

Boudreau, J., & Cascio, W. (2017). Human capital analytics: Why are we not there? Journal of Organizational Effectiveness: People and Performance, 4(2), 119-126.

Brunton G, Oliver S, Thomas J.(2020) Innovations in framework synthesis as a systematic review method. Res Syn Meth. 2020;11: 316–330

Carroll C, Booth A & Cooper K (2011) A worked example of “best fit” framework synthesis: a systematic review of views concerning the taking of some potential chemopreventive agents. BioMed Central Medical Research Methodology 11, 29.

Chau, P.Y. and Hui, K.L. (2001). Determinants of small business EDI adoption: an empirical investigation. Journal of Organizational Computing and Electronic Commerce, 11(4), 229-252.

Chen J., Chen Y., Du X., Li C., Lu J., Zhao S., Zhou X. (2013), Big data challenge: a data management perspective, Frontiers of Computer Science, 7 (2) pp. 157-164

Cheng, M. M., & Hackett, R. D. (2019). A critical review of algorithms in HRM: Definition, theory, and practice. Human Resource Management Review, 100698. https://doi.org/10.1016/j.hrmr.2019.100698

Chwelos, P., Benbasat, I. and Dexter, A. S. (2001) ‘Empirical Test of an EDI Adoption Model’, Information Systems Research 12(3): 304–21

Côrte-Real, N., Oliveira, T., & Ruivo, P. (2017). Assessing business value of big data analytics in European firms. Journal of Business Research, 70, 379-390. https://doi.org/10.1016/j.jbusres.2016.08.011

Côrte-Real, N., Ruivo, P., Oliveira, T. and Popovič, A., (2019). Unlocking the drivers of big data analytics value in firms. Journal of Business Research, 97, pp.160-173

Cronin, B., Morath, R., Curtin, P., & Heil, M. (2006). Public sector use of technology in managing human resources. Human Resource Management Review, 16(3), 416-430

Dahlbom, P., Siikanen, N., Sajasalo, P., & Jarvenpää, M. (2019). Big data and HR analytics in the Digital Era. Baltic Journal of Management, 15(1), 120-138.

Davenport, T. H. (2018). From analytics to artificial intelligence. Journal of Business Analytics, 1(2), 73-80.

Davenport, T. H., Barth, P., & Bean, R. (2012). How 'Big Data'is Different. MIT Sloan Management Review, 54, 43–46.

Davenport. T(2013). Competing on analytics: The new science of winning Journal of Information Technology Case and Application Research, 15(4), 59-61. https://doi.org/10.1080/15228053.2013.10845729

Daylami, N., Ryan, T., Olfman, L. and Shayo, C. (2005), "System sciences", HICSS '05, Proceedings of the 38th Annual Hawaii International Conference, Big Island, HI, January 3-6.

Delen, D. and Zolbanin, H., 2018. The analytics paradigm in business research. Journal of Business Research, 90, pp.186-195.

Deliotte(2015) HR and people analytics. Stuck in neutral, https://www2.deloitte.com/us/en/insights/focus/human-capital-trends/2015/people-and-hr-analytics-human-capital-trends-2015.html

DiClaudio, M. (2019), "People analytics and the rise of HR: how data, analytics and emerging technology can transform human resources (HR) into a profit center", Strategic HR Review, Vol. 18 No. 2, pp. 42-46

Douthit, S. and Mondore, S. (2014). 'Creating a business-focused HR function with analytics and integrated talent management'. People and Strategy, 36: 4, 16– 21.

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. International Journal of Information Management, 48, 63-71.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... & Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International Journal of Information Management, 57, 101994.

Dwivedi, Y. K., Khan, N., & Papazafeiropoulou, A. (2007). Consumer adoption and usage of broadband in Bangladesh. Electronic Government, an International Journal, 4(3), 299-313.

Dwivedi, Y. K., Rana, N. P., Janssen, M., Lal, B., Williams, M. D., & Clement, M. (2017). An empirical validation of a unified model of electronic government adoption (UMEGA). Government Information Quarterly, 34(2), 211-230.

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the unified theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model. Information Systems Frontiers, 21(3), 719-734.

Erevelles, S., Fukawa, N. and Swayne, L., (2016). Big Data consumer analytics and the transformation of marketing. Journal of Business Research, 69(2), pp.897-904.

Esteves, J. and Curto, J. (2013), "A risk and benefits behavioral model to assess intentions to adopt big data", Journal of Intelligence Studies in Business, Vol. 3 No. 1, pp. 37-46.

Fernandez, J. (2019). The ball of wax we call HR analytics. Strategic HR Review, 18(1), 21-25.

Fitz-enz, J. and Mattox, J.R. II (2014), Predictive Analytics for Human Resources, John Wiley & Sons, Inc,

Gale, N, Heath,G, Cameron, E, Rashid, S, & Redwood, S(2013) Using the framework method for the analysis of qualitative data in multi-disciplinary health research. BMC Medical Research Methodology 2013 13:117.

Gandomi, A. and Haider, M. (2015), "Beyond the hype: big data concepts, methods, and analytics", International Journal of Information Management, Vol. 35 No. 2, pp.137-144

Gelbard, R., Ramon-Gonen, R., Carmeli, A., Bittmann, R. M., & Talyansky, R. (2018). Sentiment analysis in organizational work: Towards an ontology of people analytics. Expert Systems, 35(5), e12289. https://doi.org/10.1111/exsy.12289

Goode, S & Stevens, K. (2000). An analysis of the business characteristics of adopters and non-adopters of World Wide Web technology. Information Technology and Management. 1, pp 129–154(2000)

Greasley, K., & Thomas, P. (2020). HR analytics: The onto-epistemology and politics of metricised HRM. Human Resource Management Journal. https://doi.org/10.1111/1748-8583.12283

Green, D. (2017). The best practices to Excel at people analytics. Journal of Organizational Effectiveness: People and Performance, 4(2), 137-144.

Grover, V. (1993), "An empirically derived model for the adoption of customer-based Inter organizational systems", Decision Sciences, Vol. 24 No. 3, pp. 603-640.

Guenole, N., Ferrar, J., & Feinzig, S. (2017). Power of People, The: Learn How Successful Organizations Use Workforce Analytics To Improve Business Performance, Pearson

Haeger, D. L., & Lingham, T. (2014). A trend toward work–life fusion: A multi-generational shift in technology use at work. Technological Forecasting and Social Change, 89, 316-325.

Hashem, I. A., Yaqoob, I., Anuar, N. B., Mokhtar, S., Gani, A., & Ullah Khan, S. (2015). The rise of "big data" on cloud computing: Review and open research issues. Information Systems, 47, 98-115.

Hazen, B. T., Boone, C. A., Ezell, J. D., & Jones-Farmer, L. A. (2014). Data quality for data science, predictive analytics, and big data in supply chain management: An introduction to the problem and suggestions for research and applications. International Journal of Production Economics, 154, 72-80.

Hota, J. and Ghosh, D. (2013), “Workforce analytics approach: an emerging trend of workforce management”, Workforce Management, pp. 167-179.

Hsu, C., Lin, J.C. (2016). Factors affecting the adoption of cloud services in enterprises. Inf Syst E-Bus Manage 14, 791–822

Huselid, M. A. (2018). The science and practice of workforce analytics: Introduction to the HRM special issue. Human Resource Management, 57(3), 679-684.

Ingham, J. (2011), “Using a human capital scorecard as a framework for analytical discovery”, Strategic HR Review, Vol. 10 No. 2, pp. 24-29.

Jeyaraj, A., Rottman, J.W. and Lacity, M.C. (2006), “A review of the predictors, linkages, and biases in IT innovation adoption research”, Journal of Information Technology, Vol. 21 No. 1, pp. 1-23.

Kamal, M. (2006), “IT innovation adoption in the government sector: identifying the critical success factors”, Journal of Enterprise Information Management, Vol. 19 No. 2, pp. 192-222.

Kapoor, K. K., Dwivedi, Y. K., & Williams, M. D. (2014a). Rogers’ innovation adoption attributes: A systematic review and synthesis of existing research. Information Systems Management, 31(1), 74-91.

Kapoor, K. K., Dwivedi, Y. K., & Williams, M. D. (2014b). Innovation adoption attributes: a review and synthesis of research findings. European Journal of Innovation Management, 17(3), 327-348.

Karacapilidis, N., Tzagarakis, M., & Christodoulou, S. (2013). On a meaningful exploitation of machine and human reasoning to tackle data-intensive decision making. Intelligent Decision Technologies, 7(3), 225-236.

Kossek, E. E., Young, W., Gash, D. C., & Nichol, V. (1994). Waiting for innovation in the human resources department: Godot implements a human resource information system. Human Resource Management, 33(1), 135-159.

Kostkova, P., Brewer, H., De Lusignan, S., Fottrell, E., Goldacre, B., Hart, G., Koczan, P., Knight, P., Marsolier, C., McKendry, R. A., Ross, E., Sasse, A., Sullivan, R., Chaytor, S., Stevenson, O., Velho, R., & Tooke, J. (2016). Who owns the data? Open data for healthcare. Frontiers in Public Health, 4. https://doi.org/10.3389/fpubh.2016.00007

Labrinidis, A., & Jagadish, H. V. (2012). Challenges and opportunities with big data. Proceedings of the VLDB Endowment, 5(12), 2032-2033.

Lawler, E.E., Levenson, A. and Boudreau, J.W. (2004) HR Metrics and Analytics: Use and Impact. Human Resource Planning, 27, 27-35.

Lee, J (2004) Discriminant Analysis of Technology Adoption Behavior: A Case of Internet Technologies in Small Businesses, Journal of Computer Information Systems, 44:4, 57-66

Levenburg, N. M., & Klein, H. A. (2006). Delivering customer services online: Identifying best practices of medium-sized enterprises. Information Systems Journal, 16(2), 135-155.

Levenson, A. (2005), "Harnessing the power of HR analytics", Strategic HR Review, Vol. 4 No. 3, pp. 28-31.

Levenson, A. (2017). Using workforce analytics to improve strategy execution. Human Resource Management, 57(3), 685-700.

Lievens, F and Harris. M.(2003). Research on Internet recruiting and testing: Current status and future directions. International review of industrial and organizational psychology. 131-165.

Lin, C-H., Sanders, K., Sun, J-M. J., Shipton, H., & Mooi, E. A. (2016). From Customer-Oriented Strategy to Organizational Financial Performance: The Role of Human Resource Management and Customer-Linking Capability. British Journal of Management, 27(1), 21-37.

Lipkin, J. (2015). Sieving through the data to find the person: HR's imperative for balancing big data with people centricity. Cornell HR Review (September), 1-5. Retrieved from http://www.digitalcommons.ilr.cornell.edu

Low, C., Chen, Y. and Wu, M. (2011), “Understanding the determinants of cloud computing adoption”, Industrial Management & Data Systems, Vol. 111 No. 7, pp. 1006-1023.

Marler, J. H., & Boudreau, J. W. (2016). An evidence-based review of HR analytics. The International Journal of Human Resource Management, 28(1), 3-26.

Marler, J. H., & Fisher, S. L. (2013). An evidence-based review of e-HRM and strategic human resource management. Human Resource Management Review, 23(1), 18-36.

Marler, J. H., & Parry, E. (2016).Human resource management, strategic involvement and e-HRM technology. International Journal of Human Resource Management, 27(19), 2233-2253.

Martinsons, M. G. (1994). Benchmarking human resource information systems in Canada and Hong Kong. Information & Management, 26(6), 305-316.

McAfee, A., Brynjolfsson, E., Davenport, T.H., Patil, D.J. and Barton, D., (2012). Big data. The management revolution. Harvard Business Review, 90(10), 61–67.

McIver, D., Lengnick-Hall, M. L., & Lengnick-Hall, C. A. (2018). A strategic approach to workforce analytics: Integrating science and agility. Business Horizons, 61(3), 397-407.

Mikalef, P., Boura, M., Lekakos, G. and Krogstie, J., 2019. Big data analytics and firm performance: Findings from a mixed-method approach. Journal of Business Research, 98, pp.261-276

Minbaeva, D. B. (2017). Building credible human capital analytics for organizational competitive advantage. Human Resource Management, 57(3), 701-713.

Musawa M.S. and Wahab E., (2012), “The adoption of electronic data interchange (EDI) technology by Nigerian SMEs: A conceptual framework”, Journal of Business Management and Economics Vol. 3(2). pp. 055-068

Ngai, E.W.T, Karen, K.L.M, Riggins, F.J. and Candace, Y.Yi. (2008), “RFID research: an academic literature review (1995-2005) and future research directions”, International Journal of Production Economics, Vol. 112 No. 2, pp. 510-520.

Ozgen, K. (2013). Self-efficacy beliefs in mathematical literacy and connections between mathematics and real world: The case of high school students. Journal of International Education Research, 9(4), 305–316.

Panayotopoulou, L., Vakola, M., & Galanaki, E. (2007). E-HR adoption and the role of HRM: Evidence from Greece. Personnel Review, 36, 277–294

Pape, T. (2016), “Prioritizing data items for business analytics: framework and application to human resources”, European Journal of Operational Research, Vol. 252 No. 2, pp. 687-698.

Philip Chen, C., & Zhang, C. (2014). Data-intensive applications, challenges, techniques and technologies: A survey on big data. Information Sciences, 275, 314-347.

Premkumar, G. and Roberts, M. (1999), “Adoption of new information technologies in rural small businesses”, Omega, Vol. 27 No. 4, pp. 467-484.

Provost, F & Fawcett, T. (2013). Data Science for Business.

Ramaswamy, S., (2013). What the Companies Winning at Big Data Do Differently. Bloomberg, June: http://www. bloomberg. com/news/2013–06-25/what-the-companies-winning-at-big-data-do-differently. html.

Ritu Agarwal, Vasant Dhar (2014) Editorial—Big Data, Data Science, and Analytics: The Opportunity and Challenge for IS Research. Information Systems Research 25(3):443-448.

Rogers, E.M. (2003), Diffusion of Innovations, 5th ed., Free Press, New York, NY. Tornatzky, L.G. and Fleischer, M. (1990), The Processes of Technological Innovation, Lexington Books, Lexington, MA.

Roslyn Vargas, Yuliya V. Yurova, Cynthia P. Ruppel, Leslie C. Tworoger & Regina Greenwood (2018) Individual adoption of HR analytics: a fine grained view of the early stages leading to adoption, The International Journal of Human Resource Management, 29:22, 3046-3067,

Scullen, S. E., Mount, M. K., & Goff, M. (2000). Understanding the latent structure of job performance ratings. Journal of Applied Psychology, 85(6), 956-970.

Shet, Patil, Chandawarkar (2019a). "Competency based superior performance and organizational effectiveness." International Journal of Productivity and Performance Management, vol. 68, no. 4, 2019, pp. 753-773

Shet, Sateesh. V. (2020b) "Strategic talent management – contemporary issues in international context." Human Resource Development International, vol. 23, no. 1, 2019, pp. 98-102.

Shet, Sateesh V (2020c)” Leadership: making an impact, inspiring organization, and getting to the next level” Human Resource Development International, 24(2):1-6

Simón, C., & Ferreiro, E. (2017). Workforce analytics: A case study of scholar-practitioner collaboration. Human Resource Management, 57(3), 781-793. https://doi.org/10.1002/hrm.21853

Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of big data challenges and analytical methods. Journal of Business Research, 70, 263-286. https://doi.org/10.1016/j.jbusres.2016.08.001

Steve LaValle, Eric Lesser, Rebecca Shockley, Michael S. Hopkins and Nina Kruschwitz, (2010), Sloan Management Review, December 21, 2010

Stone, D. L., & Lukaszewski, K. M. (2009). An expanded model of the factors affecting the acceptance and effectiveness of electronic human resource management systems. Human Resource Management Review, 19(2), 134-143.

Stone, D. L., Deadrick, D. L., Lukaszewski, K. M., & Johnson, R. (2015). The influence of technology on the future of human resource management, Human Resource Management Review, 25(2), 216-231.

Strohmeier, S. (2007). Research in e-HRM: Review and implications. Human Resource Management Review, 17(1), 19-37.

Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and a path forward. California Management Review, 61(4), 15-42.

Tansley, C., & Newell, S. (2007). A knowledge-based view of agenda-formation in the development of human resource information systems. Management Learning, 38(1), 95-119.

Tanya Bondarouk, Emma Parry & Elfi Furtmueller (2017) Electronic HRM: four decades of research on adoption and consequences, The International Journal of Human Resource Management, 28:1, 98-131, DOI:

Taylor, G. S., & Davis, J. S. (1989). Individual privacy and computer-based human resource information systems. Journal of Business Ethics, 8(7), 569-576.

The DeLone and McLean model of information systems success: A ten-year update. (2003). Journal of Management Information Systems, 19(4), 9-30.

Thomas J, O'Mara-Eves A, Harden A, Newman M. Synthesis methods for combining and configuring textual or mixed methods data. In: Gough D, Oliver S, Thomas J, eds. An Introduction to Systematic Reviews. 2nd ed. London: Sage; 2017: 211-250.

Thong, J. (1999), “An integrated model of information systems adoption in small businesses”, Journal of Management Information Systems, Vol. 15 No. 4, pp. 187-214.

Thong, J.Y.L., Yap, C.S. and Raman, K.S. (1996), “Top management support, external expertise and information systems implementation in small businesses”, Information Systems Research, Vol. 7 No. 2, pp. 248-267

Tursunbayeva, A, Di Lauro, S & Pagliari, C 2018, 'People analytics-A scoping review of conceptual boundaries and value propositions', International Journal of Information Management, vol. 43, pp. 224-247

Ulrich, D. (1997), Human Resources Champions: The Next Agenda for Adding Value and Delivering Results, Harvard Business School Press, Boston, MA.

Ulrich, D., & Dulebohn, J. H. (2015). Are we there yet? What's next for HR? Human Resource Management Review, 25(2), 188-204.

van den Heuvel, S., & Bondarouk, T. (2016). The rise (and fall) of HR analytics: a study into the future applications, value, structure, and system support. Paper presented at 2nd HR Division International Conference, HRIC 2016, Sidney, Australia

Vargas, R., Yurova, Y. V., Ruppel, C. P., Tworoger, L. C., & Greenwood, R. (2018). Individual adoption of HR analytics: A fine grained view of the early stages leading to adoption. The International Journal of Human Resource Management, 29(22), 3046-3067.

Venkatesh, V., Thong, J., & Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. Journal of the Association for Information Systems, 17(5), 328-376.

Wamba, S., Gunasekaran, A., Akter, S., Ren, S., Dubey, R. and Childe, S., 2017. Big data analytics and firm performance: Effects of dynamic capabilities. Journal of Business Research, 70, pp.356-365.

Wang, Y., & Hajli, N. (2017). Exploring the path to big data analytics success in healthcare. Journal of Business Research, 70, 287-299.

Waters, S. D., Streets, V., Johnson-Murray, R., & McFarlane, L. (2018). The practical guide to HR analytics: Using data to inform, transform, and empower HR decisions. SHRM

Wieringa, J., Kannan, P., Ma, X., Reutterer, T., Risselada, H. and Skiera, B., 2019. Data analytics in a privacy-concerned world. Journal of Business Research,. Volume 122, January 2021, Pages 915-925

Wolfe, R., Wright, P. and Smart, D. (2006), "Radical HRM innovation and competitive advantage: the moneyball story", Human Resource Management, Vol. 45 No. 1, pp. 111-126.

Yasmin, M., Tatoglu, E., Kilic, H., Zaim, S. and Delen, D., 2020. Big data analytics capabilities and firm performance: An integrated MCDM approach. Journal of Business Research, 114, pp.1-15.

Figures and Tables

Fig 1: Framework synthesis method

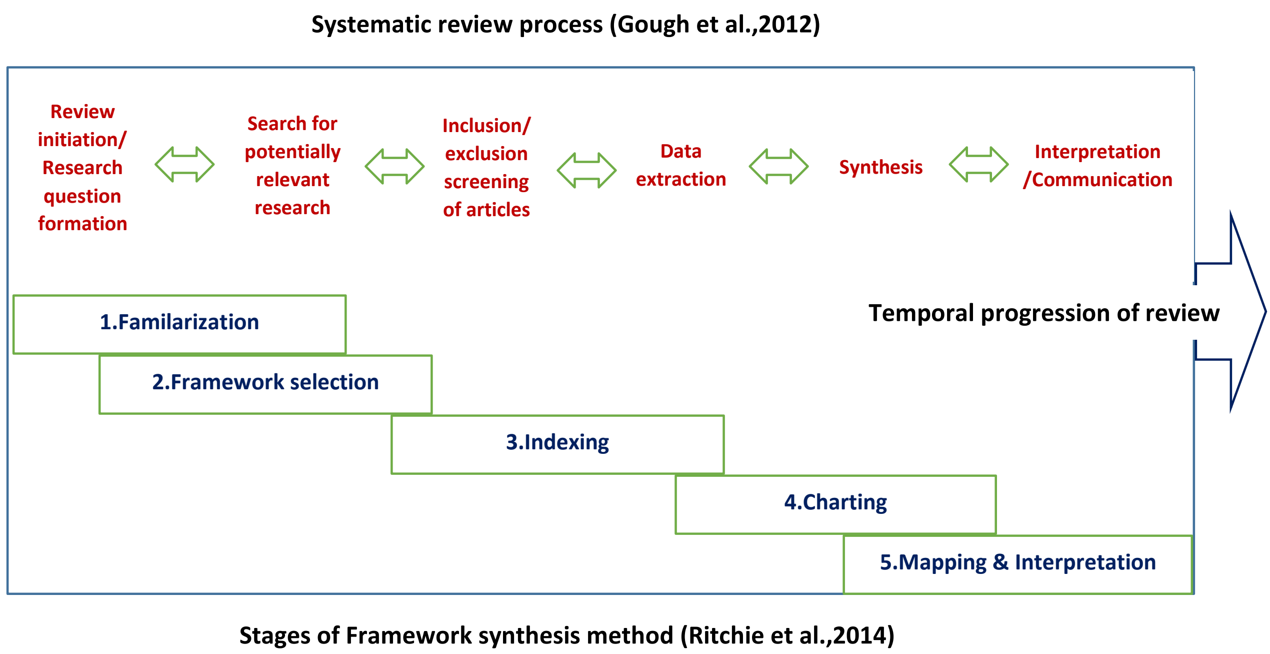

Fig 2 : Framework for Adoption of data analytics in HRM

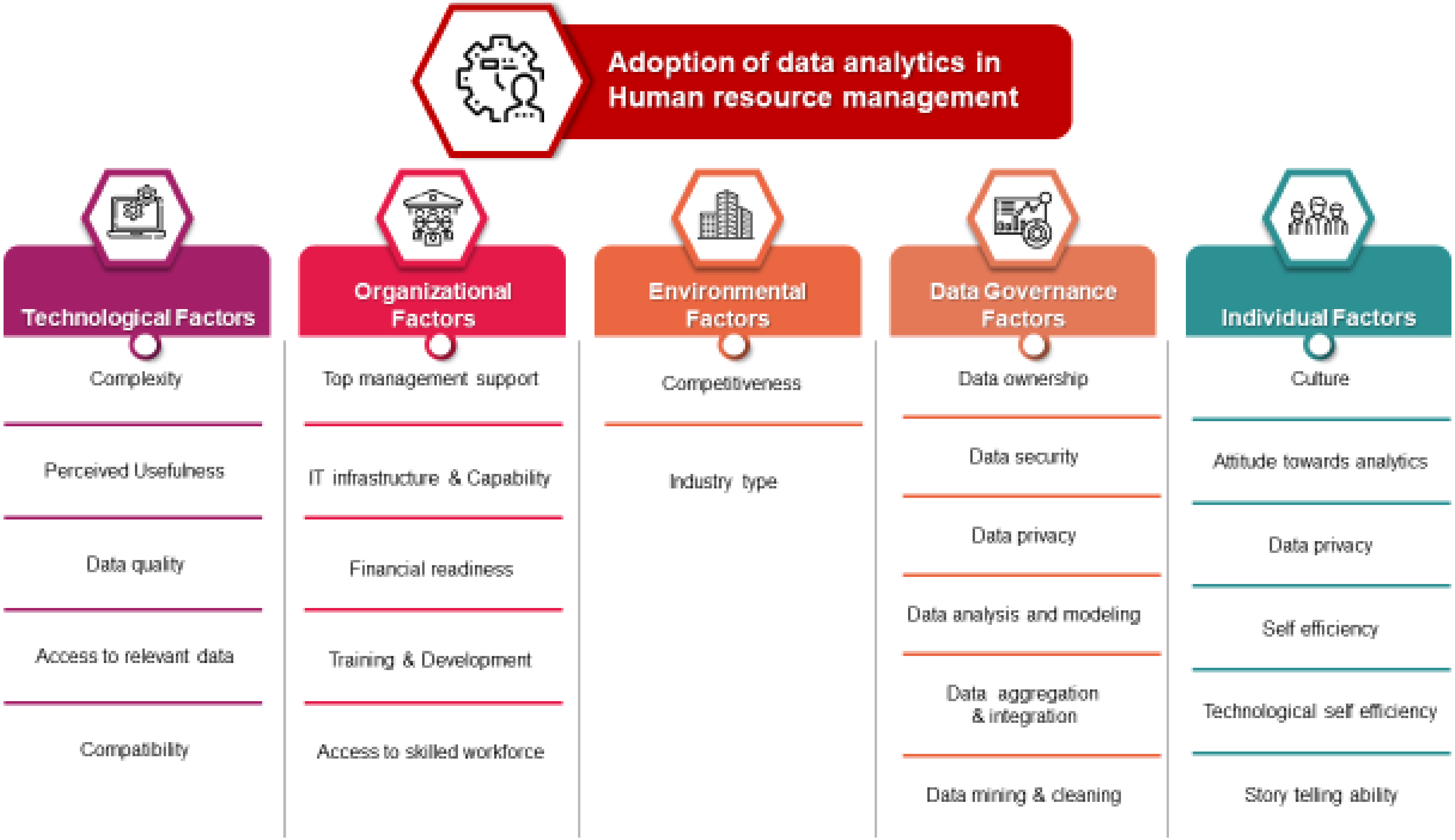

Table 1 : **Human Resource Analytics Challenges Matrix**

HR Analytics Challenges Matrix						
Author	**Challenges**	**Technological**	**Organizational**	**Environmental**	**Data Governance**	**Individual**
Anderson, 2017	Lack of the implementation of good software solutions,	√				
Anderson, 2017	Bad data/lack of proper data				√	
Anderson, 2017	Too few resources		√			
Anderson, 2017	Lack of organization-wide buy-in.		√			
Strohmeier, 2018	Lack of understanding of tools for specific people challenges	√				
Marler & Boudreau, 2017	Lack of understanding of tools for specific people challenges	√				
Huselid,2018	Lack of talent information infrastructure		√			√
Angrave et al., 2016	Lack of strategic understanding of contribution of human capital analytics to business		√			
Marler and Boudreau, 2017	Integration of Data spread across the enterprise		√		√	
Dahlbom, Siikanen & Sajasalo, 2020	Data access				√	
Dahlbom, Siikanen & Sajasalo, 2020	Data piracy				√	
Dahlbom, Siikanen & Sajasalo, 2020	Data security				√	
Dahlbom, Siikanen & Sajasalo, 2020	Ethical issues in data		√		√	
Bondarouk et al. 2017	Include top management support	√				
Bondarouk et al. 2017	User acceptance		√			
Bondarouk et al. 2017	Communication and collaboration between units		√			
Bondarouk et al. 2017	HR skills and expertise		√			√
Bondarouk et al. 2017	Leadership		√			√
Bondarouk et al. 2017	Supportive culture		√			
Kossek et al., 1994	Lack of top management support		√			
Olivas-Lujan et al., 2007	Employees' mindsets					√
Olivas-Lujan et al., 2007	Stakeholder commitment			√		
Cronin et al., 2006	And internal marketing		√			
Panayotopoulou et al., 2007	Communication and collaboration between IT & HR		√			
Tansley & Newell, 2007	Communication and collaboration between IT & HR		√			
Martin & Reddington, 2010	Training					√

Panayotopoulou et al., 2007	Training					√
Marler & Boudreau, 2017	Lack of theoretical development	√				
Marler & Boudreau, 2017	Lack of methodical development	√				
Anderson, 2017	Lack of storytelling ability					√
Boudreau & Casico (2017	Lack of presentation and selling skills on HR analytics					√
Boudreau & Casico, 2017	Struggling to move from operational reporting to analytics.	√	√			√
Pape, 2016	Efficiency and effectiveness		√			
Scullen et al. 2000	Unsynchronized data				√	
Rasmussen & Ulrich, 2015	Integration of HRMS with management data	√	√		√	
Cappelli, 2017	Lack of high quality data				√	
Cappelli, 2017	Lack of analytical capabilities					√
Cappelli, 2017	Techniques for small data	√				
Minbaeva, 2018	Lack of credible team for HCA		√			√
Minbaeva, 2018	Demonstrating value of HCA		√			
Deliotte, 2015	Lack of organizational readiness		√			
Deliotte, 2015	Lack of capability gaps					√
Deliotte, 2015	Poor data quality				√	
Deliotte, 2015	Lack of business case		√			
Lee, 2017	Lack of understanding data architecture				√	
Watson, 2014	Lack of understanding data architecture				√	
Hamilton & sodman,2020	Lack of understanding data architecture				√	
Hamilton & sodman,2020	Data responsibility				√	√
Hamilton & sodman, 2020	Data transmission				√	
Hamilton & sodman, 2020	Data archiving				√	
Hamilton & sodman, 2020	Locating data				√	
Rasmussen & Ulrich, 2015	Should HRA be part of HR or of the central analytics team		√			
Angrave et al., 2016	Lack of capability to gain insights from data for organizational benefits		√			√
Angrave et al., 2016	Incompetence of HR Department		√			√
Angrave et al., 2016	Non credibility of HR department in business vertical		√			
Sivathanu & Pillai, 2018	Integration of Industry 4.0			√		

Sivathanu & Pillai, 2018	Integration of iot			√		
DiClaudio, 2019	Capability of contractor/outsource manpower			√		
DiClaudio, 2019	Integration at the enterprise level		√			
DiClaudio, 2019	Appropriately manipulate data to provide critical evidence and insights for the business	√				√
DiClaudio, 2019	Lack of skilled professionals for data analytics					
DiClaudio, 2019	Individuals who know how to identify problems and address those with business solutions					√
DiClaudio, 2019	Assess potential solutions based on the literature					√
DiClaudio, 2019	Rigorously test solutions can ultimately	√				
Fernandez, 2018	Understanding the bias decision made by AI products	√				√
Fernandez, 2018	Setting up core in HR Technology and Data	√	√			
Green, 2017	Lack of storytelling ability					√
Marler & Bordreau, 2016	Integration with e-HRM and HRIS	√	√			
Martinsons. 1994	Budgetary constraints		√			
Martinsons, 1994	Lack of technically qualified professional or					√
Bondarouk et al., 2017	Supportive leaders,		√			
Bondarouk et al., 2017	Technology adoptive culture,	√				
Bondarouk et al., 2017	And organizational level trust		√			
Boudreau and Lawler, 2015	Unable to move from descriptive to predictive	√	√			√
Fitz-enz& Mattox, 2014	Identification of problem associated with HRA		√			√
Dahlbom, Siikanen & Sajasalo, 2020	Lack of linking matrices from HR to business level		√			√
Minbaeva, 2018	In-house development of HR analytics professionals		√			√
Vargas et al., 2018	Slow rate of adoption of HR Analytics		√			
Rasmussen & Ulrich, 2015	Framing the practical business challenges		√			
Angrave et al..2016	Lack of understanding of algorithms in HR analytics	√				√
Minbaeva, 2018	Lack of understanding of algorithms in HR analytics	√				√
Janssen, van der Voort, & Wahyudi,2017	Lack of research skills for research methodology, including reliability and construct validity(					√
McAfee et al., 2017	Lack of research skills for research methodology, including reliability and construct validity					√
Marler & Boudreau, 2017	Conflict on data and belief				√	√
Tursunbayevaa, Lauroc, & Pagliaria	Ethical issues in data				√	
Fitz-enz, Phillips, & Ray, 2012	Misunderstanding of HR Analytics		√			

Appendix 1. ENTREQ Checklist Enhancing transparency in reporting the synthesis of qualitative research: ENTREQ (Tong et al.,2013) (only for review)

#	**Areas**	**Guide and description**	**Comments**
1	Aim	State the research question that will be addressed by the synthesis.	Synthesing the information on challenges of adoption of HRA and proposing framework for adoption of HRA to address those challenges
2	Synthesis methodology	Identify the synthesis methodology or theoretical framework which underpins the synthesis, and describe the rationale for choice of methodology	Since this research proposes for framework for adoption of HRA, the synthesis framework is more suitable as the process will enable the creation of an HRA adoption framework using a systematic approach.
3	Approach to searching	Indicate whether the search was pre-planned (comprehensive search strategies to seek all available studies) or iterative (to seek all available concepts until their theoretical saturation is achieved).	Search was an iterative process. Since the domain of HRA is multidisciplinary, the knowledge from other domains need to be contextualized. Hence, there is constant search for the emerging HRA contexual knowledge, and this process moves back and forward during the research phase.
4	Inclusion criteria	Specify the inclusion/exclusion criteria (e.g. in terms of population, language, year limits, type of publication, study type).	We used the search terms to test the inclusion criteria for the papers selected for the study.
5	Data sources	Describe the information sources used (e.g. electronic databases—psycINFO, Econlit—grey literature databases—digital thesis, policy reports—relevant organizational websites, experts, information specialists, generic web searches (Google Scholar) hand searching, reference lists), and when the searches are conducted; provide the rationale for using the data sources.	Data were sourced from Scopus, WoS, Google Scholar. Besides, few practitioner reports were considered.
6	Electronic Search strategy	Describe the literature search (e.g. provide electronic search strategies with population terms, terms related to experiential or social phenomena, filters for qualitative research, and search limits).	Since the process was an iterative search, this was continuous and was not a one-time data source generation. This is the advantage of the framework synthesis approach
7	Study screening methods	Describe the process of study screening and sifting (e.g. title, abstract and full text review, number of independent reviewers who screened studies).	Two reviewers were involved in the coding process of challenges. All the papers were screened with title, abstract and key words with draft framework to check the extraction of knowledge from each paper.
8	Study characteristics	Present the characteristics of the included studies (e.g. year of publication, country, population, number of participants, data collection, methodology, analysis, research questions).	Since the research question was focusing on the challenges and adoption factors, we neglected the demographics data and rather concentrated on the challenges and adoption factors.
9	Study selection results	Identify the number of studies screened and provide reasons for study exclusion (e.g. for comprehensive searching, provide the numbers of studies screened and reasons for exclusion indicated in a figure/flowchart; for the iterative searching, give reasons for	Since this study was an iterative search process, we continued with the search throughout the research phase as HRA is an emerging topic

		study exclusion and inclusion based on modifications regarding the research question and/or contribution to theory development).	
10	Rationale for appraisal	Describe the rationale and approach used to appraise the included studies or selected findings (e.g. assessment of conduct (validity and robustness), assess reporting (transparency), asses content and the utility of findings).	Two reviewers were involved in the process independently to establish inter-rate reliability. The coding of challenges was systematically done using spreadsheet
11	Appraisal items	State the tools, frameworks and criteria used to appraise the studies or selected findings (reviewer developed tools; describe the domains assessed: research team, study design, data analysis and interpretations, reporting).	The process of framework synthesis has been explained with the steps undertook.
12	Appraisal process	Indicate whether the appraisal was conducted independently by more than one reviewer and if consensus was required.	Two reviewers
13	Appraisal results	Present results of the quality assessment and indicate which articles, if any, were weighted/excluded based on the assessment and give the rationale.	To maintain the quality, only articles published in Scopus and WoS were used. Only limited consulting practitioner reports were referred to, which are again cited in the previous literature.
14	Data extraction	Indicate which sections of the primary studies were analysed and how the data extracted from the primary studies was? (e.g., all texts under the headings "results /conclusions" were extracted electronically and entered into a computer software).	Only challenges as contents were extracted from each selected paper
15	Software	State the computer software used, if any.	MS Excel for spreadsheet
16	Number of reviewers	Identify who was involved in coding and analysis.	Co researchers
17	Coding	Describe the process for coding of data (e.g. line by line coding to search for concepts).	Explained in the method
18	Study comparison	Describe how were comparisons made within and across studies (e.g., subsequent studies were coded into pre-existing concepts, and new concepts were created when deemed necessary).	Explained in the method
19	Derivation of themes	Explain whether the process of deriving the themes or constructs was inductive or deductive.	Using thematic analysis
20	Quotations	Provide quotations from the primary studies to illustrate themes/constructs, and identify whether the quotations were participant quotations of the author's interpretation.	Using content analysis for challenges identification
21	Synthesis output	Present rich, compelling and useful results that go beyond a summary of the primary studies (e.g., new interpretation, models of evidence, conceptual models, analytical framework, development of a new theory or construct).	Emerging framework out of the challenges to propose framework for adoption of HRA.