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Review

Human Resources Analytics for Public Personnel Management: Concepts, Cases, and Caveats

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Abstract: The advancement of data technology such as machine learning and artificial intelligence has broadened the scope of human resources (HR) analytics, commonly referred to as "people analytics." This field has seen significant growth in recent years as organizations increasingly rely on algorithm-based predictive tools for HR-related decision making. However, its application in the public sector is not yet fully understood. This study examined the concepts and practices of HR analytics through a thematic review, and proposed a five-step process (define, collect, analyze, share, and reflect) for implementation in the public sector—the process aims to assist with the integration of HR analytics in public personnel management practices. By analyzing cases in both the public and private sectors, this study identified key lessons for functional areas such as workforce planning, recruitment, HR development, and performance management. This research also identified the necessary conditions for introducing HR analytics in public organizations, including data management, staff capabilities, and acceptance, and discussed the potential challenges of privacy, integrity, algorithmic bias, and publicness.

Keywords: HR analytics; people analytics; data management; algorithm; talent analytics

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1. Introduction

The qualitative nature of personnel management has often led HR-related decisions to be based on managers' gut feelings, experiences, and intuition (Johnson et al. 2022; Ekka 2021). As the business landscape becomes more competitive and complicated, HR's analytical role in identifying and utilizing top talent becomes more crucial (Rousseau and Barends 2011; Hamilton and Sodeman 2019). Additionally, advancements in technology such as machine learning, cognitive computing technology, and artificial intelligence (AI) allow HR professionals to analyze large amounts of data to address complex HR challenges and make better decisions (Chowdhury et al. 2023; Johnson et al. 2022; Zeidan and Itani 2020).

HR analytics has emerged as a contemporary trend that differentiates it from traditional performance monitoring methods (Isson and Harriott 2016; Pan et al. 2022). Both public and private organizations have implemented HR analytics to assess the effectiveness of their current HR practices (Qamar and Samad 2021), such as recruitment and training programs, and determine if they are contributing to the organization's goals (Coulthart and Riccucci 2022; Momin and Mishra 2015). For example, a study found that 79% of large organizations with over 10,000 employees have data analytics roles in the HR department (Margherita 2021). Furthermore, in the Global Human Capital Trends survey, HR analytics ranked second among emerging HR trends (Tursunbayeva et al. 2021).

Despite high expectations for HR analytics, recent findings suggest that organizations' data analysis capabilities may not be sufficient (Gurusinghe et al. 2021; Van den Heuvel and Bondarouk 2017). For example, in a survey of over 7000 HR professionals from 35 countries, 55% reported needing help with analytics implementation (KIRD 2021). One reason for this gap in capacity may be that organizations are new to advanced HR analytics tools and are facing challenges such as poor data quality and difficulty in building a strong business case for implementation (Llorens 2021; Minbaeva 2018). The public sector has lower levels of adoption of HR analytics compared to the private sector, according to a survey of over 400 government HR leaders, though public sector HR managers agree on the need to develop advanced analytics capabilities (Boston Consulting Group 2016).

The public sector often has a distinct approach to HR management (Brown 2004; Johnson et al. 2022). For example, the public sector may prioritize values such as accountability and transparency, and may face specific challenges such as political interference and budget constraints (Kravariti and Johnston 2020; Pencheva et al. 2020). These distinct nature can influence the adoption and implementation of data-driven analytics in the public sector HR (Chowdhury et al. 2023; Gamage 2016). Therefore, it is important to study the application of HR analytics in the public sector to understand how it can be adapted to fit the specific demands and challenges of the public sector (Plimmer et al. 2019; Sousa et al. 2022). This can help ensure that HR analytics is effectively used in the public sector to enhance personnel management and achieve desired results that are aligned with public interest.

This article begins by examining the definitions, concepts, core components, and process of HR analytics through a thematic literature review. Then, we present cases of HR analytics adoption in real-world situations in order to identify the necessary conditions for implementation. The final section offers key considerations for the successful implementation of HR analytics in public organizations and discusses potential issues and future challenges.

2. Concepts and Definitions

HR analytics aims to support organizations in achieving their strategic objectives through the use of evidence-based HR research (Johnson et al. 2022; Margherita 2021). It involves the systematic identification and quantification of the people drivers of business outcomes, with the purpose of making better decisions that can improve HR practices and organizational performance (Van den Heuvel and Bondarouk 2017). Key elements of HR analytics include an evidence-based approach to people-related decision making, the use of systematic methods of analysis and visualization of HR data, serving the needs of executives and top decision-makers, and being a multi-process and multi-application effort with a wide range of potential impacts (Margherita 2021; Zeidan and Itani 2020). Network technologies such as 5G and IoT can collect various HR data, which can be stored using cloud technology and analyzed efficiently using automation technologies such as machine learning and AI (Raisch and Krakowski 2021; Shrivastava et al. 2018; Chung and Kim 2020). In the public sector, data-driven HRM is a strategic process that aims to improve HR decisions and policies throughout the government by collecting, measuring, and using HR data, while also considering issues such as privacy, security, equity, and ethics (Llorens 2021; OECD 2019).

Scholarly definitions of HR analytics have varied (Tursunbayeva et al. 2018), and the concept itself has gained multiple, somewhat interchangeable labels, such as people analytics, talent management analytics, human capital analytics, algorithm-based HR decision making, and workforce analytics (Nocker and Sena 2019; Leicht-Deobald et al. 2022; Saputra et al. 2022). These different terms all refer to the use of data in HR, but may have different focuses depending on the area of application (Giermindl et al. 2022). Electronic HRM (e-HRM) and HRIS (human resource information systems) also introduce related concepts as they highlight the strategic use of data in people-related decision making. In this study, we use the term "HR analytics" as it is the most commonly used term in recent literature in the field (Margherita 2021).

Common features of HR analytics include advanced technologies for data analysis, the use of various (big) data sources, and the support of strategic decision making. In the public sector, the use of HR analytics is often referred to as data-driven HRM or human governance analytics (Sousa et al. 2022). Falletta and Combs (2021) proposed a definition of HR analytics based on a survey of practitioners from Fortune 1000 companies—this study identified common elements such as metrics, external benchmarks, decision making, value creation, advanced statistical analysis, and data visualization to emphasize that HR analytics is a "process" with interconnected steps (Falletta and Combs 2021). Van den Heuvel and Bondarouk (2017) also characterized HR analytics as a process rather than a tool, arguing that the success of HR analytics practices depends on well-formulated research questions, a strong dataset, and effective analysis (Van den Heuvel and Bondarouk 2017).

In HR analytics, there are several levels of analysis that organizations can progress through as they mature in their use of data and technology (Margherita 2021). These include descriptive analysis, which illustrates the past or current problems; predictive analytics, which seeks to identify potential/future issues; and prescriptive analytics, which guides organizations towards the most effective course of action. While descriptive analysis involves summarizing the current state, predictive analysis uses techniques such as correlation analysis, regression modeling, and structural equation modeling to answer "what-if" questions (King 2016). More advanced data-driven decision making may involve conducting experimental algorithm-based studies to understand how exactly human capital inputs impact organizational performance (Fitz-Enz and John Mattox 2014; Gelbard et al. 2018). Many organizations are still in the process of transitioning from descriptive or predictive to prescriptive analytics, which represents the ultimate goal of fully leveraging data technology in HR (Gelbard et al. 2018; Song and Kim 2020).

3. Process of HR Analytics Implementation

The advancement of algorithm-based HR analytics has distinguished it from traditional performance monitoring in several ways (Johnson et al. 2022). One significant difference is the ability to not only monitor performance data, but also contextual performance factors such as employee engagement and health, as well as employee behavior outside of the workplace. This is made possible through the utilization of novel data sources, including internet browser histories, social media data mining, keystrokes, electronic calendars, and location data from wearable devices (Chowdhury et al. 2023; Sousa et al. 2022; Yang et al. 2021). Additionally, algorithm-based HR decision-making tools have the ability to integrate real-time data from various sources that were previously kept separate, resulting in the creation of consolidated employee profiles. Algorithms have also significantly progressed in their ability to analyze data, with the capacity to be classified as aforementioned descriptive, predictive, or prescriptive approaches (Sousa et al. 2022). These developments have important implications for the extent to which organizations can make informed decisions about the workforce.

Several procedural approaches to implementing HR analytics have been proposed by researchers. One such approach is outlined by Fink (2017), who suggests a seven-step process for creating value and aligning HR analytics with organizational goals: (1) asking the right question, (2) identifying the appropriate method to answer the question, (3) locating or generating necessary data, (4) effectively analyzing the data, (5) developing insights from the analysis, (6) taking action based on those insights, and (7) measuring the results to determine the effectiveness of the action. Song and Kim (2020) propose a six-stage process: (1) prioritizing goals, (2) establishing logic, (3) gathering data, (4) preprocessing data, (5) analyzing data, and (6) making decisions—this process emphasizes the importance of preprocessing data, including cleaning and standardizing data formats, as a separate step.

Green (2017) introduced an eight-step model for HR analytics that focuses on stakeholder buy-in: (1) framing business questions, (2) building hypotheses, (3) gathering data, (4) conducting analyses, (5) revealing insights, (6) determining recommendations, (7) communicating the point effectively, and (8) implementing and evaluating. Falletta and Combs (2021) also prioritize stakeholders in their HR analytics cycle, which includes (1) determining stakeholder requirements, (2) defining the HR research/analytics agenda, (3) identifying data sources, (4) gathering data, (5) transforming data, (6) communicating intelligent results, and (7) enabling strategy and decision making. IBM presents its own four levels of HR analytics: (1) setting the direction, (2) defining the approach, (3) growing capability, and (4) implementation—IBM's model emphasizes cultivating organizational competency for HR analytics (Seo et al. 2020; Tursunbayeva et al. 2018).

Other conceptualizations emphasize specific procedural elements of HR analytics. Deloitte Insights (2018) organized its six-step process around big data smart principles focused on intra-organizational consensus: agree on customer objectives, identify relevant data, design analysis framework, implement analytics, allocate resources, provide feedback and reflect insights into the business process. Margherita (2021) highlighted three drivers (input, process, and output) for HR analytics implementation—in this model, "input" refers to the availability of a vast amount of integrated HR data of various sources and types, "process" includes the adoption and development of advanced analytics technologies, and "output" features the design of value-added HR metrics and advanced visualization/reporting systems (Margherita 2021). Klimoski et al. (2016) drew a clear, logical connection between the analysis target and the expected result—their LAMP (Logic, Analysis, Measure, and Process) framework consists of logic (the story that connects numbers and outcomes), analysis (drawing the right conclusion), measure (using the right numbers), and process (using data to influence decisions).

Figure 1 summarizes the five common elements of the HR analytics process as suggested by the literature. The first step ("Define") is to define the problem and subject of analysis clearly. The second stage ("Collect") is sourcing, collecting, and securing appropriate data. In the third stage ("Analyze"), the relevant analytical framework is implemented. The fourth step ("Share") involves sharing the insights derived from the analysis results with members of the organization through storytelling. The final step ("Reflect") is decision making and implementation based on the analysis results. As the ultimate goal of HR analytics is to support an organization's strategic decision making, all steps should be accompanied by meaningful actions and genuine feedback.

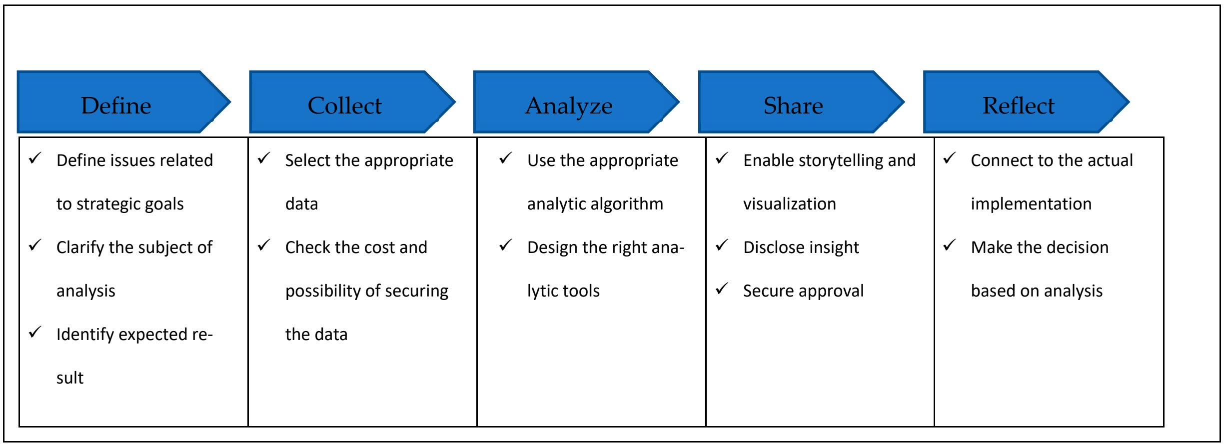

Figure 1. Common Elements of HR Analytics Processes.

In the "Define" stage of the HR analytics process in the public sector, it is important to clearly identify the problem and subject of analysis. This involves understanding the specific organizational issues that need to be addressed in the public sector, taking into account the unique nature of the government organizations. HR analytics should consider factors such as the goals of the public organization, the needs and expectations of citizens and other stakeholders, and the legal and regulatory environment in which the organization operates. They should also think about the expected results of the HR analytics process, including how the insights and recommendations generated through the process will be used to improve public personnel management and support the government's overall mission.

In the “Collect” stage of HR analytics, the focus of data collection in HR analytics may differ between the public and private sectors due to the different priorities of these organizations. Public sector organizations are often driven by a mission to serve citizens and the broader community, and as a result, they may place a greater emphasis on data related to citizen needs and taxpayer satisfaction. In contrast, private sector organizations are typically more focused on maximizing profits and shareholder value, and as a result, they may place a greater emphasis on data related to financial performance, such as profit margin or return on investment. However, it is important to note that the specific focus of data collection will vary depending on the needs of each organization; therefore, it is crucial for HR analytics in the public sector to carefully consider the specific data needs of their organization and to work with relevant stakeholders to identify and collect the appropriate data. It is also important to ensure that the data are collected and stored in a secure and confidential manner, in compliance with any relevant privacy laws and regulations. Collection process should ensure that the data is available in a usable format, considering a variety of factors, including quality of data, systems or technologies used to collect and store the data, or a standardization in data collection processes.

In the “Analyze” stage of HR analytics, the relevant analytical framework is implemented by selecting the appropriate algorithm and designing the effective predictive tools to ensure accurate and meaningful analysis. HR analytics in the public sector should consider the specific goals and needs of their organization when selecting the algorithm and tools, ensuring that they are suitable for the type and volume of data being analyzed and capable of providing the desired level of detail and accuracy. HR analysts in the public sector may consider partnering with external vendors or developing in-house expertise through training and development programs (Johnson et al. 2022). Public organizations must exercise caution and carefully evaluate the possibility of algorithmic biases and detrimental effects associated with the utilization of HR analytics during the analysis phase.

The “Share” stage of HR analytics in the public sector involves the communication of insights and recommendations derived from the analysis to internal management and external stakeholder. To do this, HR analytics should use clear and simple language and provide context and background information to help managers understand the significance of the insights. Data visualization and other tools, such as charts, graphs, and infographics, can be effective in illustrating the results and their implications for the organization in a visually appealing and easy-to-understand manner. It is important for HR analytics to tailor their storytelling approach to the specific needs and goals of the public organization and to consider the challenges and opportunities facing the organization, as well as the benefits and implications of the insights for different stakeholders.

The “Reflect” stage of HR analytics in the public sector involves using the insights and recommendations from the analysis to inform decision making and drive meaningful change within the government organization. HR analytics should identify specific actions that can be taken based on the insights generated by the analysis. This may involve implementing new policies or procedures, reorganizing HR departments or teams, or making changes to the way that HR services are delivered. It is important to develop and implement plans for monitoring and evaluating the effectiveness of the changes. It is also important to be proactive in seeking various feedback throughout the implementation process, and to be open to adapting and refining the plans based on this feedback. Predictive insights can be useful in the public sector, but they may need to be implemented through changes to laws and policies; therefore, it is important to secure stakeholder support especially when it requires legislation.

4. Cases

There is a growing interest in HR analytics as more public and private organizations are adopting data-driven approaches into their work processes (Chowdhury et al. 2023; Johnson et al. 2022). Some organizations focus on improving specific HR processes, while others aim to directly link HR analytics to overall organizational performance improvement

(Llorens 2021; Margherita 2021). This section examines a number of public and private cases of HR analytics adoption, yielding lessons broadly classified into four functional areas: workforce planning, HR development, recruitment and selection, and performance improvement.

4.1. Workforce Planning

There has been a significant increase in the amount of information available about the workforce planning efforts of public sector organizations, especially as these organizations have become aware of the potential loss of labor and skills due to the retirement of the baby boomer generation (Llorens 2021; Sousa et al. 2022). As a result, they have begun conducting workforce planning to anticipate the impact of this potential employee exodus and to identify, as accurately as possible, what their future workforce should look like and how to bridge the gap between the present and the future (Anderson 2004).

Various organizations have implemented workforce planning models that often include supply/demand analysis, gap analysis, and solution analysis (Johnson et al. 2022). These steps are conducted with the goal of aligning the organization's workforce with its strategic direction and ensuring that the right people are in the right jobs at the right time (Berman et al. 2021). The implementation of workforce planning in the public sector can vary, including centralized and decentralized or hybrid approaches, mandatory and elective processes, one-time and ongoing or institutionalized efforts, and dynamic and static approaches (Anderson 2004). There has also been a significant amount of sharing and exchange of methods, practices, and procedures among jurisdictions, with many central government agencies such as the United States Office of Personnel Management and the Texas Office of Planning and Budget providing guidelines, techniques, and tools for their constituent agencies to use in developing workforce plans. Predictive HR analytics can be used to forecast potential workforce shortages by analyzing long-term trends (OECD 2019). Workforce planning includes creating a comprehensive long-term HR plan, forecasting recruitment needs, developing succession plans, enhancing promotion and transfer processes, and decreasing employee turnover (Momin and Mishra 2015; Ekka 2021).

The Australian Public Service (APS) is a well-known example of a public sector organization that uses HR analytics to forecast workforce demand and supply and create a long-term workforce planning strategy. The APS has shifted from a focus on operational processes to a capacity-building approach with the introduction of their Workforce Planning Capability Development Programme, which assesses the capabilities of workforce planning practitioners within each institution to enhance their "analytics and insight" skills (Australian Public Service Commission 2021). By improving the competency of practitioners responsible for workforce planning, the APS is reported to secure talent with analytical abilities, a necessary condition for introducing HR analytics.

A case study using Australian public sector workforce datasets analyzed the changing proportions of ethnic employees, employees with disabilities, and Aboriginal people in each salary band and identified implications for promoting diversity and cultivating talent for future leadership (Ghosh et al. 2016). Similarly, the Public Service Commission of the state of New South Wales in Australia has adopted a data-driven approach to designing and monitoring progress on diversity and inclusion policies (OECD 2019). Based on this analysis, the Commission set the goal of increasing the ratio of women in senior roles by 50% by 2025. These cases demonstrate how quantitative analytics data can enhance the legitimacy of social goals of public organizations.

The Mexican Ministry of Energy implemented a workforce planning program to identify skills gaps in the oil and gas industry over a ten-year period. To do this, they analyzed economic variables such as oil prices and exchange rates that have a strong impact on the demand and supply of skilled labor. The program used HR analytics identify current and future skills gaps in the industry. By providing the Mexican government with evidence of these skill gaps, the Ministry of Energy was able to increase the likelihood of stakeholder investment in national workforce planning initiatives (OECD 2019). Additionally, the program allowed the Ministry of Energy to address labor issues outside the organization, by identifying and addressing skills shortages in the industry.

The private sector offers many examples of the use of HR analytics in workforce planning. Cisco utilized natural language processing (NLP) and predictive modeling techniques to establish strategic talent planning—through these processes, they identify the skills needed to achieve strategic goals and then decide how to "buy, build, and borrow" these talents based on job market data, recruitment announcements at other companies, and expert interviews. For example, when analysis showed the value of user experience (UX)/user interface (UI) skills, Cisco secured appropriate specialists through upskilling and reskilling methods (KIRD 2021). Similarly, Coca-Cola Enterprises analyzed various data sources, including the HR system, the case management system for the service center, and onboarding/recruitment tools, to segment tasks by skill set—this allowed Coca-Cola Enterprises to create a natural talent development pipeline and ensure the right skill set was assigned to the appropriate task (CIPD 2013).

To mitigate the cost of employee turnover, some large corporations have used predictive analytics of HR data to model "flight risk" (Nocker and Sena 2019; Saputra et al. 2022). Arellano et al. (2017) studied a global quick-service restaurant chain that analyzed each employee's personality and cognitive skills through psychometric assessments and monitored employee behavior and collaboration through sensors. The company classified frontline employees into four clusters/archetypes and found that career development and cultural norms had a stronger impact on the turnover rate than compensation. This use of HR analytics enabled the company to increase customer satisfaction, service speed, and sales performance and significantly reduce attrition among new joiners (Arellano et al. 2017). Other companies, such as Credit Suisse and BBVA USA, used NLP tools to analyze survey feedback from active and former employees and managers to identify the causes of high turnover at specific branches. Based on the results, these companies established an action plan to improve compensation structure and onboarding training, seemingly reducing their turnover rates.

4.2. Human Resource Development

HR analytics can be a valuable tool for improving staff training and development and supporting organizational learning (Johnson et al. 2022). By analyzing data on employee skills and competencies, organizations can identify training needs and develop targeted programs to address them. HR analytics can also be used to evaluate the effectiveness of training programs and identify patterns in employee learning, which can help organizations optimize their delivery. For example, HR analytics is a powerful tool that allows both public and private organizations to identify and support top performers through targeted development programs. This application allows organizations to nurture and support top-performers through appropriate HR development programs, such as opportunities for specialization (Hamilton and Sodeman 2019). Through this process, the organization can identify appropriate career paths and training programs for younger and newly recruited employees based on the accumulated data of high, or hyper, performers.

IBM has implemented a number of HR analytics tools to assist with employee development and career advancement (Tursunbayeva et al. 2018). One such tool is a personalized learning platform that uses real-time data to identify skill gaps between organizational needs and employee capabilities, as well as appropriate trainings to address these gaps (Seo et al. 2020). This use of HR analytics can encourage employees to take the initiative to address their own skill gaps and continuously improve their skills and competencies. To further support ongoing professional development, IBM offers Your Learning, a platform that uses AI and Watson cognitive technologies. Your Learning provides tailored learning to each learner based on their goals, needs, and interests, and helps optimize the learning process by ensuring that learners have access to the most relevant and effective learning materials (Tursunbayeva et al. 2018). In addition, IBM Watson Career Coach is a virtual assistant that aligns an employee's career goals with the goals of the organization—it does this by learning about the employee's preferences and interests through interactions and updates, and making recommendations for existing job opportunities and how to navigate future career moves. Watson Career Coach can help employees map out their career path and build the skills they need to progress in their career, empowering them to take control of their career development while helping organizations retain and develop their existing talent.

Lockheed Martin, a global aerospace and defense company, uses HR analytics to understand the relationship between employee training and performance in order to identify top performers and the most effective training programs. To further leverage people analytics, the company created the position of Senior Staff People Analytics & Technology. This staff member is responsible for managing the design and implementation of analytic solutions, analyzing operational activities to inform HR decision making, and creating datasets for analysis using mathematical and statistical methods. They also provide consultation to clients and may lead cross-functional teams to address HR issues. This position reports to the Senior Manager and works closely with HR functional organizations to understand human capital needs, determine the long-term technical strategy and roadmap, and integrate data from various sources for HR development purposes (Klimoski et al. 2016).

The South Korean government's national HR development intelligent open platform is a public sector example of the use of HR analytics in employee training (Kim 2021). Using big data technology, AI analytics, and deep learning tools, this platform utilizes various data sources such as individual personnel data and learning history to customize employee-specific training content for public organizations from a catalog of over 500,000 items. A data-driven approach allows civil servants to more easily skip unnecessary trainings, prepare better for their current roles, and search for future career opportunities (Hur et al. 2019). The use of HR analytics in this way may reduce the time and cost of training programs while improving both performance and employee satisfaction.

4.3. Recruitment and Selection

HR analytics has been increasingly used in the recruitment and selection process in recent years as a way to improve the efficiency and effectiveness of finding and hiring the best candidates for positions (Johnson et al. 2022; Seo et al. 2020). By analyzing various data sources on past recruitment and selection processes, HR analytics can identify trends and patterns that can inform future recruitment and selection strategies (Llorens 2021; Pan et al. 2022). Tools such as chatbots, screening software, and automation tools, have become commonplace in the industry and are being used to streamline various recruitment and selection tasks (Albert 2019).

One specific application of HR analytics in recruitment and selection is the use of data-driven job matching (Albert 2019). By analyzing data on the characteristics, skills, and experiences of successful candidates for particular positions, HR analysts can develop more accurate job descriptions and personas that can help to attract the most qualified candidates. This can increase the chances of finding the best candidates for open positions. Data-driven job matching can also help to improve the overall quality of hires by ensuring that candidates are a good fit for the role and the organization.

Another application of HR analytics in recruitment and selection is the use of predictive analytics (Shrivastava et al. 2018). In the context of recruitment and selection, this could involve predicting which candidates are most likely to be successful in a particular role based on their characteristics, qualifications, and past performance. By using predictive analytics, HR professionals can more accurately target their recruitment efforts and prioritize the most promising candidates, saving time and resources that might otherwise be spent on less qualified candidates (Albert 2019).

Unilever, a leading company in the field, utilizes HR analytics in their recruitment process by collecting and analyzing applicant data from LinkedIn profiles through the use of machine learning technology. These data include predicting an applicant's behavior, attitude, and job-related aptitudes. The feedback from this analysis is then provided to the applicant within 48 h. In addition, Unilever also incorporates AI during interviews to evaluate the content of responses, facial expressions, emotion levels, and truthfulness of the interviewee, comparing them to the ideal candidate for the specific job. The incorporation of HR analytics helps the organization make evidence-based and job-specific hiring decisions, rather than relying on subjective evaluations.

Watson Recruitment is a tool developed by IBM that uses artificial intelligence (AI) to assist with the recruitment process. It allows HR departments to quickly analyze the organization's entire employment history, combining that information with external data sources to determine the key attributes desired for an open position. Watson Recruitment can then scan applicants using AI to identify the most appropriate candidates for the next stage of the recruitment process. The Watson Candidate Assistant is another tool developed by IBM that is designed to help facilitate the latter part of the recruitment process—it uses AI to analyze candidates' CVs, qualifications, and work experience, and match the right person to the most appropriate role.

Additionally, IBM utilizes chatbots on its recruitment platform, which are then analyzed through natural language processing (NLP). When IBM uses chatbots on its recruitment platform, the chatbot interacts with the applicant through the platform, asking questions and receiving responses in natural language (Tursunbayeva et al. 2018). The responses are then analyzed through a process called natural language processing (NLP), which is a type of artificial intelligence that allows computers to understand, interpret, and generate human language. NLP algorithms are used to analyze the text of the responses, extracting meaning and identifying patterns and trends. These data are then used to make decisions or predictions, such as whether the applicant is a good fit for the job or is likely to be a successful employee.

Rolls-Royce, a British luxury automobile maker, has replaced their traditional assessment methods with a shorter, more engaging assessment tool based on data analytics, which effectively identifies the most talented and highest potential candidates. Opower, a software company, also uses predictive HR analytics to determine the optimal number of interviewers and interviewees for a hiring panel (Nocker and Sena 2019). These cases demonstrate that the implementation of HR analytics tools in the recruitment process can streamline hiring decisions, reduce costs, and assist HR departments in selecting the right individuals for the organization.

HR analytics can be used to assist in the selection of candidates also for leadership positions (Saputra et al. 2022). The data can come from a variety of sources, such as employee surveys, performance reviews, awards, e-mail records, social media data, approved documents, and performance evaluation comments. By processing and coding this data, organizations can identify the traits and behaviors that are most important for a successful leader in their organization. For example, Google's Project Oxygen used employee data and performance reviews to identify eight desired traits for manager leadership (Gelbard et al. 2018), which were then used as a guide for the roles and responsibilities of managers (Shrivastava et al. 2018). POSCO, a steel-making company, used the BEI (behavioral event interview) technique and analyzed e-mail records and other sources of unstructured data to evaluate the performance feedback behavior of leaders and identify the optimal behavior for team building (Kim et al. 2020)—they have also attempted to address the classical principal-agent problem (or information asymmetry) between its board members and HR department with the implementation of an automated recommendation system for manager hiring. To do this, they analyzed ten years of structured and unstructured HR data, including personality analysis, educational background, performance review data, formal qualifications, language proficiency, and work-related awards. They used this analysis, along with supplemental surveys on skills and experience, to rate candidate fit for each position and identify priority candidates. Studies have found that POSCO's system has increased board member satisfaction with hiring decisions and reduced the workload of the HR department (Kim 2021; Seo et al. 2020).

4.4. Performance Improvement

Traditionally, employee performance has been evaluated through periodic reviews, but these methods have been known to have shortcomings, such as cognitive bias and inaccuracy (Johnson et al. 2022). Utilizing HR analytics tools, however, may offer a more comprehensive and fair evaluation of employee performance on a continuous basis (Charbonneau and Doberstein 2020). These tools can gather more extensive samples of an employee's work, reducing the workload for managers and providing ongoing feedback and predictions (Llorens 2021). By analyzing large amounts of data, such as keystrokes, pauses, employee communications, and other digital exhaust, using natural language processing, the technology can identify areas that require attention, such as rewards, sanctions, or further analysis (Cappelli et al. 2020). Additionally, real-time "micro-learning" modules can be provided to help improve performance (Johnson et al. 2022). By using data-driven insights, HR analytics may pinpoint areas that need improvement and create strategies to boost the productivity and capabilities of both individual employees and teams. Working closely with managers and employees, they can implement new processes, systems, and foster a positive work environment that encourages professional development for all staff.

Amazon, an American e-commerce tech company, implemented several HR analytics programs in recent years to better understand and engage with its workforce. One such program is "Connections," a daily feedback program that utilizes pop-up surveys to gather information about employee perceptions of the work environment. This includes data on the appropriateness of meeting times, the frequency of positive feedback, and other factors that may impact employee satisfaction and productivity. The data collected through Connections are used to identify areas for improvement in the company's culture and to inform changes that may enhance the work experience for Amazon employees. In addition to Connections, Amazon has also introduced "Forte," a data-driven employee review program that aims to streamline the review process and emphasize employee strengths. This program is designed to provide a more positive and constructive review experience for employees, rather than focusing solely on areas for improvement. Both Connections and Forte have been implemented in an effort to address Amazon's reputation as a demanding workplace, which was publicized in a New York Times article that depicted employees crying at their desks due to a lack of work–life balance.

Other organizations use HR analytics to capture "sentiments," or feedback, in order to improve workplace culture, which has been shown to be closely related to organizational performance (Gelbard et al. 2018). For example, Coca-Cola Enterprise (CCE) has started using HR analytics to track and analyze sentiment within the organization and identify strengths and weaknesses in workplace culture, such as the correlation between leaders' communication styles and business outcomes (CIPD 2021). CCE has used engagement data to create the majority of its HR insights and is now increasing the level of insights developed through the use of longitudinal data to track sentiment within the organization. CCE is also working on building analytics capability within HR, focusing on building a strong foundation in data literacy and analytics within HR and partnering with other teams to leverage their expertise in data management and analysis.

JP Morgan Chase, an American multinational financial services company, is using data analytics to improve its workforce and business performance. The Global Head of Workforce Analytics has been building the bank's analytics team over the past years to analyze data and make informed decisions about the workforce. The team also focuses on maintaining a balance between meeting the demand for analytics from the business and prioritizing their work, as well as using data ethically and in compliance with privacy laws. The goal of the workforce analytics team at JP Morgan Chase is to use data to enhance the employee experience and drive business success. To achieve this goal, the bank has implemented the "Workplace Activity Data Utility" (WADU), a data collection platform that monitors employee activities such as attendance, calls, and calendars. However, some employees have expressed concerns about the system and have taken steps to avoid detection, such as using a "mouse jiggler" to prevent the virtual workspace from timing out due to inactivity.

Sentiment analysis can help organizations identify triggers for employee dissatisfaction, particularly in regard to organizational culture, and inform efforts to address issues in a timely manner (Gelbard et al. 2018; Saputra et al. 2022). There are various sources of data that organizations can use to gather sentiments for HR analytics. One common method is through surveys or focus groups, where employees are directly asked for feedback on their experiences and perceptions within the company. However, it is important to consider any ethical issues that may arise when collecting and analyzing sentiments data (Gelbard et al. 2018). For example, employees may be concerned about their privacy if they feel that their responses are being monitored or tracked. In order to address these concerns, it is important for organizations to have clear policies and processes in place to protect employee privacy and ensure that the data collection and analysis is conducted in an ethical manner. Another source of sentiments data is social media, where employees may express their opinions and experiences informally (Gelbard et al. 2018; Deng et al. 2021). While this can provide valuable insights, it is important to consider the potential for misinformation in this type of data (Drage and Mackereth 2022). Additionally, there may be privacy concerns if employees are not aware that their social media activity is being monitored or analyzed by the organization (Chansukree et al. 2022). Another potential source of sentiments data is email or other internal communication channels (Gelbard et al. 2018). However, emails may contain sensitive or confidential information that should not be shared outside of the organization such as HR analytics vendors. In order to address these concerns, organizations may need to implement appropriate safeguards and processes to protect employee privacy and ensure that the data collection and analysis is conducted ethically.

4.5. Case Synthesis

Table 1 synthesizes the findings from the above cases. The four general application areas for HR analytics in the public and private sectors (workforce planning, HR development, recruitment/selection, and performance improvement) are organized by analysis objective(s), types of data used, and the resulting insight (see Table 1).

As shown in Table 1, in the area of workforce planning, HR analytics can be used to identify skill gaps and verify whether the right people are placed in the right positions. It can also be used to retain top performers by analyzing labor market data, work portal documents, and individual profile data such as employment information, personal details, educational background, and work history. Employee behavior and collaboration data collected by sensors can also be used to improve workforce planning. Insights gained from the use of HR analytics in this area include essential skills for performance and long-term workforce supply and demand plans. In the area of HR development, HR analytics can be used to identify training needs and assess the effectiveness of current training programs by analyzing training content and individual training history, as well as performance appraisal data. Insights gained from the use of HR analytics in this area include automated and individualized training recommendations, as well as the correlation between training and performance. In the area of recruitment and selection, HR analytics can be used to efficiently and timely recruit talented applicants and nudge desired manager behaviors. This can be achieved by analyzing CV data, social media data, AI-assisted interview data, job market data, past candidates' recruitment information, employee surveys, and email records. Insights gained from the use of HR analytics in this area include person-job fit of applicants, performance predictions, hiring process improvements, and desired manager competencies and traits. In the area of performance improvement, HR analytics can be used to analyze HR factors influencing organizational outcomes and detect employee sentiment related to performance. This can be achieved by analyzing administrative data, turnover data performance appraisal data, financial statistics, external/internal social media data, and anonymous bulletin board data. Insights gained from the use of HR analytics in this area include understanding performance-inducing HR factors and negative elements affecting employee satisfaction.

Table 1. Case Synthesis: Applications of HR Analytics.

	Analysis Objective	Types of Data Used	Resulting Insights
Workforce Planning	▪ Identify skill gaps ▪ Verify whether the right people are placed in the right position ▪ Retain top performers	▪ Labor market data ▪ Work portal documents ▪ Individual profile data (employment information, personal detail, educational background, work history, performance reviews) ▪ Employee behavior and collaboration data collected by sensors	▪ Essential skills for performance ▪ Long-term workforce supply and demand plan
HR Development	▪ Identify training needs ▪ Check the effectiveness of current training programs	▪ Training content ▪ Individual training history ▪ Performance appraisal data	▪ Automated and individualized training recommendation ▪ Correlation between training and performance
Recruitment and Selection	▪ Recruit talented applicants in efficient and timely manner ▪ Nudge desired manager behaviors ▪ Expanding the candidate pool	▪ CV data ▪ Social media data ▪ AI-assisted interview data ▪ Job market data ▪ Past candidates' recruitment information ▪ E-mail records	▪ Person-job fit of the applicant ▪ Performance prediction ▪ Hiring process improvement ▪ Desired manager competencies and traits
Performance Improvement	▪ Analyze HR factors influencing organizational outcomes ▪ Detect employee sentiment related to performance	▪ Administrative data ▪ Turnover data ▪ Employee surveys ▪ Performance appraisal data ▪ Financial statistics ▪ Pop-up questions data ▪ External/internal social media data ▪ Anonymous bulletin board	▪ Performance-inducing HR factors ▪ Negative elements affecting employee satisfaction

5. Conditions Necessary for Adopting HR Analytics

The literature has identified certain conditions necessary for the successful utilization of HR analytics in an organization's HR decision-making processes (Chowdhury et al. 2023; Gelbard et al. 2018; Johnson et al. 2022; Peeters et al. 2020; Minbaeva 2018; Dahlbom et al. 2020; Marler and Boudreau 2017). These necessary conditions can be grouped into three main categories: data management, staff capabilities, and acceptance. Data management refers to the systematic collection and organization of data, ensuring its quality and integrity. Staff capabilities include having skilled analysts and technical capacity to perform HR analytics (Albert 2019; Cho et al. 2021). Acceptance refers to the organization-wide adoption of HR analytics, including culture that leverages evidence-based decisions, the involvement of various stakeholders and the linking of HR analytics with current and future strategy discussions (Dahlbom et al. 2020; Gurusinghe et al. 2021; Im et al. 2012).

5.1. Data Management

Proper data management, including securing data for analysis, ensuring data quality, and building data governance, is critical for the successful adoption and implementation of

HR analytics and for its contribution to organizational strategic goals (Gelbard et al. 2018; Johnson et al. 2022). An organization must be able to define its purpose for undertaking HR analytics and collect data fit for analysis: inaccurate data may make the analysis results unreliable and misinform decision making (Llorens 2021; Seo et al. 2020). Data may be drawn from various sources, and may be structured, unstructured, longitudinal, cross-sectional, qualitative, and/or quantitative (Peeters et al. 2020).

Peeters et al. (2020) suggested three causes of low data quality. First, a database that is poorly integrated may produce out-of-date or faulty data. Second, data are often the result of human input, which can be incorrect or incomplete. Finally, a single concept may have various data definitions in different areas (divisions or subsidiaries) (Nocker and Sena 2019; Peeters et al. 2020). These drivers of low data quality illustrate the need for systematic and integrated data management.

Effective data governance requires the integration of not only HR department data but also internal and external data to solve data silo issues (Sousa et al. 2022). The public sector often faces particular challenges to data integration, as its data may be scattered across separate, often siloed, organizations with differing formats. According to a survey, 25–30% of the total time invested in analysis is spent on data cleaning due to the lack of integration. In order to address these data quality problems, it is necessary not only to standardize the data format but also to build data governance into the HR analytics platform. Data governance ranges from developing a more comprehensive system in partnership with other organizations (e.g., finance, payroll, and other human resources data) to managing organizational data in an integrated manner (Nocker and Sena 2019; Levenson and Fink 2017). To avoid the negative effects of data silos, the government authorities must establish sector-wide formal guidelines for data standardization and systematic data management across departments and/or agencies (Bodie et al. 2017): the recent move towards the whole-of-government approach may work well to address the public sector's data management issues in HR analytics.

5.2. Staff Capabilities

The successful adoption of HR analytics requires the presence of specialists with advanced data analysis skills (Gurusinghe et al. 2021; Johnson et al. 2022; Green 2017). Minbaeva (2018) identified key competencies such as the ability to measure variables, build causal models, test them correctly, and tell a compelling story, with an emphasis on the ability to present consistent and persuasive outcomes through analysis. Nocker and Sena (2019) proposed that analytical competencies include basic multivariate models, advanced multivariate models, data preparation, research design, and quantitative data collection and analysis, with the most valuable tool being the ability to analyze complex relationships among variables and extract useful meaning for the organization. Falletta and Combs (2021) defined seven competencies of a world-class HR analytics team: good data, storytelling, business acumen, visualization techniques, psychology skills, expertise in statistics, and change management. At the core of these various framework is the ability to explain insights from the analysis in a way that non-specialists can easily understand (Pan et al. 2022).

In addition to analytical skills, the literature suggests that storytelling and understanding overall workflows are important but often undervalued staff capabilities in the context of HR analytics (Gurusinghe et al. 2021). Storytelling is essential for sharing insights with relevant stakeholders, particularly top management, in a way that is intuitive and persuasive (Hamilton and Sodeman 2019; Kim et al. 2023). Storytellers should ask themselves three questions: What do you want your audience to know? How do you want your audience to feel? What do you want your audience to do? (Levenson and Fink 2017). HR analysts should be able to integrate advanced reporting, visualization techniques, and dashboards of people-related metrics with business KPIs to effectively convey insights and persuade their audience (Gelbard et al. 2018; Margherita 2021). Additionally, analysts must have a deep understanding of the broader business context and workflow in order to develop a detailed model of the "why" question, which can serve as an analytical framework for data collection (Minbaeva 2018). This institutional knowledge can ensure that analysis results address the real solution, such as improving organizational processes or performance (Zeidan and Itani 2020).

However, securing analytic talent can be difficult. A McKinsey report estimated that the United States alone could face a shortage of 140,000–190,000 workers with “deep analytical skills,” as well as a deficit of 1.5 million managers and analysts with the know-how to analyze big data and leverage it for effective decision making (Klimoski et al. 2016). Careful recruitment of employees with analytical backgrounds in HR, combined with training on data literacy, can do much to strengthen the analytical capabilities of organizations (Patre 2016).

In the public sector, building staff capabilities in HR analytics can be challenging due to a number of factors (Llorens 2021). One issue is the lack of a clear career progression path for data scientists in government, making it difficult to attract and retain top talent (OECD 2019). Additionally, the public sector may face constraints on resources, including funding and time, which can limit the ability to invest in training and development for staff (Chowdhury et al. 2023; Nocker and Sena 2019). Another challenge is the need to build a culture that values the use of data and evidence in decision making, which can be difficult to change in traditional bureaucratic organizations (Minbaeva 2018). According to Coulthart and Riccucci (2022), a significant divide exists between public sector employees who regularly use data in their work, such as investigators and front-line agents, and those who do not. To address these challenges, the public sector can take a number of steps. One option is to create dedicated positions for data scientists, as has been achieved by the U.S. Office of Personnel Management and Global Affairs Canada. Another option is to invest in training and development programs, such as the Fast Stream program in the UK Civil Service, to build the necessary skills among existing staff. When public organizations lack formal expertise in data science, leaders should seek out the informal knowledge networks of their employees to access analytical insights (Coulthart and Riccucci 2022).

5.3. Acceptance

The adoption and implementation of HR analytics within an organization are not just about having the right technical skills and resources, but also about ensuring that the organization is ready and willing to embrace this new way of making decisions (Gelbard et al. 2018). One crucial aspect of this readiness is the organization’s culture and values (Johnson et al. 2022). It is important that HR analytics is aligned with and supportive of these, as it will be more likely to be accepted and integrated into the organization’s decision-making processes. Therefore, HR professionals should take the time to understand the culture and values of their organization, and consider how HR analytics can be used to support and enhance these (Llorens 2021). By aligning HR analytics with the values of the organization, HR professionals can increase the chances of successful adoption and implementation of HR analytics.

All relevant stakeholders must understand and support the use of data-driven approaches in HR decision making, including senior management, who must provide the necessary resources and support (Tursunbayeva et al. 2021; Peeters et al. 2020; Minbaeva 2018). Some executives may view the process as a threat to their authority, so it is important for all stakeholders to agree that evidence should be seen as an aid to human judgement rather than a replacement (Klimoski et al. 2016). Line managers, who handle essential data and directly impact human capital, productivity, and firm performance, may see HR departments’ data usage as a pretense for workforce reduction (Albert 2019; Hamilton and Sodeman 2019). As HR departments have the exclusive authority to access and manage sensitive HR data, they may have a complex relationship with other departments in terms of political and competitive power within the organization (Gelbard et al. 2018; KIRD 2021). To address these strained relations, the HR analytics team should provide sufficient information to line managers and gather sufficient feedback before implementation (Peeters et al. 2020). Employees, as the primary providers of data, must also be convinced of the importance of data collection and analysis. Some employees may be motivated to distort or sabotage data collection if they perceive that data-driven initiatives are not aligned with their interests (Hamilton and Sodeman 2019). The analytics team should empower employees to better understand the importance of their work and become familiar and comfortable with the data analysis process (Hamilton and Sodeman 2019).

Acceptance of HR analytics in the public sector can be particularly challenging due to the bureaucratic culture and norms that exist within these government organizations. Public sector organizations often have hierarchical structures and established ways of doing things, which can make it difficult to introduce new approaches such as HR analytics. HR analytics is likely to conflict with the existing organizational culture in the public sector—this use of big data requires a shift in both existing processes and workplace culture (Allen et al. 2020; Llorens 2021). Public sector agencies, with their dependence on long-established norms, may find the change more jarring than their private counterparts (Zeidan and Itani 2020). Additionally, the values and norms of the public sector, such as transparency and accountability, may conflict with the data-driven HR decision making. In order to successfully adopt HR analytics in the public sector, it is important for management to consider the organizational readiness for this technology. This includes understanding the culture and values of the organization, ensuring that all relevant stakeholders are involved and supportive of HR analytics, and aligning HR analytics with existing decision-making processes and strategies.

One way to ensure the support and cooperation of various stakeholders in the adoption of HR analytics is to establish an HR analytics task force (Nocker and Sena 2019; Pan et al. 2022). This approach was taken by the LEGO Group, a Danish toy production company, when they noticed a decrease in their net promoter score (E-NPS) in their annual pulse survey, which threatened their organizational culture. In response, the company formed a task force consisting of employees from HR, business-unit management, and corporate management (Minbaeva 2018). This task force solicited the opinions of a variety of stakeholders, including the owning family, and used data analysis to identify the root cause of the problem. By involving various stakeholders in the analysis agenda-setting stage and collecting a wide range of opinions, the analysis team can gain a more thorough understanding of the organization's challenges and deliver more meaningful insights.

In addition to establishing an HR analytics task force, public sector management should focus on informing employees about the benefits and importance of HR analytics, and empowering them to understand and become familiar with the data analysis process (Chowdhury et al. 2023; Im et al. 2014). Coulthart and Riccucci (2022) propose that public organizations should set up small teams, referred to as "skunk works", to experiment with data technologies, and that leadership should coordinate this trial-and-error process in partnership with front-line employees who can make the technology more relevant to their needs. By addressing the unique challenges and considerations of the public sector, and ensuring that all relevant stakeholders are involved and supportive of HR analytics, public sector management can increase the chances of successful implementation of HR analytics.

5.4. Synthesis: Conditions Identified

Actions to facilitate the three necessary conditions for HR analytics (data management, staff capabilities, and acceptance) can be grouped according to the three overarching aspects identified above: IT infrastructure, culture, and institution (see Table 2).

In the area of data management, IT infrastructure actions include creating a high-quality, integrated database environment and implementing analytics tools for big data. Cultural actions involve seeking consensus on the necessity of data collection and management and fostering a positive attitude towards data sharing. Institutional actions include establishing guidelines for data format standardization and regulations for data quality management and data sharing.

Table 2. Necessary Conditions for the Adoption of HR Analytics by Action Item.

	IT Infrastructure	Culture	Institution
Data Management	▪ Build the integrated database ▪ Connect the data system for interoperability ▪ Establish the analytics tools for big data processing	▪ Reach consensus on the necessity of data collection and integration ▪ Cultivate positive attitude for data sharing	▪ Formulate the guideline for data format standardization ▪ Establish regulations for data quality management and data sharing
Staff Capabilities	▪ Design the training program for improving the digital literacy ▪ Position data experts in each division as well as the HR department	▪ Give autonomy to data analysis staff ▪ Tolerate trial and error/failure	▪ Define the analysis competency ▪ Implement the hiring process for the right talent ▪ Offer reasonable compensation package for data experts
Acceptance	▪ Disclose the analysis process and outcome in a transparent manner ▪ Form task force as HR analytics agent	▪ Reflect insights on decision-making ▪ Leverage top management support ▪ Cultivate collaboration between silos	▪ Institutionalize data engagement ▪ Share best practices ▪ Give incentives for analytics adoption

To enhance staff capabilities, IT infrastructure actions include providing training programs to improve digital literacy and positioning data experts in various departments. Cultural actions include empowering data analysis staff to innovate and tolerating trial and error/failure. Institutional actions involve defining analysis competencies, implementing a hiring process for skilled data scientists, and offering competitive compensation packages.

To gain acceptance of HR analytics, IT infrastructure actions include disclosing the analysis process and outcome transparently and establishing a task force to act as an HR analytics agent. Cultural actions include incorporating insights into decision making, gaining top management support, and fostering collaboration between silos. Institutional actions involve institutionalizing data engagement, sharing best practices, and offering incentives for analytics adoption.

6. Caveats for Public Sector Adoption

Public sector organizations have begun to adopt data analytics for HR purposes (Johnson et al. 2022), though it is important to consider the unique challenges and ethical considerations that may arise in this context. While technology firms and business consultants may present a largely positive view of the benefits of data analytics (Giermindl et al. 2022; Leicht-Deobald et al. 2022), public sector organizations should carefully evaluate the potential impacts and consequences of these tools (Zuiderwijk et al. 2021). This may include considering issues of privacy, transparency, power imbalance, algorithmic bias and accountability, as well as the broader social and cultural implications of implementing novel technologies in the public sector (Kim et al. 2022; Llorens 2021). As with any new technology, it is crucial for public sector organizations to approach the adoption with caution, ensuring that they have appropriate policies and processes in place (Albert 2019; Choi et al. 2020; Otto 2018). While all organizations may face obstacles to the effective adoption of HR analytics, these barriers are especially impactful in the public sector.

The potential benefits of utilizing algorithm-based HR analytics, such as increased objectivity and efficiency in the decision-making process, have made it a popular tool in various industries including the public sector. However, it is important to recognize that these algorithms are not immune to biases (Alon-Barkat and Busuioc 2023; Drage and Mackereth 2022). Research has shown that HR algorithms can be influenced by biases present in the data used to train them, leading to the perpetuation of inequalities and discrimination (Gal et al. 2020; Leicht-Deobald et al. 2022). For example, Drage and Mackereth (2022) suggested that efforts to eliminate the influence of gender and race in AI systems are misguided as they fail to comprehend the true nature of gender and race and instead, treat them as independent characteristics rather than complex and pervasive social systems that shape power dynamics. This is particularly concerning in the public sector, where the use of these algorithms can raise questions about the alignment with the public interest.

As the complexity of the task increases, it becomes harder to understand how AI-assisted analytics tolls arrived while this is particularly important in the realm of HR where decisions about rewards and adverse actions are made (Johnson et al. 2022). In these cases, it is crucial for there to be algorithmic accountability, which means being able to explain and justify the decisions that were made by HR analytics—for example, school teachers in Texas successfully sued their school district after experiencing negative consequences from an analytics-based performance evaluation system that was not able to be explained (Johnson et al. 2022). Therefore, it is crucial that organizations carefully consider the potential biases and negative impacts of algorithm-based HR analytics before implementing them in the public sector. To mitigate these biases, public organizations can use diverse and representative datasets, implement fairness metrics and explainability techniques, and engage in ongoing dialogue with stakeholders.

The use of HR analytics has also been linked to decline in organizational trust and increased tension between compliance and integrity in the workplace. Algorithms used for HR analytics can create a power imbalance between management and employees, leading to decreased feelings of autonomy and control (Giermindl et al. 2022). It is important for organizations to consider the potential negative effects of HR analytics on employee well-being and commitment, as well as the potential impacts on personal integrity, which refers to the consistency between one's self-image and expected behavior in a particular role (Leicht-Deobald et al. 2022).

HR analytics practices are likely to spark privacy/security concerns over the personal information of civil servants. In particular, many organizations develop digital tracking systems that collect audio, geolocation, accelerometer, and other data from employees throughout their workday (Hamilton and Sodeman 2019; Sovova et al. 2017). Employees may be concerned about compromised privacy or the feeling of being surveilled (Gumzej 2021; Tursunbayeva et al. 2021). Some jurisdictions have legislation that protects employees' privacy—for example, the EU's General Data Protection Regulation safeguards "high-risk" data, or those most likely to threaten the rights and freedoms of individuals (OECD 2019).

Additionally, data collection should be limited to job-related purposes (Tursunbayeva et al. 2021), though this distinction may be unclear in the public sector. A less controversial approach may be the use of real-time data sources to track actual employee output (Bodie et al. 2017; Cho and Melisa 2021; Hamilton and Sodeman 2019). HR analytics practitioners should understand which approaches to data storage, access, or analysis are permitted in their jurisdiction, and acknowledge the co-dependencies between technologies, laws, and attitudes about what data should and should not be protected (Tursunbayeva et al. 2021).

Public organizations should recognize the importance of human judgment and moral imagination in HR decision making, rather than relying solely on these algorithm-based tools (Raisch and Krakowski 2021; Tursunbayeva et al. 2021). The use of HR analytics in the public sector can be problematic if there is a blind faith in the accuracy and objectivity of these algorithms. Research has shown that technology-based decision making can lead to an "illusion of control," causing decision-makers to overestimate their own effectiveness and leading to inflated performance evaluations (Alon-Barkat and Busuioc 2023; Giermindl et al. 2022). This belief in the superiority of data-based decisions can also contribute to a "one size fits all" approach, where rules are blindly followed without considering the context or specific goals of an organization (Leicht-Deobald et al. 2022). This can undermine trust and discourse between individuals within an organization and replace trust in human capacities with a reliance on technology-based compliance (Giermindl et al. 2022).

Additionally, the belief in the infallibility of these algorithms can be risky, as machine errors are often more dramatic and have more unpredictable outcomes compared to human mistakes (Giermindl et al. 2022; Leicht-Deobald et al. 2022). For example, Amazon shut down an applicant screening system that inappropriately excluded qualified women applicants because the data showed that the overwhelming majority of successful hires had previously been men (Reuters 2018). Additionally, tests to confirm the personality or aptitude of candidates in the process of promotion and recruitment can overlook moral character and cultural or ethnic differences (Raisch and Krakowski 2021). These ethical issues can arise if the HR analytics implementation process lacks transparency: to address them, organizations must develop and publish clear guidance in the form of an ethical charter. For example, Kakao, an IT company, publishes principles to increase trust and transparency during the HR analytics process, including prohibitions on associating data with the reputation of an individual or organization and on employee discrimination (KIRD 2021). Such principles should be communicated up front, along with the purpose of the analysis and the expected impacts on employees.

To effectively apply HR analytics in public sector organizations, it is critical to understand the nature of publicness in government agencies (Llorens 2021; Sagarik et al. 2018). The HR policies of public organizations are often constrained by more legislation and regulations than those in the private sector (Johnson et al. 2022; Kim and Cho 2014). In some jurisdictions, strict rules govern layoffs, promotions, and the use of performance-based compensation and other incentives. In addition, public agencies may have little freedom to move people into different positions or locations (OECD 2019), and are often more siloed than their private sector counterparts. The complexity of organizational structure in the public sector can make it difficult to collaborate with relevant ministries/agencies or external vendors as required in the HR analytics process (Johnson et al. 2022; Zeidan and Itani 2020). Meanwhile, successful deployment of HR analytics requires a certain level of investment and time, which may be obstructive for public agencies due to their budget constraints and politically oriented timeframes (Anderson 2004; Cho 2017; Green 2017).

7. Conclusions

HR analytics may offer opportunities for algorithm-based decision making in real time through predictive technology and automation. This data-driven process can contribute to enhancing the organization's performance, but it also may help secure acceptance and justification for the automated decision making itself. Private sector firms have led the practice of HR analytics up to this point, though public organizations have begun to introduce the concept, calling for a closer look at its nature and challenges within the field of public administration. Using a thematic literature review on HR analytics, this article explores concepts, cases, and caveats in applying HR analytics in public sector organizations.

This analytics tool may be used to focus and inform workforce planning, position management, HR development, recruitment, selection, and workplace culture. One of the essential elements for the successful introduction of HR analytics is data management, which integrates and links data and maintains adequate data quality. In addition, it is necessary to develop staff capabilities with expertise in data technology. Efforts are needed to support key stakeholders, and top management, line managers, and employees should be included in the adoption of the new analytics process. In the public sector, special attention should be paid to privacy/security issues, ethics of algorithms, power imbalance and the publicness of government organizations.

This study is based on early observations with only anecdotal evidence available, as the use of HR analytics in the public sector is still in the early stages. This means that more research is needed to fully understand the nature and challenges of HR analytics in the public sector. Future research should aim to collect rich empirical evidence from different cases to assess the success factors of new technology adoption. This could include a variety of research methods such as case studies, surveys, and experiments. Additionally, it would be useful to consider a range of different public sector organizations to gain a more comprehensive understanding of the potential benefits and challenges of HR analytics in this context.

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