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*Original Research*

# Hot Topics and Directions of Human Resource Analytics Based on a Hybrid Method (Bibliometric Analysis, Fuzzy Delphi Method and SWARA)

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## Abstract

Due to the emergence of big data during the recent decades, data analytics played an important role in organizations, especially in human resource management (HRM). Despite increasing attention to data analytics in HRM, there is still a gap in this research scope. According to the dispersion of existing relevant studies, this study aimed to reveal the hot topics, as well as the future directions of this field. Therefore, the present study utilized a hybrid method based on bibliometric analysis (co-word analysis), Fuzzy Delphi, and SWARA (Step-Wise Weight Assessment Ratio Analysis) and evaluated 87 articles from the Scopus database. The co-word results extracted a total of 40 keywords, and then the indicators were measured according to experts' opinions and the fuzzy Delphi method (FDM) and were prioritized using the SWARA method. Based on the analysis results, HR analytics and human resource data analytics are the most important cases, and then people analytics, human capital analytics, workforce analytics, data analytics, big data, analytical competencies, predictive HR analytics capability, and HR analyst are ranked third to tenth. The top 6 keywords for future directions are strategy, HR processes, big data, competencies, technology, and evidence.

**Keywords:** Co-word Analysis, Fuzzy Delphi Method, Hot Topics, Human Resource Analytics, SWARA.

## Introduction

Many organizations utilize data about individuals to make decisions about the workforce. The emergence of digitization and the availability of huge volumes of data have helped the use of analytics to solve various business problems (Chen, Chiang & Storey, 2012). Therefore, an increasing volume of literature has found the importance of data-based decision-making and analytics that significantly affect the business world (Davenport & Dyché, 2013; Tan, Zhan, Ye & Chang, 2015; Tiwari & Raju, 2022). Additionally, the emergence of technologies such as artificial intelligence, machine learning, data mining, and the Internet of Things (IoT) (Margherita, 2021) has accelerated the increasing demand for the use of various tools related to data analytics in HRM and can efficiently analyze people-related data for advanced decision-making (Marler & Boudreau, 2017; Arora, Prakash, Dixit, Mittal & Singh, 2022). It has also developed studies that have led HRM toward the science of data-based decision-making about human capital. Meanwhile, data-based decision-making has not yet significantly affected HRM because it has already affected other business functions such as marketing and finance (Boudreau & Ramstad, 2005). However, companies such as Google emphasize a data-based approach to workforce decision-making (McCartney, Murphy & Mccarthy, 2021) because they consider human resource analytics beyond the utilization of criteria in human resources and assume it as an evidence-based approach, including statistical methods and techniques that analyze the effects of HR activities to make better data-based decisions to improve organizational performance (Marler & Boudreau, 2017). However, human resource analytics is still in its early stage (Fernandez & Gallardo-Gallardo, 2021; Falletta & Combs, 2021) because there are many issues, for example, the slower speed of adoption (Angrave, Charlwood, Kirkpatrick, Lawrence & Stuart, 2016), insufficient attention among management researchers (Marler & Boudreau, 2017), and many controversies that still exist about human resource analytics that are sometimes considered as a management fad (Rasmussen & Ulrich, 2015). However, others believe that human resources rarely deal with the concept of big data, and thus the use of human resource software, hence, the big data analytics expertise is impractical in human resource management (Cappelli, 2017). Even though organizations have understood the importance of human resource analytics and its potential strategic effect, there is still an unclear picture of human capital inputs that are necessary for the effective implementation of human resource analytics (Huselid, 2018). There is still a misconception about the use of HR analytics in HRM, and thus the lack of clarity on the reasons, that prevent its adoption and implementation, hinders the progress of HR analytics. Therefore, questions about the successful implementation of HR analytics in organizations remain unanswered. To this end, the present research provides further insight into the HR analytics literature that may be useful for HR professionals to better implement this technology. Additionally, it addresses the concerns raised by researchers (Marler & Boudreau, 2017) to conduct more scientific empirical research on human resource analytics.

This research aimed to study three premises. First, investing in Human Resource Analytics (HRA) is a strategic move toward HRM. HRA will be of significant value when the HR function has become a strategic function (Angrave et al., 2016; Minbaeva, 2018). Even though HRA is considered a must-have tool in HRM, there are significant gaps in how its application affects the company's strategic function (Suoniemi, Meyer-Waarden, Munzel, Zablah & Straub, 2020). Second, Kozielski (2019) found that companies, especially companies in developing countries, are skeptical about the application of data and its benefits in HRM. There is also a significant gap regarding the lack of sufficient attention from researchers and academics to data analytics in HRM (Marler & Boudreau, 2017) in understanding how organizations can use HRA to influence organizational results (McIver, Lengnick-Hall &

Lengnick-Hall, 2018; Schiemann, Seibert & Blankenship, 2018; Huselid, 2018). Third, although there are bibliometric studies in the field of HRA, such as Arora et al., (2022) and Abellán-Sevilla and Ortiz-de-Urbina-Criado (2023), however, these studies lack a deep examination of the link between knowledge structure in presenting current issues and future directions of the application of HRA in specific areas of HRM.

According to Su, Yu and Zhang (2020), quantitative and qualitative approaches provide a systematic overview of human resource analytics studies to discover the shortcomings of the present study and future directions and developments scientifically and accurately. Therefore, this research recommends a hybrid method based on bibliometric analysis, fuzzy Delphi, and SWARA. Bibliometric analysis (co-word analysis) is implemented to analyze the general state of the published literature and reveal key research issues. The fuzzy Delphi technique is used to identify vital indicators from experts' judgments due to the complexity and diversity of this issue, and finally, SWARA is utilized to prioritize the indicators. The results are also utilized to explore hot topics and future research directions of HR analytics. The main objective is to determine trends for improving future studies.

There are two contributions in this study, encompassing (1) useful directions for future studies suggested by, founded on a review relating to extant literature, providing bibliometric status relating to human resource analytics, and (2) the decisive matters in need of further investigations are identified for both scholars and practices.

## Literature Review

The concept of data-driven HR, often referred to as HRA, was introduced in 1984 when Dr. Jac Fitz-enz proposed metrics that could measure the impact of HR function on the organization (Marler & Boudreau, 2017). Then, this concept was referred to as people analytics. The term has since been used under various names, but it was only in the 21st century that the phenomenon gained attention. Since then, there has been an exponential increase, and the variety of names for the topic reflects its emergent nature (ibid). Names such as HR analytics, talent analytics, workforce analytics, and human capital analytics have been used. HRA refers to an evidence-based approach to making better decisions about people and business that includes a range of tools and technologies from simple reporting of HR metrics to predictive modeling (Bassi, 2011). Van den Heuvel and Bondarouk (2017) defined HRA as the systematic identification and quantification of the people who drive business results intending to make better decisions. Marler & Boudreau (2017) argued that it is a defined action that uses Information Technology (IT) and descriptive, visual, and statistical analyses of data related to HR processes to influence business and enable data-driven decision-making. HRA is a proactive and systematic process for the ethical collection, analysis, communication, and application of Evidence-Based Human Resource (EBHR) research and analytical insights to help organizations achieve their strategic goals (Falletta & Combs, 2021). The above definitions emphasize that HRA (1) is a tool that improves the decision-making efficiency of managers; (2) it is a systematic method for analyzing and visualizing data for HR purposes; (3) it is an evidence-based approach to employee issues.

The literature identifies three types of analytics that describe the maturity level of HRA in organizations, starting from descriptive analytics to predictive analytics and prescriptive analytics (Fitz-Enz & Mattox, 2014; Fitz-Enz, 2009). Descriptive analytics answers the question: What happened in the past? Descriptive analytics is conducted using various measurement tools for primary reporting, including tools generated from mobile and cloud-based software applications (Fitz-Enz & Mattox, 2014). Predictive analytics answers this question: What will happen? Why will it happen? How will it happen? Predictive analytics can be used to make evidence-based predictions about future results (Edwards & Edwards, 2019; Fitz-Enz & Mattox, 2014). Finally, prescriptive analytics uses the findings of predictive analytics to prescribe specific actions and predict organizational changes (Hunt, 2014).

The literature review of several qualitative studies, such as Chalutz Ben-Gal (2019), Margherita (2021), Tursunbayeva, Di Lauro and Pagliari (2018), and Marler and Boudreau (2017), revealed that they have played a vital role in shaping this field. Margherita (2021) conducted a systematic literature review to outline the concept of HRA and identify and categorize important topics in HRA and identified 106 key research topics related to three main areas, namely, HRA empowerment, applications, and value. Chalutz Ben-Gal focused on Return on Investment (ROI)-based analysis of HRA. The results of the study showed that experimental and conceptual studies in HRA generate more ROI compared to technical and case-based studies. In addition, the results showed that workforce planning and recruitment and selection are the two HR functions that have the highest ROI. Marler and Boudreau (2017) conducted an evidence-based review and focused on the definition of HRA, how and why it works, HRA results, and its effective moderators, and concluded that despite the evidence that links HRA to organizational function, the adoption of HRA is very low. In addition, King (2016) provided a review of the supportive and critical literature on HRA, discusses university involvement in the implementation of analytics practices, and uses a case study to illustrate how quantitative tools may positively impact HRM and HR development. Using a hybrid framework approach, Shet, Poddar, Samuel & Dwivedi (2021) first identified challenges that hinder HRA implementation and then developed a framework to explain various factors that influence HRA adoption in organizations. This study identifies key aspects related to technical, organizational, environmental, data governance, and individual factors that influence HRA adoption. Thakral, Srivastava, Dash, Jasimuddin & Zhang (2023) systematically reviewed the literature to identify active research areas, created a roadmap for future studies in HRA, and identified four categories of HRA research areas, namely HR functions, statistical techniques, organizational results, and employee characteristics.

## Materials and Methods

In the present study, data were extracted from the Scopus database, the largest interdisciplinary electronic database that is widely used by many researchers in different fields, especially social sciences, for bibliometric analysis (Zhu & Liu, 2020; Donthu, Kumar & Pattnaik, 2020). The following keywords in the field of "Business, Management, and Accounting" from 2010 to 2023 were used to retrieve data from the Scopus database: "Human resource analytics", "People analytics", "Workforce analytics", "human capital analytics", "data analytics in human resource management (HRM)", and "talent analytics". The search was limited only to publications in English and resulted in 136 initial results. The final database contained 87 articles after screening for irrelevant items. The search strategy is shown in Figure 1.

This study examined the publication trends of the HRA over the last 13 years, from 2010 until 2023. In this study, we did not set the initial data for the first papers indexed in the Scopus database. Consequently, 2010 was the initial publication year indexed in Scopus. The search strategy for hot papers was as follows:

TITLE-ABS-KEY ( "Human resource analytics" OR "Human resources analytics" OR "HR analytics" OR "Data analytics in human resource management " OR "People analytics" OR "Workforce analytics" OR "Human capital analytics" OR "Talent analytics" ) AND ( LIMIT-TO ( SUBJAREA , "BUSI" ) ) AND ( LIMIT-TO ( DOCTYPE , "ar" ) OR LIMIT-TO ( DOCTYPE , "re" ) ) AND ( LIMIT-TO ( PUBSTAGE , "final" ) ) AND ( LIMIT-TO ( SRCTYPE , "j" ) ) AND ( LIMIT-TO ( LANGUAGE , "English" ) )

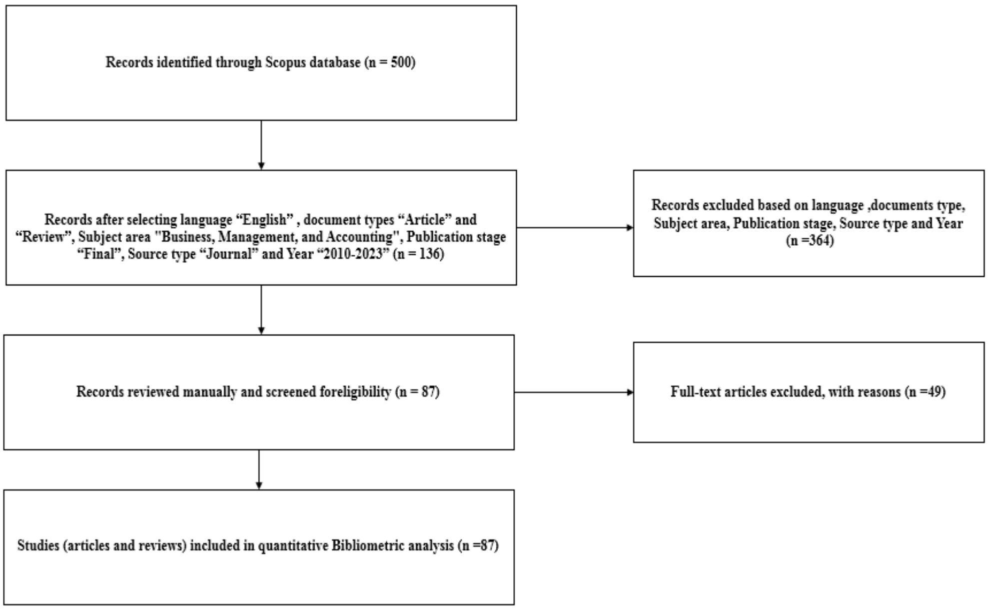


*Figure 1: Selection Strategy and Research Protocol*

First, data analysis was performed using bibliometric analysis (co-words analysis) and VOSviewer software to classify the themes of human resource analytics. Keywords, simultaneous frequencies, and clustering of keywords were reviewed to indicate themes for future studies. Thereafter, the fuzzy Delphi technique screened the indicators. There is no precise mechanism to identify the number of people or panels in each study. It is usually recommended to use a mix of people with multiple expertise. Furthermore, heterogeneous groups are better than homogeneous ones. Powell (2003) holds that 6 out of 12 members are ideal for the Delphi technique. According to Schmidt (1997), 5-10 members are sufficient if a combination of experts with different expertise is used. Somerville (2008) holds that less than 10 members are considered in some Delphi studies. In this study, the fuzzy Delphi technique was used to screen and identify the final indicators according to 15 experts (experts and academics in data science and HRM), and purposive sampling was conducted. Even though experts utilize their competencies and mental abilities to make comparisons, it is worth noting that the traditional process of quantifying people's views cannot fully reflect the human thinking style. In other words, the use of fuzzy sets is more compatible with linguistic, and sometimes ambiguous human explanations, and it is thus better to use fuzzy sets (fuzzy numbers) to make long-term predictions and make decisions in the real world (Kahraman, 2009). Therefore, this study triangular fuzzy numbers used to fuzzify the experts' views. The experts' opinions about the importance of each index were collected and fuzzified according to the 7-degree fuzzy spectrum of Table 1.

*Table 1*
*The 7-Degree Fuzzy Spectrum of Indicator Evaluation*

| Linguistic Variable | Fuzzy Scale |
|---|---|
| Absolutely Unimportant | (0.0,0.0,0.1) |
| Unimportant | (0.0,0.1,0.3) |
| Slightly Unimportant | (0.1,0.3,0.5) |
| Neutral | (0.3,0.5,0.7) |
| Slightly Important | (0.5,0.7,0.9) |
| Important | (0.7,0.9,1.0) |
| Absolutely Important | (0.9,1.0,1.0) |

First, the expert's opinions were collected about the importance of each indicator and were fuzzified with the scale in Table 1. Thereafter, the expert's opinions should be aggregated. Various methods have been proposed to aggregate the views of n respondents. These aggregation methods are experimental and have been presented by different researchers. The fuzzy mean method was used in this study.

Equation 1: Fuzzy arithmetic mean

$$F_{AVE} = \left(\left\{\frac{\sum l}{n}\right\}, \left\{\frac{\sum m}{n}\right\}, \left\{\frac{\sum u}{n}\right\}\right)$$

The aggregation of mean triangular and trapezoidal fuzzy numbers can be usually summarized by a definite value that is the best corresponding mean. This operation is called de-fuzzification. The centroid method according to an equation proposed by Tzeng and Tang (1993) was used for de-fuzzification in this study.

Equation 2: De-fuzzification by the centroid method

$$DF_{ij} = \frac{[(u_{ij} - l_{ij}) + (m_{ij} - l_{ij})]}{3} + l_{ij}$$

Furthermore, the Step-Wise Weight Assessment Ratio Analysis (SWARA) was used to determine the weights of indicators of hot topics and future directions in human resource analytics. SWARA is a new multi-criteria decision-making method introduced by Keršuliene, Zavadskas & Turskis (2010). This method is used to calculate the weights of indicators. Evaluating the weights of indicators is important in multi-criteria decision-making (MCDM). SWARA is a weighing method in which the expert's opinion is very important. In this method, experts first sort the indicators in order of importance. The most important index is placed first and gets a score of one. Finally, the indicators are ranked based on average values of relative importance. Fuzzy SWARA (F-SWARA) works like SWARA, in other words, it can be used to calculate the weights of indicators that are also fuzzy. This method was introduced by Mavi, Goh & Zarbakhshnia (2017). In this study, the method presented by Perçin (2019) was used for F-SWARA. Based on the fuzzy spectrum in Table 2, each expert's opinion about the relative importance of the indicators was fuzzified. When the opinion of several experts is used, the fuzzy arithmetic mean (Equation 1) is used to aggregate the experts' opinions. In the third step, the coefficient of value ($K_j$), fuzzy weight, and final weight of the indicators are measured. The $K_j$ coefficient is obtained as follows:

Equation 3: Estimation of the coefficient of value

$$K_j = \begin{cases} \tilde{1} & j = 1 \\ S_j + \tilde{1} & j > 1 \end{cases}$$

The fuzzy number 1 ($\tilde{1}$) has a value of (1, 1, 1).

The initial weight of indicators $(Q_j)$ is calculated by Equation 2. It should be noted that the weight of the first indicator, the most important indicator, is considered equal to 1.

Equation 4: Estimation of initial weights of indicators

$$Q_j = \begin{cases} \tilde{1} & j = 1 \\ \dfrac{K_{j-1}}{K_j} & j > 1 \end{cases}$$

In the last step, SWARA is used to measure the final weights of the indicators as the normalized weights according to Equation 5. Normalization is done using a simple linear method.

Equation 5: Normalization by simple linear method

$$W_j = \frac{\tilde{Q}_j}{\sum \tilde{Q}_j}$$

The coefficient of value, initial weight, and final normal weight are estimated after measuring the mean opinion of the experts. Finally, the calculated weights should be de-fuzzified. It is usually possible to aggregate the mean of triangular and trapezoidal fuzzy numbers by a definite value as the best corresponding mean. This operation is called de-fuzzification. There are numerous methods for defuzzification. In this study, the centroid method (Equation 2) is used for de-fuzzification.

*Table 2*

*Linguistic Terms and Their Triangular Fuzzy Equivalents*

| Linguistic Variable | Fuzzy Scale |
|---|---|
| Very low (VL) | (0.00, 0.00, 0.30) |
| Low (L) | (0.00, 0.25, 0.50) |
| Medium (M) | (0.30, 0.50, 0.70) |
| High (H) | (0.50, 0.75, 1.00) |
| Very high (VH) | (0.70, 1.00, 1.00) |

## Results

### Co-word analysis

Co-word analysis can identify and visualize the evolution of different keywords by creating network relationships among words that include the co-occurrence of keywords (Callon, Courtial, Turner & Bauin, 1983). This analysis is used by researchers to discover hot topics for a certain period and explore future research directions. From the co-word results, a total of 40 keywords are extracted from databases and classified into five clusters. Figure 2 shows a dataset of indicators and the relationship structure in a conceptual network.

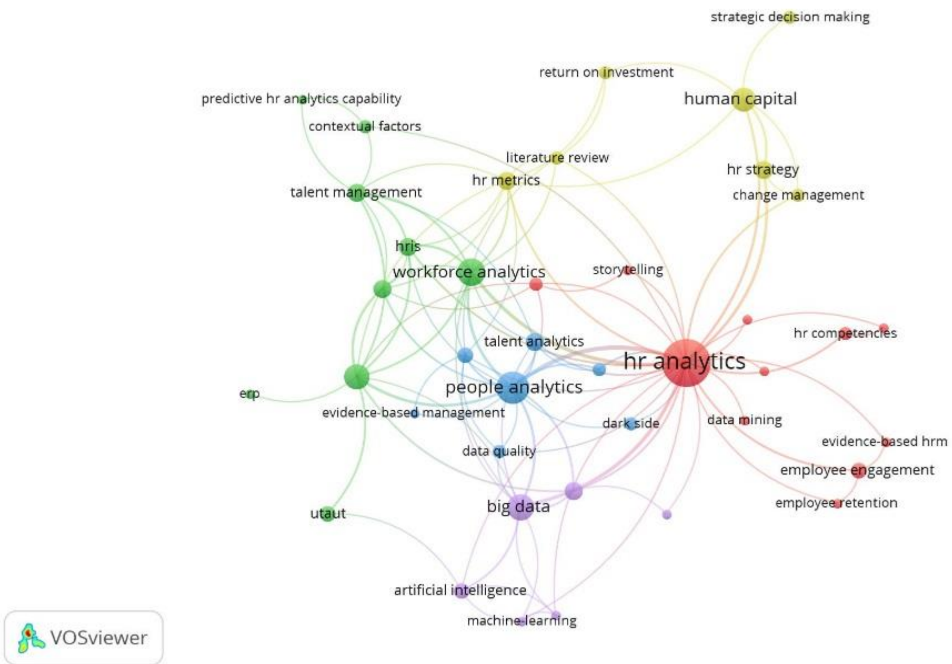


*Figure 2: Co-occurrence of author keywords by clusters (cluster 1: red; cluster 2: green; cluster 3: blue; cluster 4: yellow and cluster 5: purple)*

Concerning Table 3, the Occurrence weight and average published year reveal that there are newer keywords, such as the following: Storytelling and analytical competencies from cluster 1; Predictive HR analytics capability from cluster 2; human capital analytics and talent analytics from cluster 3; HR metrics from cluster 4; artificial intelligence, Machine learning and Turnover in cluster 5.

*Table 3*
*Co-occurrence of author keywords*

| ID | Keyword | Cluster | Occurrence | Average published year |
|---|---|---|---|---|
| 1 | Analytical competencies | 1 | 1 | 2022.50 |
| 2 | Data infrastructure | | 1 | 2022.00 |
| 3 | Data mining | | 1 | 2020.00 |
| 4 | Employee engagement | | 3 | 2020.00 |
| 5 | Employee retention | | 1 | 2022.00 |
| 6 | Evidence-based human resource management | | 1 | 2018.00 |
| 7 | HR analytics | | 4 | 2019.73 |
| 8 | HR analyst | | 2 | 2021.50 |
| 9 | Human resource competencies | | 2 | 2022.00 |
| 10 | Performance appraisal | | 1 | 2017.00 |

| ID | Keyword | Cluster | Occurrence | Average published year |
|---|---|---|---|---|
| 11 | Storytelling | | 1 | 2023.50 |
| 12 | Contextual factors | 2 | 2 | 2021.00 |
| 13 | Enterprise Resource Planning | | 1 | 2012.00 |
| 14 | Human resource information systems | | 4 | 2018.00 |
| 15 | Human resource data analytics | | 9 | 2019.22 |
| 16 | Predictive HR analytics capability | | 1 | 2021.50 |
| 17 | Strategic Human Resource Management | | 4 | 2018.25 |
| 18 | Talent management | | 4 | 2019.00 |
| 19 | UTAUT model | | 3 | 2019.00 |
| 20 | Workforce analytics | | 11 | 2019.45 |
| 21 | Algorithm | 3 | 2 | 2020.50 |
| 22 | Dark side | | 2 | 2019.50 |
| 23 | Data quality | | 2 | 2021.00 |
| 24 | Evidence-based management | | 1 | 2021.00 |
| 25 | Human capital analytics | | 3 | 2021.67 |
| 26 | People analytics | | 17 | 2020.94 |
| 27 | Talent analytics | | 4 | 2021.50 |
| 28 | Change management | 4 | 2 | 2017.00 |
| 29 | HR metrics | | 4 | 2018.75 |
| 30 | Human resource strategy | | 4 | 2017.25 |
| 31 | Human Capital | | 8 | 2017.25 |
| 32 | Literature review | | 2 | 2017. 00 |
| 33 | Return on investment | | 2 | 2016.50 |
| 34 | Strategic decision making | | 2 | 2018.00 |
| 35 | Artificial intelligence | 5 | 3 | 2022.00 |
| 36 | Big data | | 10 | 2020.80 |
| 37 | Data analytics | | 4 | 2020.50 |
| 38 | Evidence-based decision making | | 1 | 2020.00 |
| 39 | Machine learning | | 1 | 2022.00 |
| 40 | Turnover | | 1 | 2022.00 |

**FDM and SWARA results**

The co-word analysis suggests 40 keywords for evaluation based on the expert's judgment. Table 4 presents the fuzzy average and the de-fuzzified output of the values related to the indicators. The de-fuzzified value greater than 0.7 is acceptable, and any indicator with a score lower than 0.7 is rejected (Wu & Fang, 2011).

*Table 4*
*The results of screening the indicators (first round)*

| Indicators | Fuzzy average | Crisp value | Result |
|---|---|---|---|
| Analytical competencies | (0.68,0.847,0.94) | 0.822 | Accepted |
| Data infrastructure | (0.663,0.843,0.937) | 0.814 | Accepted |
| Data mining | (0.747,0.873,0.927) | 0.849 | Accepted |
| Employee engagement | (0.693,0.847,0.927) | 0.822 | Accepted |
| Employee retention | (0.647,0.81,0.907) | 0.788 | Accepted |
| Evidence-based human resource management | (0.66,0.827,0.913) | 0.800 | Accepted |
| HR analytics | (0.64,0.823,0.92) | 0.794 | Accepted |
| HR analyst | (0.693,0.847,0.927) | 0.822 | Accepted |
| Human resource competencies | (0.66,0.833,0.94) | 0.811 | Accepted |
| Performance appraisal | (0.7,0.86,0.94) | 0.833 | Accepted |
| Storytelling | (0.667,0.823,0.907) | 0.799 | Accepted |
| Contextual factors | (0.353,0.527,0.687) | 0.522 | Rejected |
| Enterprise Resource Planning | (0.43,0.603,0.747) | 0.593 | Rejected |
| Human resource information systems | (0.71,0.857,0.933) | 0.833 | Accepted |
| Human resource data analytics | (0.62,0.793,0.9) | 0.771 | Accepted |
| Predictive HR analytics capability | (0.72,0.877,0.963) | 0.853 | Accepted |
| Strategic Human Resource Management | (0.73,0.87,0.933) | 0.844 | Accepted |
| Talent management | (0.69,0.843,0.933) | 0.822 | Accepted |
| UTAUT model | (0.273,0.42,0.577) | 0.423 | Rejected |
| Workforce analytics | (0.66,0.84,0.943) | 0.814 | Accepted |
| Algorithm | (0.243,0.363,0.53) | 0.379 | Rejected |
| Dark side | (0.35,0.443,0.55) | 0.448 | Rejected |
| Data quality | (0.677,0.837,0.92) | 0.811 | Accepted |
| Evidence-based management | (0.6,0.797,0.92) | 0.772 | Accepted |
| Human capital analytics | (0.567,0.767,0.9) | 0.745 | Accepted |
| People analytics | (0.653,0.813,0.913) | 0.793 | Accepted |
| Talent analytics | (0.727,0.877,0.947) | 0.850 | Accepted |
| Change management | (0.347,0.507,0.667) | 0.507 | Rejected |
| HR metrics | (0.707,0.863,0.947) | 0.839 | Accepted |
| Human resource strategy | (0.667,0.83,0.92) | 0.806 | Accepted |
| Human Capital | (0.667,0.83,0.92) | 0.806 | Accepted |
| Literature review | (0.483,0.643,0.783) | 0.636 | Rejected |
| Return on investment | (0.62,0.81,0.92) | 0.783 | Accepted |
| Strategic decision making | (0.663,0.827,0.927) | 0.806 | Accepted |
| Artificial intelligence | (0.65,0.82,0.913) | 0.794 | Accepted |
| Big data | (0.733,0.887,0.957) | 0.859 | Accepted |
| Data analytics | (0.703,0.853,0.927) | 0.828 | Accepted |
| Evidence-based decision making | (0.613,0.79,0.893) | 0.765 | Accepted |
| Machine learning | (0.667,0.823,0.907) | 0.799 | Accepted |
| Turnover | (0.683,0.853,0.957) | 0.831 | Accepted |

The "contextual factors", "Enterprise Resource Planning", "UTAUT model ", "Algorithm", "Dark side", "Change Management", and "Literature review" were scored less than the threshold level and were thus excluded. Items with scores of above 0.7 were used for the second round. Fuzzy Delphi analysis continued for the remaining indicators in the second round. At this stage, 33 indices were evaluated based on the expert's opinion. Table 5 presents the results of fuzzy Delphi in the second round.

*Table 5*
*Fuzzy average and fuzzy screening of indicators (round two)*

| Indicators | Fuzzy average | Crisp value | Result |
|---|---|---|---|
| Analytical competencies | (0.723,0.88,0.957) | 0.853 | Accepted |
| Data infrastructure | (0.69,0.867,0.96) | 0.839 | Accepted |
| Data mining | (0.68,0.86,0.96) | 0.833 | Accepted |
| Employee engagement | (0.683,0.863,0.953) | 0.833 | Accepted |
| Employee retention | (0.643,0.837,0.953) | 0.811 | Accepted |
| Evidence-based human resource management | (0.717,0.883,0.967) | 0.856 | Accepted |
| HR analytics | (0.707,0.877,0.967) | 0.850 | Accepted |
| HR analyst | (0.747,0.903,0.967) | 0.872 | Accepted |
| Human resource competencies | (0.76,0.91,0.98) | 0.883 | Accepted |
| Performance appraisal | (0.72,0.877,0.963) | 0.853 | Accepted |
| Storytelling | (0.727,0.89,0.967) | 0.861 | Accepted |
| Human resource information systems | (0.583,0.783,0.92) | 0.762 | Accepted |
| Human resource data analytics | (0.66,0.84,0.943) | 0.814 | Accepted |
| Predictive HR analytics capability | (0.697,0.87,0.967) | 0.845 | Accepted |
| Strategic Human Resource Management | (0.69,0.867,0.96) | 0.839 | Accepted |
| Talent management | (0.68,0.843,0.947) | 0.823 | Accepted |
| Workforce analytics | (0.683,0.853,0.957) | 0.831 | Accepted |
| Data quality | (0.74,0.897,0.98) | 0.872 | Accepted |
| Evidence-based management | (0.693,0.86,0.957) | 0.837 | Accepted |
| Human capital analytics | (0.543,0.777,0.913) | 0.744 | Accepted |
| People analytics | (0.733,0.893,0.973) | 0.866 | Accepted |
| Talent analytics | (0.733,0.887,0.957) | 0.859 | Accepted |
| HR metrics | (0.697,0.87,0.967) | 0.845 | Accepted |
| Human resource strategy | (0.787,0.92,0.97) | 0.892 | Accepted |
| Human Capital | (0.72,0.877,0.963) | 0.853 | Accepted |
| Return on investment | (0.733,0.893,0.973) | 0.866 | Accepted |
| Strategic decision making | (0.677,0.85,0.95) | 0.826 | Accepted |
| Artificial intelligence | (0.707,0.877,0.967) | 0.850 | Accepted |
| Big data | (0.743,0.9,0.973) | 0.872 | Accepted |
| Data analytics | (0.687,0.857,0.95) | 0.831 | Accepted |
| Evidence-based decision making | (0.753,0.907,0.973) | 0.878 | Accepted |
| Machine learning | (0.61,0.8,0.927) | 0.779 | Accepted |
| Turnover | (0.66,0.847,0.96) | 0.822 | Accepted |

None of the questions were removed in the second round, indicating the end of the Delphi rounds. Even though no new indicator was added or removed in the second round, one more round continued to ensure more certainty. At this stage, 33 indicators were evaluated based on the experts' opinions. Table 6 presents the results of fuzzy Delphi in the third round.

*Table 6*
*Fuzzy average and fuzzy screening of indicators (third round)*

| Indicators | Fuzzy average | Crisp value | Result |
|---|---|---|---|
| Analytical competencies | (0.717,0.883,0.967) | 0.856 | Accepted |
| Data infrastructure | (0.733,0.893,0.973) | 0.866 | Accepted |
| Data mining | (0.7,0.873,0.96) | 0.844 | Accepted |
| Employee engagement | (0.683,0.863,0.953) | 0.833 | Accepted |
| Employee retention | (0.733,0.893,0.973) | 0.866 | Accepted |
| Evidence-based human resource management | (0.707,0.877,0.967) | 0.850 | Accepted |
| HR analytics | (0.647,0.84,0.947) | 0.811 | Accepted |
| HR analyst | (0.633,0.83,0.953) | 0.805 | Accepted |
| Human resource competencies | (0.677,0.86,0.947) | 0.828 | Accepted |
| Performance appraisal | (0.75,0.903,0.98) | 0.878 | Accepted |
| Storytelling | (0.763,0.913,0.973) | 0.883 | Accepted |
| Human resource information systems | (0.667,0.853,0.947) | 0.822 | Accepted |
| Human resource data analytics | (0.807,0.94,0.987) | 0.911 | Accepted |
| Predictive HR analytics capability | (0.763,0.913,0.973) | 0.883 | Accepted |
| Strategic Human Resource Management | (0.733,0.893,0.973) | 0.866 | Accepted |
| Talent management | (0.657,0.847,0.947) | 0.817 | Accepted |
| Workforce analytics | (0.683,0.863,0.953) | 0.833 | Accepted |
| Data quality | (0.807,0.94,0.987) | 0.911 | Accepted |
| Evidence-based management | (0.69,0.867,0.96) | 0.839 | Accepted |
| Human capital analytics | (0.657,0.847,0.947) | 0.817 | Accepted |
| People analytics | (0.84,0.96,1) | 0.933 | Accepted |
| Talent analytics | (0.707,0.877,0.967) | 0.850 | Accepted |
| HR metrics | (0.727,0.89,0.967) | 0.861 | Accepted |
| Human resource strategy | (0.69,0.867,0.96) | 0.839 | Accepted |
| Human Capital | (0.69,0.867,0.96) | 0.839 | Accepted |
| Return on investment | (0.727,0.89,0.967) | 0.861 | Accepted |
| Strategic decision making | (0.71,0.88,0.96) | 0.850 | Accepted |
| Artificial intelligence | (0.717,0.883,0.967) | 0.856 | Accepted |
| Big data | (0.717,0.883,0.967) | 0.856 | Accepted |
| Data analytics | (0.7,0.873,0.96) | 0.844 | Accepted |
| Evidence-based decision making | (0.707,0.877,0.967) | 0.850 | Accepted |
| Machine learning | (0.72,0.883,0.98) | 0.861 | Accepted |
| Turnover | (0.7,0.873,0.96) | 0.844 | Accepted |

None of the questions were removed in the second and third rounds, indicating the end of the Delphi rounds. An approach to the end of Delphi is to compare the mean scores of two consecutive rounds. If the difference between the two steps is smaller than the very low threshold (0.2), then the survey process is stopped (Cheng & Lin, 2002). Based on the results of Table 7, the difference is less than 0.2 in all cases; hence, we can finish the Delphi rounds and conclude that the 30 identification indices have the necessary validity according to the experts. The indicators were finally prioritized using the SWARA after confirming the research indicators and interviewing the experts using the fuzzy technique.

*Table 7*
*The difference between the definitive values of the first and second rounds*

| Indicators | Result (Round 2) | Result (Round 3) | difference | Result |
|---|---|---|---|---|
| Analytical competencies | 0.853 | 0.856 | 0.003 | Agreement |
| Data infrastructure | 0.839 | 0.866 | 0.027 | Agreement |
| Data mining | 0.833 | 0.844 | 0.011 | Agreement |
| Employee engagement | 0.833 | 0.833 | 0.0 | Agreement |
| Employee retention | 0.811 | 0.866 | 0.055 | Agreement |
| Evidence-based human resource management | 0.856 | 0.850 | 0.006 | Agreement |
| HR analytics | 0.850 | 0.811 | 0.039 | Agreement |
| HR analyst | 0.872 | 0.805 | 0.067 | Agreement |
| Human resource competencies | 0.883 | 0.828 | 0.055 | Agreement |
| Performance appraisal | 0.853 | 0.878 | 0.025 | Agreement |
| Storytelling | 0.861 | 0.883 | 0.022 | Agreement |
| Human resource information systems | 0.762 | 0.822 | 0.06 | Agreement |
| Human resource data analytics | 0.814 | 0.911 | 0.097 | Agreement |
| Predictive HR analytics capability | 0.845 | 0.883 | 0.038 | Agreement |
| Strategic Human Resource Management | 0.839 | 0.866 | 0.027 | Agreement |
| Talent management | 0.823 | 0.817 | 0.006 | Agreement |
| Workforce analytics | 0.831 | 0.833 | 0.002 | Agreement |
| Data quality | 0.872 | 0.911 | 0.039 | Agreement |
| Evidence-based management | 0.837 | 0.839 | 0.002 | Agreement |
| Human capital analytics | 0.744 | 0.817 | 0.073 | Agreement |
| People analytics | 0.866 | 0.933 | 0.067 | Agreement |
| Talent analytics | 0.859 | 0.850 | 0.009 | Agreement |
| HR metrics | 0.845 | 0.861 | 0.016 | Agreement |
| Human resource strategy | 0.892 | 0.839 | 0.053 | Agreement |
| Human Capital | 0.853 | 0.839 | 0.014 | Agreement |
| Return on investment | 0.866 | 0.861 | 0.005 | Agreement |
| Strategic decision making | 0.826 | 0.850 | 0.024 | Agreement |
| Artificial intelligence | 0.850 | 0.856 | 0.006 | Agreement |
| Big data | 0.872 | 0.856 | 0.016 | Agreement |
| Data analytics | 0.831 | 0.844 | 0.013 | Agreement |
| Evidence-based decision making | 0.878 | 0.850 | 0.028 | Agreement |
| Machine learning | 0.779 | 0.861 | 0.082 | Agreement |
| Turnover | 0.822 | 0.844 | 0.022 | Agreement |

Based on the analysis results (Table 8), HR analytics and Human resource data analytics are the most important cases, and then people analytics, human capital analytics, workforce analytics, data analytics, big data, analytical competencies, predictive HR analytics capability, and HR analyst are ranked third to tenth.

*Table 8*
*Calculation of the final normal weights of the indicators*

| X | average values of relative importance | Kj | Qj | Wj | Crisp | Normal |
|---|---|---|---|---|---|---|
| HR Analytics | (1,1,1) | (1,1 ,1) | (1,1,1) | (0.096,0.194,0.329) | 0.2062 | 0.1315 |
| Human Resource Data Analytics | (0.093,0.2,0.467) | (1.093,1.2,1.467) | (0.682,0.833,0.915) | (0.066,0.161,0.3) | 0.1759 | 0.1121 |
| People Analytics | (0.1,0.233,0.487) | (1.1,1.233,1.487) | (0.459,0.676,0.831) | (0.044,0.131,0.273) | 0.1494 | 0.0953 |
| Human Capital Analytics | (0.08,0.25,0.5) | (1.08,1.25,1.5) | (0.306,0.541,0.77) | (0.029,0.105,0.253) | 0.1290 | 0.0823 |
| Workforce Analytics | (0.127,0.3,0.553) | (1.127,1.3,1.553) | (0.197,0.416,0.683) | (0.019,0.081,0.224) | 0.1080 | 0.0689 |
| Data Analytics | (0.08,0.25,0.5) | (1.08,1.25,1.5) | (0.131,0.333,0.633) | (0.013,0.064,0.208) | 0.0950 | 0.0606 |
| Big Data | (0.1,0.25,0.5) | (1.1,1.25,1.5) | (0.087,0.266,0.575) | (0.008,0.052,0.189) | 0.0830 | 0.0529 |
| Analytical Competencies | (0.04,0.133,0.407) | (1.04,1.133,1.407) | (0.062,0.235,0.553) | (0.006,0.045,0.182) | 0.0777 | 0.0496 |
| Predictive HR Analytics Capability | (0.12,0.283,0.527) | (1.12,1.283,1.527) | (0.041,0.183,0.494) | (0.004,0.035,0.162) | 0.0672 | 0.0429 |
| HR Analysts | (0.08,0.2,0.46) | (1.08,1.2,1.46) | (0.028,0.152,0.457) | (0.003,0.03,0.15) | 0.0608 | 0.0388 |
| Data Infrastructure | (0.14,0.367,0.593) | (1.14,1.367,1.593) | (0.018,0.112,0.401) | (0.002,0.022,0.132) | 0.0517 | 0.0330 |
| Data Quality | (0.14,0.317,0.553) | (1.14,1.317,1.553) | (0.011,0.085,0.352) | (0.001,0.016,0.116) | 0.0444 | 0.0283 |
| Human Capital | (0.14,0.3,0.54) | (1.14,1.3,1.54) | (0.007,0.065,0.309) | (0.001,0.013,0.101) | 0.0382 | 0.0244 |
| Strategic Human Resource Management | (0.12,0.233,0.487) | (1.12,1.233,1.487) | (0.005,0.053,0.276) | (0,0.01,0.091) | 0.0337 | 0.0215 |
| Evidence-Based Human Resource Management | (0.113,0.25,0.487) | (1.113,1.25,1.487) | (0.003,0.042,0.248) | (0,0.008,0.081) | 0.0299 | 0.0191 |
| Human Resource Strategy | (0.02,0.1,0.38) | (1.02,1.1,1.38) | (0.002,0.038,0.243) | (0,0.007,0.08) | 0.0291 | 0.0186 |
| Performance Appraisal | (0.113,0.217,0.46) | (1.113,1.217,1.46) | (0.002,0.032,0.218) | (0,0.006,0.072) | 0.0260 | 0.0166 |
| Return On Investment | (0.14,0.3,0.56) | (1.14,1.3,1.56) | (0.001,0.024,0.191) | (0,0.005,0.063) | 0.0225 | 0.0144 |
| Human Resource Competencies | (0.107,0.267,0.507) | (1.107,1.267,1.507) | (0.001,0.019,0.173) | (0,0.004,0.057) | 0.0202 | 0.0129 |
| Talent Analytics | (0.24,0.433,0.627) | (1.24,1.433,1.627) | (0,0.013,0.139) | (0,0.003,0.046) | 0.0161 | 0.0103 |

| X | average values of relative importance | Kj | Qj | Wj | Crisp | Normal |
|---|---|---|---|---|---|---|
| Employee Retention | (0.113,0.283,0.533) | (1.113,1.283,1.533) | (0,0.01,0.125) | (0,0.002,0.041) | 0.0144 | 0.0092 |
| Talent Management | (0.173,0.367,0.6) | (1.173,1.367,1.6) | (0,0.008,0.107) | (0,0.001,0.035) | 0.0122 | 0.0078 |
| Turnover | (0.153,0.35,0.587) | (1.153,1.35,1.587) | (0,0.006,0.092) | (0,0.001,0.03) | 0.0105 | 0.0067 |
| HR Metrics | (0.2,0.367,0.593) | (1.2,1.367,1.593) | (0,0.004,0.077) | (0,0.001,0.025) | 0.0087 | 0.0056 |
| Strategic Decision Making | (0.147,0.283,0.54) | (1.147,1.283,1.54) | (0,0.003,0.067) | (0,0.001,0.022) | 0.0076 | 0.0048 |
| Artificial Intelligence | (0.04,0.15,0.42) | (1.04,1.15,1.42) | (0,0.003,0.065) | (0,0.001,0.021) | 0.0073 | 0.0046 |
| Employee Engagement | (0.06,0.183,0.447) | (1.06,1.183,1.447) | (0,0.002,0.061) | (0,0,0.02) | 0.0068 | 0.0044 |
| Evidence-Based Decision Making | (0.04,0.167,0.433) | (1.04,1.167,1.433) | (0,0.002,0.059) | (0,0,0.019) | 0.0066 | 0.0042 |
| Human Resource Information Systems | (0,0.117,0.393) | (1,1.117,1.393) | (0,0.002,0.059) | (0,0,0.019) | 0.0065 | 0.0042 |
| Data Mining | (0.02,0.183,0.447) | (1.02,1.183,1.447) | (0,0.002,0.057) | (0,0,0.019) | 0.0064 | 0.0041 |
| Machine Learning | (0.08,0.183,0.447) | (1.08,1.183,1.447) | (0,0.001,0.053) | (0,0,0.017) | 0.0059 | 0.0038 |
| Storytelling | (0.04,0.2,0.46) | (1.04,1.2,1.46) | (0,0.001,0.051) | (0,0,0.017) | 0.0057 | 0.0036 |
| Evidence-Based Management | (0.02,0.15,0.42) | (1.02,1.15,1.42) | (0,0.001,0.05) | (0,0,0.016) | 0.0056 | 0.0035 |

## Discussion

A summary of the significant issues of HR analytics, as indicated by co-word analysis and fuzzy Delphi technique screening by expert opinions, seeks to create opportunities to promote filling gaps in HR analytics. These cases are suggested to promote progress in the development of research on this topic and provide recommendations for themes of interest for future exploration. Therefore, six categories of study fields are discussed below, the most important of which are detected based on the extracted weights of the indicators, using the SWARA technique (Table 8):

1) HR strategy and analytics: This category evaluates the strategic HRM towards strategic decision-making and covers human capital and human capital analytics as the most important matters. McIver et al. (2018) and Minbaeva (2018) emphasize that HR analytics has a strategic nature, in other words, they consider the use of data analytics in HRM to be a transformational change because they believe that HR participation is at a strategic level in the organization (Hamilton & Sodeman, 2020). In this regard, Sharma and Sharma (2017) hold that HR analytics is a mechanism for creating and strengthening the strategic role of human resources. HR data

will be valuable when they can answer strategic questions about how people create value for the organization (Angrave et al., 2016).

According to King (2016), a strategic understanding of how human capital contributes to the organization's strategic decisions must be established before using data analytics in HRM. HRA research forms an integral part of the Strategic Human Resource Management (SHRM) research field, and SHRM theories can help to clarify the phenomenon of HRA. At the same time, HRA can be used as a tool to verify and validate the assumptions behind SHRM research and to understand the HRM-function relationship. From a practical point of view, according to the resource-based theory, HRA can be considered both as a source of competitive advantage and as a means of creating competitive advantage by individuals.

2) HR processes and analytics: The second category promotes HR processes based on data analytics. This category comprises the most basic HR processes, including talent management and analytics, retention, performance evaluation, and turnover. According to studies, HR analytics is used for a more comprehensive and fair evaluation of employee performance (Cho, Choi & Choi, 2023), retaining, and employing talented people (Fernandez & Gallardo-Gallardo, 2021), predicting turnover (Álvarez-Gutiérrez Stone, Castaño & García-Izquierdo, 2022), and improving employee training and development (Johnson, Coggburn & Llorens, 2022). For example, analytics can support talent management decisions, such as identifying strategic positions of organizations that affect organizational function, identifying a talent pool to fill such positions, monitoring talent function, and managing talent retention (Gurusinghe, Arachchige & Dayarathna, 2021). The role of HRA is vital in retaining skilled employees. HRA is the automation of the HR process that helps to identify the most competent or skilled employees of the organization and also to retain them to create organizational value (Fernandez, 2019). According to Chalutz Ben-Gal (2019), both recruitment and retention rely on descriptive and predictive analytics, and ROI is expected to increase with the use of data analytics in HRM practices. Researchers have highlighted the need to solve problems related to subjective biases in performance evaluation (Bol & Smith, 2011; Maas & Torres-González, 2011; Fehrenbacher, Schulz & Rotaru, 2018; Alves & Lourenço, 2023). Providing objective measures is one of the ways to reduce bias in supervisory ratings (Dai, Kuang & Tang, 2018); this is where HRA can play an important role. According to Sharma and Sharma (2017), the HR function has transformed with the advent of HR information systems, and there are possibilities that analytics by providing performance data will turn HR into a strategic business partner.

3) Big data and HR analytics: The third category goes deeper into this field by focusing on big data. This category comprises data quality and infrastructure. Studies emphasize that only focusing on big data in HRM does not achieve progress in HR analytics because the huge and complex volume of big data and their successful use in HRM require a vast time and effort; hence, the quality and availability of data are considered too effective in the success of HR analytics (McIver et al., 2018; Dahlbom, Siikanen, Sajasalo & Jarvenpää, 2020; Karwehl, 2021). Hence, before engaging in analytics, it is necessary to review the data to ensure that it has appropriate metrics and that metrics are consistently collected and stored (Fitz-Enz & Mattox, 2014). Indeed, according to Andersen (2017), bad data is one of the biggest challenges when considering the quality of HRA. He states that low-quality HR data has much damage to organizations. Therefore, to ensure better data quality and avoid additional costs, it is important to understand why bad data happens. The first reason is the need for a coherent data strategy. In other words, more than a purely operational approach to data is needed to ensure adequate

data quality. Furthermore, response analytics is assumed to be the problem when, in reality, it is only a data collection tool. So, to get the most out of HRA, you need to go through a strategic data process and decide what data is strategically important to you. Finally, the lack of critical data sources affects data quality. In general, analytics and decision-making based on weak and low-quality data need to make more sense (ibid).

4) HR analytics and competencies: The fourth category emphasizes the HR analyst's competencies. The most important competencies include analytical skills and the ability to analyze and predict human resources. Studies emphasize that appropriate competencies, especially the ability and competence to perform HR data analytics and transform them into valuable insights, are necessary to integrate HRM with data analytics (Angrave et al., 2016; Minbaeva, 2018; Kryscynski, Reeves, Stice-Lusvardi, Ulrich & Russell, 2018; McCartney et al., 2021; fu, Keegan & McCartney, 2023). HR often needs more analytical capability required for data-driven HR. Angrave et al. (2016) stated that the need for HR personnel with analytical knowledge is the most common reason why data-driven HR is not widely adopted. In other words, data-driven HR requires a different type of competency than the traditional HR competency that HR personnel possess today. Angrave et al. (2016) argued that future HRA tools must be based on the needs of the HR unit; otherwise, data-driven HR will not create value. According to them, HR personnel need to develop their skills to acquire knowledge about data-driven working methods to ensure HR functions succeed in today's big data challenge.

5) HR analytics and technology: The fifth category refers to the necessary technology to analyze HR data, using data mining, machine learning, and artificial intelligence. The emergence of technologies facilitates data collection and analysis and makes HR analytics available to almost every organization (McIver et al. 2018). In other words, technology as an enabler of progress toward measurements enables HR experts to facilitate their work and measure activities (Strohmeier, Collet & Kabst, 2022). In general, technological advances (including automation technology, powerful HR information systems, and various data collection systems) not only enable organizations to acquire and process large amounts of data faster and cheaper but also enable HR managers to maximize data to improve function. In addition, this technology affects today's strategic planning as more companies try to collect and manage data about people through HR information systems (Schiemann et al., 2018).

6) HR analytics and evidence: The sixth category refers to an evidence-based approach in HRM. Issues such as HRM and evidence-based decision-making are also reflected in this category. Studies have attributed the positive effect of HR analytics on organizational performance to the use of evidence-based management practices (McCartney & Fu, 2022). Similarly, other studies have reported that HR analytics aims to support organizations in achieving their strategic goals through an evidence-based approach (Margherita, 2021; Johnson et al., 2022). According to Marler and Boudreau (2017), HR analytics enables human resources to benefit from decision-making on strategic business issues, using evidence-based management. In other words, an evidence-based approach provides dual goals: helping organizations make better decisions in the field of HR and helping HR managers convince stakeholders that the right decisions have been made (Rousseau & Barends, 2011). Therefore, HRA is a necessary step towards EBHR. In a world with greater access to a broader set of data, including data about people and their behaviors, HRA offers an opportunity to get better HR at a lower cost. In short, HRA has the potential to change beliefs and evidence within HR for the better (Van der Togt & Rasmussen, 2017).

## Conclusion

The present study emphasizes the value of the current status of scientific production of HR analytics according to articles published up to 2023 and reports that it is a dynamic, emerging, and trending field. More studies should be conducted on HR analytics because the world has an increasing technology that can benefit more from it in its organizational performance whether enterprises are large, small, or medium. Research fields of HR analytics can cover the study of the six aforementioned research topics. In summary, this research can be interesting to academics and experts who seek to explore the outcome of this theme and contribute to developing knowledge in this scientific field.

The following research areas are suggested based on the analysis obtained from the present research:

1) Although HRM research is based on SHRM studies, there are few theoretical framework studies (for example, theories and strategy frameworks) that challenge the assumption that HRA follows strategic goals. Therefore, more research is needed based on strong theoretical frameworks in the field of HRA.

2) Further studies should analyze the impact of adopting HRA on HR measures. Currently, there are a few studies on the relationship between data analytics and HR practices such as comprehensive and fair evaluation of employee performance (Cho, Choi & Choi, 2023), retaining, and employing talented people (Fernandez & Gallardo-Gallardo, 2021), predicting turnover (Álvarez-Gutiérrez et al., 2022), and improving employee training and development (Johnson et al. 2022); however, further studies on other HR practices are recommended.

3) More research is needed on the technology needed to analyze HR data. Researchers should focus on more studies related to big data, machine learning, and artificial intelligence. In other words, IT infrastructure investment affects technology maturity and subsequently facilitates the implementation of information systems such as HRA. Therefore, organizations with an IT infrastructure that can support data analytics will be more mature in using such processes.

4) If you want to have an analysis-oriented organization, people inside the organization must have a more analytical mindset. One of the key concerns in organizations is HR's incompetence in analytical skills. Analytical incompetence has been seen as an obstacle in adopting HRA. Therefore, it is recommended that organizations think about how to improve the analytical skills of HR experts.

5) Given the value of HR data analytics in the context of evidence-based decision-making, as well as its potentially broader impact on organizational strategic results, it can be concluded that the field holds promise for HRM experts to do so because they create significant added value for company function by providing important insights related to business trends and organizational results.

## Limitations

This study has some limitations, first, it used the Scopus database. Despite the wide scope of this database, it covers low-impact sources. Therefore, future studies should use other databases or combine different sources to increase the generalizability of results. Second, only research articles and review articles were used in the review process. Therefore, the relevant books along with book chapters should be included in future studies to expand data coverage. Third, the panel of experts consisting of only 15 members can induce analysis bias due to understanding, practice, and familiarity with the research area. Future studies are recommended to increase the number of respondents to avoid such problems.

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