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Trends and Perspectives in Enhancing the Competitiveness of Slovak Businesses Through Predictive HR Analytics

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Abstract
The use of HR analytics has been on the rise in recent years, with organizations increasingly recognizing its potential to improve HR processes, increase employee productivity and engagement, and reduce costs. The research presented in this paper extends the knowledge base, especially the characteristics of the degree of implementation of HR analysis into working systems of human resources management utilized within businesses operating within the Slovakian context, emphasizing their role in bolstering and enhancing competitiveness within the European economic arena. Although there was a clear interest in the use of predictive analytics in Slovak companies, there was still a lot of room for improvement and adoption of this approach in HR practice. The authors' findings also suggest that companies in Slovakia are increasingly aware of the value of data-driven decision-making in HR and are willing to invest in these technologies to gain a competitive advantage. The objective of this study is to ascertain contemporary human resource management instruments utilized within businesses operating within the Slovakian context. The authors assumed that the perceived importance of the data approach in HR among Slovak companies is strong, and companies are open to learning more about this approach. A sample of 841 respondents was collected throughout 2020, sample included enterprises from the Slovak Republic. The interviews were conducted via phone in November 2022. The interview respondents are 7 HR representatives. The authors' findings suggest that companies in Slovakia are increasingly aware of the value of data-driven decision-making in HR and are willing to invest in these technologies to gain a competitive advantage.

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1. Introduction

The orientation towards innovation as a means to achieve a competitive advantage, within the context of a global environment marked by significant competition (Starecek et al., 2023; Kapler 2021; Copuš 2019; Hitka et al., 2018), primarily stems from the influence of globalization policy of the European Union, aimed at creating a unified market with the free movement of goods and people, a free space for the provision of services, and the free movement of capital (Nedeliaková et al., 2019; Olexová, Gajdoš 2016; Kruger 2023; Urbancová, Vnouckova, 2015; Štaffenová, Kucharčíková, 2023), and presently influenced by substantial turbulence associated with the emergence of new technologies in robotics and digitalization as part of the Fourth Industrial Revolution, has become a commonplace aspect of managerial work (Papula et al., 2019; Rosak Szyrocka 2022; Jankelová et al., 2020; Sirkova et al., 2016).

HR analytics, also known as people analytics, workforce analytics, or talent analytics, refers to the process of collecting, analyzing, and interpreting data related to an organization's employees. The goal of HR analytics is to use data-driven insights to improve HR practices, enhance employee engagement and retention, and ultimately, drive better business outcomes (Gupta, Megha 2020). HR Analytics is the practice of using data-driven decision-making in HR. It involves the systematic identification and quantification of people drivers of business outcomes, which requires engagement with statistics. The focus of HR analytics is on what people are doing, how engaged they are, how much and why they are absent, how competent they are, and how these factors influence business outcomes (Jain et al., 2020). The term HR analytics is too narrow and implies exclusivity to human resources (Wojčák, 2018; Starecek 2021; Hitka 2017), whereas proper analytics should include financial and other data as well.

2. Theoretical Background

Data-driven approaches to human resources have become increasingly popular and prevalent in recent years, as more organizations recognize the potential benefits of using data to inform decision-making in areas such as hiring, performance management, and employee development. One of the key advantages of a data-driven approach is that it allows organizations to make more objective and evidence-based decisions, rather than relying on subjective judgments or biases (Lawler et al., 2021). By collecting and analyzing data on various aspects of HR, such as employee engagement, turnover rates, and training outcomes, organizations can gain valuable insights into the strengths and weaknesses of their HR practices and identify areas where improvements can be made.

HR analytics is changing the way people are managed by enabling HR professionals to make data-driven decisions, test HR policies and interventions, and become more involved in decision-making on a strategic level. This, in turn, adds value to the organization by enhancing its efficiency and effectiveness (Van der Rijt et al., 2019).

2.1. History of HR analytics

The history of HR analytics dates back to the 1950s when organizations started to collect data on employees' performance and behavior (Boudreau 2018). In these early days, the perception of HR analytics was limited to basic data collection and storage. Companies would collect data on employees' demographics, job roles, salaries, and performance, but there was little analysis or insight into the data. Decisions about hiring, firing, promotions, and pay were often made based on subjective assessments, rather than objective data-driven insights (Bondarouk et al., 2017). In the beginning of HR analytics, data was typically collected manually through paper records, making the process of data collection time-consuming and prone to errors. As a result, the data collected was often incomplete or inaccurate, limiting the insights that could be drawn from it (Kavanagh, Thite 2019). Furthermore, there was limited technology available to analyse the data that was collected and data analysis was often conducted manually. This made it difficult to identify patterns or trends in the data and limited the insights that could be derived from it (Huang, Niu 2019).

The first term that was used was HR measurement and HR metrics Dr.Jac Fitzenz published Measurement Imperative in 1978, he also set up the Saratoga Institute in 1980 to develop and benchmark metrics in HR. He also pioneered a list of 30 metrics that can be used by any company to measure its effectiveness and efficiency. The proposed activities included staff retention, staffing, compensation, competency, and development. The proposal is perceived as the beginning of the data-capturing activity in HRM and its relevancy in organizations (Fernandez, Gallardo-Gallardo 2021). As HR information systems and software tools became more sophisticated in the 1980s, organizations began to realize the potential of HR analytics to inform decision-making (Marr 2018).

In 1995, Mark Huselid conducted research on the strategic impact of high-performance work systems. The study revealed that HR policies and practices have a significant impact on business performance. Furthermore, it was discovered that the effect is unique to each organization, depending on its culture and business environment (Phillips, Connell 2003). HR analytics has become increasingly sophisticated, with companies using data to optimize workforce planning, performance management, and compensation strategies. For example, they would analyse employee performance data to identify high-performing individuals and develop strategies to retain them (Kavanagh, Thite 2019). They would also use data to identify performance gaps and develop targeted training programs to close those gaps.

In addition to these areas, companies also began to use HR analytics to evaluate the impact of HR practices on broader business outcomes, such as productivity, profitability, and customer satisfaction. This enabled them to make more strategic decisions about their workforce and to align their HR function more closely with their overall business goals (Bondarouk, Ruël 2019).

There were several trends that have contributed to the growing popularity of analytics over the last few years. Firstly, there has been an increase in the availability of HR data due to the integration of technology and work. This has resulted in more employee data being captured and easier access to it. Secondly, there has been an increase in analytical capabilities due to improvements in computing power and the availability of data analytical skills. This has made it easier to analyse large volumes of data. Thirdly, big data analysis has become increasingly popular, making it easier to undertake. Lastly, there has been an increasing return on investment in data analytics (Margherita 2021).

2.2. Evolutionary Stages of HR Analytics

HR analytics evolved in four stages of evolution – data collection and storage, descriptive analytics, predictive analytics, and prescriptive analytics (Nascimento et al., 2019).

Employee data collection: This was the first stage of HR analytics, where companies began collecting data on employee demographics, job roles, salaries, and performance. However, during this stage, the focus was on data collection rather than analysis. Companies stored the data in HR information systems and used it mainly for administrative purposes such as payroll and benefits management. During this stage, companies relied on HR information systems (HRIS) to store employee data (Mayo 2018).

Descriptive analytics: The second stage of HR analytics involves using data visualization and reporting tools to analyse HR data. Organizations would generate reports on employee performance, turnover rates, and other HR metrics to gain insights into their workforce. This allowed organizations to identify patterns and trends in their HR data and make more informed decisions.

Some of the key researchers and practitioners who contributed to the development of descriptive analytics in HR include Jac Fitz-enz, who is considered the father of HR analytics, and Tom Davenport, who wrote extensively on the use of analytics in business (Bersin 2013).

Predictive analytics: The third stage of HR analytics involves using statistical methods to predict future HR trends and outcomes. Companies began using predictive analytics to forecast future employee turnover rates, identify high-potential employees, and predict future hiring needs. This enabled organizations to make proactive decisions based on data and reduce risks associated with human capital management. Some notable developments and theories in this stage include the use of regression analysis, forecasting, and predicting hiring needs. Researchers such as John W. Boudreau and Peter M. Ramstad have contributed to the development of predictive analytics in HR (Boudreau, Cascio 2017).

Prescriptive Analytics: The fourth and current stage of HR analytics involves prescriptive analytics, where organizations use machine learning and artificial intelligence to make recommendations and decisions based on HR data. This includes identifying key drivers of employee performance, recommending specific training and development programs, and identifying the best candidates for open positions (Diez et al., 2019).

The main difference between predictive and prescriptive analytics is that predictive analytics uses statistical methods and machine learning algorithms to predict future trends and outcomes, while prescriptive analytics goes a step further and makes recommendations or decisions based on the predicted outcomes (Yahia et al., 2021). In the context of HR analytics, predictive analytics would be used to predict future HR trends and outcomes, such as employee turnover rates or hiring needs, based on historical HR data. On the other hand, prescriptive analytics would use machine learning and artificial intelligence to recommend specific actions or decisions based on the predicted outcomes. For example, prescriptive analytics might recommend specific training and development programs to address skills gaps identified in predictive analytics or recommend the best candidates for open positions based on their qualifications and performance data (Marr 2021). In summary, predictive analytics is focused on predicting future outcomes while prescriptive analytics goes beyond prediction and provides recommendations or decisions to act upon the predicted outcomes.

2.3. Predictive analytics

Predictive analytics refers to the use of statistical and data mining techniques, machine learning algorithms, and artificial intelligence to analyse data and make predictions about future events or behaviors. The goal of predictive analytics is to identify patterns in data and use them to make accurate predictions that can guide decision-making (Winters 2019).

A predictive analytics process consists of a series of steps that build on each other. The entire process is iterative, so the desired result is approached in several passes, and the steps can therefore be repeated (Jaffara et al., 2019):

Step 1: Defining the objective: This involves identifying the problem or opportunity that the predictive analytics is meant to address. It concludes by clarifying the goals of the analysis for the organization and the industry and determining the data sources and their availability.

Step 2: Collecting and preparing data: This step involves gathering the relevant data from various sources, such as databases, spreadsheets, and other sources. The data is typically in a raw format, and it needs to be cleaned, organized, and formatted for analysis. Furthermore, this step involves cleaning the data, identifying, and handling missing values, and transforming the data into a format that is suitable for analysis. Data quality and consistency are crucial in this step (Siegel 2016).

Step 3: Exploratory data analysis: This step involves exploring the data to identify patterns, relationships, and outliers that can inform the development of predictive models.

Step 4: Feature selection: This step involves selecting the most relevant variables or features that will be used to predict the outcome variable. This is important to improve the accuracy and interpretability of the model.

Step 5: Building predictive models: This involves selecting appropriate predictive modeling techniques and developing models that can accurately predict the outcome variable (Wexler et al., 2017).

Step 6: Model deployment: The final step involves integrating the predictive models into the organization. This may also involve developing dashboards, reports, or other tools that enable stakeholders to interpret and use the predictions.

Step 7: Model evaluation and monitoring: This step involves testing and validating the predictive models to ensure that they are accurate and reliable. The models are typically evaluated using metrics such as accuracy, precision, recall, and F1 score (Berry, Linoff 2019).

Predictive analytics has become a popular tool for decision-making across many fields. These analytics have several advantages from which can users benefit, such as improved decision-making, increased efficiency, enhanced accuracy, cost saving, competitive advantage, and improved customer experience (Al-Tit, Eleyan 2018; Vetráková, Smerek 2019). Predictive analytics can provide: valuable insights and inform decision-making by identifying patterns and trends that may not be immediately apparent. By using data-driven insights, organizations can make decisions with greater confidence and accuracy (Nguyen et al., 2021); automate many tasks, and reduce the time and resources required for data analysis, allowing for faster and more efficient decision-making; more accurate predictions than traditional statistical methods due to its ability to handle large and complex data sets; help organizations save money by identifying areas for optimization and minimizing risks; help organizations gain a competitive advantage by identifying opportunities and risks that competitors may not be aware of. By leveraging predictive analytics, organizations can stay ahead of the curve and capitalize on emerging trends; helping organizations gain a deeper understanding of their customers' needs and preferences. By using this information to tailor products and services, organizations can improve customer satisfaction and loyalty (Xue, Sheng 2019).

Even though there are multiple benefits, it is important to be aware of the potential limitations of using predictive analytics (Zeng et al., 2019), such as limited data quality, lack of interpretability, overfitting, bias and limited scope, and ethical concerns. Predictive analytics relies heavily on the quality and completeness of historical data. If the data is incomplete or inaccurate, the predictions may also be flawed (Wang, Gupta 2020). Some predictive models, particularly those based on machine learning, may be difficult to interpret, making it challenging to understand how the model arrived at its predictions. Predictive models can become overfitted to the training data, resulting in overly optimistic predictions that may not generalize well to new data. Regularization techniques and careful selection of model parameters can help to mitigate this issue. Predictive models can perpetuate biases in the data they are trained on, leading to biased predictions. This can be a problem when the predictions are used to make important decisions, such as in hiring or lending. Predictive models are designed to predict a specific outcome based on available data. They may not be effective in predicting other outcomes or adapting to changing conditions. Predictive analytics can be used to make decisions that have significant ethical implications, such as hiring and lending decisions. It is important to ensure that these models are fair and do not discriminate against certain groups (Chen et al., 2019).

To overcome these limitations, several techniques can be used, such as data cleaning and pre-processing, regularization, usage of interpretable models, diversity in data, and continuous monitoring (Liao et al., 2017).

Big data are used to support HR in many ways, including recruitment, employee retention, performance management, and employee engagement. In the case of recruitment, for example, big data are used to analyse job postings, resumes, social media profiles, and other sources of information to identify the best candidates for open positions (Dhar 2021). This process, known as talent sourcing, helps HR departments target their recruitment efforts more effectively and efficiently.

To use big data for talent sourcing, companies need to collect and structure data from various sources, such as job boards, applicant tracking systems, and social media platforms. They might use machine learning algorithms to analyse this data and identify patterns that identify the best candidates for a given position (Cappelli, Meister 2018). Another important application of big data in HR is employee retention. By analyzing data on employee turnover, companies identify factors that contribute to high turnover rates and develop strategies to address these issues (Lawler, Levenson 2019). For example, they might use predictive analytics to identify which employees are at risk of leaving and take proactive steps to keep them engaged and motivated (Lorincová 2019; Fajčíková, Urbancová 2019). To use big data for employee retention, companies need to collect and analyse data on employee engagement, satisfaction, and other factors that affect retention rates. They use machine learning algorithms to identify patterns and develop predictive models that anticipate and prevent turnover. In addition to recruitment and retention, big data is applied in performance management and employee engagement. By analyzing data on employee performance, companies determine areas where employees need additional training or support and develop strategies to improve overall performance. They also use data on employee engagement to identify factors that contribute to high levels of engagement and develop strategies to promote engagement across the organization (Arora et al., 2022). To use big data for performance management and employee engagement, companies need to collect and analyse data on employee performance, engagement, and other relevant factors. They apply machine learning algorithms to discover patterns and develop predictive models that support the improvement of performance and engagement (Kavanagh, Johnson 2017).

Big data has facilitated the collection, storage, and analysis of vast amounts of data, enabling organizations to derive insights and make informed decisions.

The existing research predominantly centers on exploring the potential applications of predictive analytics across diverse domains, encompassing business (Verm, Singh 2019), healthcare (Tharwat 2020), finance (Zhang et al., 2019, Chen et al., 2020), insurance (Anandarajan et al., 2019), sports (Albert, Bennett 2018, Tseng and Chen 2020), SALW (Dhar, S. 2021, Gupta and Sagar 2022), among others. However, there are no studies analyzing the actual rate of implementation of HR analysis into human resources management work systems.

The research presented in this paper expands the knowledge base, especially by demonstrating the degree of implementation of HR analysis into working systems of human resources management and a change in the perception of the need for its implementation in organizations operating in Slovakia. To achieve the research goals, the authors established the following research questions:

RQ1: What is the current state of the Big Data predictive analytics to employee application in enterprises operating in Slovakia?

RQ2: What is the current level of relevance for the future of enterprises in the context of Big Data analytics to employees in human resources management systems in enterprises operating in Slovakia?

The article addresses a gap in the existing research by focusing on the actual implementation and perception of predictive HR analytics in Slovak companies. While there is extensive literature on the potential applications of predictive analytics across various domains, there is a lack of studies specifically analyzing its integration into human resources management systems within the Slovak context. This research fills that gap by evaluating how Slovak enterprises perceive and utilize predictive HR analytics, providing insights into current practices, challenges, and future potential for these technologies to enhance competitiveness in the European economic arena

The objective of this study is to ascertain contemporary human resource management instruments utilized within businesses operating within the Slovakian context, emphasizing their role in bolstering and enhancing competitiveness within the European economic arena. The authors assumed that the perceived importance of the data approach in HR among

Slovak companies is strong, and companies are open to learning more about this approach. On the contrary, the authors assumed that HR representatives in Slovak companies do not use automated HR analytics tools extensively and rely mostly on manual methods. This assumption suggests a potential lack of awareness or interest in using technology to improve HR data collection and analysis.

3. Experimental

The authors developed a questionnaire consisting of 9 sections covering various HR topics, which was distributed to Slovak companies. The survey was targeted at HR representatives and distributed via personal outreach through physical meetings or phone calls, followed by an email containing the questionnaire link. For this research, the authors focused on the last section, which investigated the implementation and perceived relevance of the data approach in Slovak companies. The questions were created to support the partial objective for the research part "Analysis of the current perception of HR analysis among companies in Slovakia". The questions were:

Question 1: To what extent do you currently use technological innovations and predictive analytics within HR systems in your company?

Question 2: How important will these technological innovations be for your business in the future?

This section contained quantitative questions, each using a 5-point Likert scale. Question 1 assessed the extent of technological innovations applied by using a scale from "do not apply" to "totally apply." Question 2 evaluated the importance of these technological innovations using a scale from "unimportant" to "important."

All questions were specifically focused and provided enough context for respondents to answer accurately. A sample of 1,162 respondents was collected throughout 2020, with a 72% response rate for completed questionnaires deemed relevant to the research. The research sample included 841 enterprises, with a balanced distribution of companies based on size (Table 1). The majority of respondents came from small-size companies (1-9 employees) in the production (32.3%) and service (48%) industries.

Table 1. The structure of the research sample

	Business area			Number of employees				TOTAL
Category	**Production**	**Services**	**Other**	**1-9**	**10-49**	**50-249**	**≥ 250**	
n	272	403	166	256	174	179	232	841
%	32.3	48.0	19.7	30.4	20.7	21.3	27.6	100

The study used primary data, which were collected by the authors themselves. To interpret the results, descriptive statistics and graphs were utilized. The collected data was analyzed, and the results were presented in the form of tables and graphs. The authors also performed various statistical analyses, including descriptive statistics and frequency analysis to explore the relationships between different variables. Finally, the authors discussed the results in the context of the research objectives and provided a summary of the findings. The aim of the analysis was to take a position on the research hypothesis (RH1) arising from the established research questions.

RH1: There is a statistically significant dependence between the actual application in the enterprise and the degree of importance for the future of the enterprise in relation to the following statement: "Big data predictive analytics is used in human resources management functions" in the field of modern tools and concepts in the human resource management system in enterprises.

Data collection through the questionnaire continued until the end of 2020, after which it was necessary to statistically process the results so that relevant materials could be prepared for structuring interviews. This was followed by the identification and approach of suitable respondents to participate in the research interview.

Methodology of structural interviews authors aimed to analyse the current perception and reality of HR analysis among companies in Slovakia. To gain more insights from companies, the authors conducted standardized interviews with 7 HR representatives who had more than 10 years of experience in the HR field. The questions used in the interviews were created based on the partial objectives of the research, which were to analyse the current perception of HR analysis among companies in Slovakia and summarize the reality of the data approach among HR representatives in Slovakia.

The questions were designed to explore the companies' methods of collecting and using HR data, measuring the success of HR initiatives, identifying areas for improvement in the use of HR data, and balancing the use of HR data with other factors such as employee feedback and intuition.

- Can you describe how your company collects and uses HR data?
- How does your company measure the success of HR initiatives?
- In what areas do you think your company could improve its use of HR data?
- How does your company balance the use of HR data with other factors such as employee feedback and intuition?
- How does your company use data to inform retention strategies?

The interviews were conducted via phone and confirmed via email over a period of one month (November 2022). The use of standardized questions ensured consistency across the interviews and allowed easy comparison of responses.

Overall, the methodology used in this study aimed to provide a comprehensive understanding of the current perception and reality of HR analysis among companies in Slovakia, and the use of standardized interviews with experienced HR representatives was an effective way to achieve this objective.

General scientific methods of induction, graphical methods, qualitative analysis of open-ended responses, time series analysis, cluster analysis, and descriptive statistics. Induction involves using specific observations or data to generalize or make predictions about a larger population or phenomenon. This method was used for summarization of qualitative data from structural interviews. Graphical methods helped in representing data visually to identify patterns and trends. Qualitative analysis of open-ended responses to gain deeper insights into employees' reasons for leaving the company. Time series analysis worked on data from questionnaires that were collected over a period of 12 months. Cluster analysis grouped observations from structural interviews into summaries based on their similarities or dissimilarities. The descriptive statistics method was applied to the analysis of the responses from the questionnaire and the data collected from the structural interviews. Furthermore, it was used to summarize and describe the main features of the data, such as the frequency, distribution, and range of responses.

4. Results

The perception of the data approach in human resources has changed over the past few years. The authors of this research paper aimed to gather data and evaluate how this approach is currently perceived among Slovak companies. To achieve this, the researcher used a questionnaire survey distributed via a Google questionnaire platform. Participants were asked to assess their manifestations of digitization of information, to which the company responded with technological innovations toward employees and customers.

The next question was focused on the internal use of predictive analytics by employees within the organization and asked respondents to assess the level of adoption of predictive analytics by their employees.

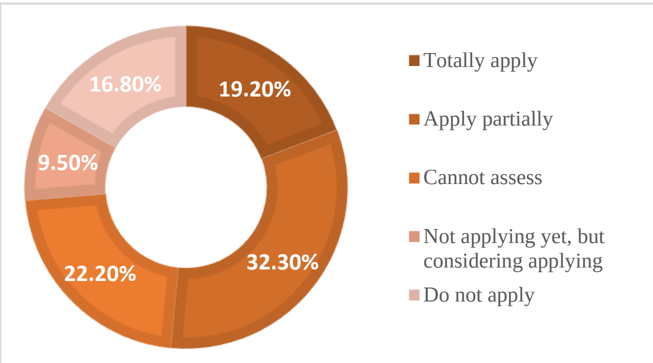

Fig 1. Application of Big data predictive analytics in HRM systems

About one-fifth (19.2%) of companies surveyed applied predictive analytics to their employees extensively (Graph 1). More than a third (32.3%) of companies applied predictive analytics to their employees partially, suggesting that they were not fully utilizing this technology. About 16.8% of companies did not apply predictive analytics to their employees at all. A significant proportion (22.2%) of companies could not assess whether they applied predictive analytics to their employees, indicating a potential lack of tracking or data collection in this area. Finally, 9.5% of companies were not currently applying predictive analytics to their employees but were considering doing so in the future. Two technological innovations were evaluated – the importance of big data analysis in employee motivation, and the importance of big data analysis for marketing purposes. Respondents were asked to evaluate the importance of these innovations towards employees, indicating whether HR representatives believed that these innovations would have a significant impact on employee satisfaction or other aspects.

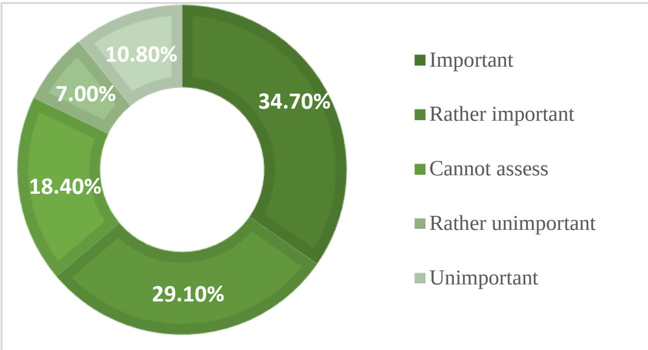

Fig 2. Importance of Big data predictive analytics in HRM systems in the future

The majority of respondents considered predictive analytics for employee motivation as important (34.7%) or rather important (29.1%) (Graph 2). A smaller proportion of respondents considered it unimportant (10.8%), cannot assess (18.4%), or rather unimportant (7%). Based on the results, the authors concluded that predictive analytics was important for local companies.

Subsequently, the authors investigated whether there was a correlation between the current degree of application and the perception of its importance in the near future. In Table 2 they are presented in the absolute frequency and the relative frequency. Individuals responsible for HR activities rated real Big Data analytics in HRM systems on a set rating scale from 1 to 5 (with 1 representing the lowest level currently applied, i.e. not applied, and 5 representing the highest level currently applied, i.e. fully applied).

Table 2. Application level and importance of Big Data predictive analytics in HRM systems for the future

		Big data predictive analytics in HRM systems	
		Actual application	Importance in the future
5	n	160	**294**
	%	19	**35**
4	n	**269**	244
	%	**32**	29
3	n	185	151
	%	22	18
2	n	84	59
	%	10	7
1	n	143	93
	%	17	11
Mean		3.26	3.69

Note: Bold font highlights the top responses.

As evident from the outcomes presented in Table 2, the practical utilization of Big Data Analytics exhibits an above-average status, as indicated by its mean score of 3.26.

Moreover, addressing the second research inquiry, the authors aimed to assess both the absolute frequency and the proportionate significance of Big Data Analytics within human resource management systems for the future sustainability of enterprises. The data analysis results reveal an average perceived importance level, with a mean score of 3.69. In light of the above, it can be inferred that the anticipated future importance surpasses the current practical implementation within specific enterprise contexts, given the higher mean score. The overall difference amounts to 0.43. The validation of the aforementioned research hypothesis facilitated a more profound comprehension of the interrelations and interdependencies among the findings. Verification of the established RH1 hypothesis was conducted via the Spearman correlation test, with the resultant findings presented in Table 3.

Table 3. Spearman´s correlation test result

Big data predictive HR analytics Correlations - Spearman's		Actual application	Importance for the future
Actual application	Correlation Coefficient	1.000	0.768*
	Sig. (2-tailed)	-	<0,001
Importance for the future	Correlation Coefficient	0.768*	1.000
	Sig. (2-tailed)	0.001	-

*Note: *Correlation is significant at the 0.01 level (2-tailed).*

The results presented in Table 3 show that there is a strong positive and at the same time statistically significant dependence (Spearman's coef. = 0.768; $p<0.001$) between the answers to the question of the actual application of Big Data predictive analytics in HRM systems in the enterprise and the question focused on the degree of importance for the future of the enterprise. Based on the foregoing, a hypothesis can be accepted.

In addition to questionnaire analysis, the authors also conducted interviews. The purpose of the interviews was to evaluate the current situation of the data approach in the companies. Also, the perception of the HR data approach and the experience of the HR representatives in this field were assessed. This information helped the authors understand the current trends and challenges in the use of data in HR, as well as identify potential areas for improvement and further research.

In summary, it can be observed that while there was a lot of variation in how companies collect and use HR data, there were some common themes such as the collection of personal details, job-related information, and payroll data. Additionally, there was a trend towards the adoption of more advanced HR systems to manage HR data, as seen in the responses of some of the respondents who mentioned the implementation of new HR systems in their companies. Additionally, companies use HR data for different purposes such as predictive analytics on hiring needs, monitoring employee satisfaction, and performance evaluation. Overall, it can be concluded that HR data collection and usage practices varied among companies and there was a trend towards adopting more advanced HR systems to manage HR data.

Companies use various methods to collect employee feedback and HR data, such as surveys, one-on-one meetings, measurable goals, and analytics. There is also a trend towards using HRIS to manage and gather more data related to HR initiatives and employee performance.

HR professionals proffered varied recommendations regarding the integration of HR analytics within their respective organizational frameworks. The majority underscored the paramount importance of establishing a robust foundation for the pervasive application of a data-driven paradigm in their routine activities. Nevertheless, conspicuous was the discernment that their comprehension of optimal data utilization within the realm of HR remained incomplete. Evidently, while HR practitioners advanced diverse strategies for the assimilation of HR analytics within their organizational milieu, it was palpable that they still lacked a comprehensive grasp of the most efficacious and efficient methodologies for leveraging data in the sphere of HR. Their insights, though indicative of familiarity with HR data collection and analysis, did not manifest a profound insight into the zenith of best practices requisite for enhancing HR management. In essence, there persists a need for a deeper exploration of the most potent means of harnessing HR analytics and its application in their day-to-day endeavors.

The companies have different approaches to balance the use of HR data with other factors such as employee feedback and intuition. Some relied heavily on HR data, while others relied more on intuition and feedback. The size of the company and the availability of tools and systems to collect and analyse HR data also seemed to play a role in their approach.

In addition to the mentioned strategies, it is important to note that some respondents may require more advanced mechanisms to effectively analyse and utilize the collected data. Responses regarding the use of data to inform retention strategies were mixed. Some mentioned the absence of current retention programs, while others discussed using data from stay-in interviews to identify issues and formulate action plans. It appears that some companies are considering the implementation of retention strategies in the future.

5. Discussion

An important aspect of HR analytics is predictive analysis. This involves using data to make predictions about future events or trends. In HR, predictive analytics can be used to forecast employee performance, turnover rates, and other key HR metrics. This can help HR departments make more informed decisions about recruitment, retention, and other aspects of HR management. The process of predictive analytics involves defining the objective, collecting, and preparing data, conducting exploratory data analysis, selecting relevant features, building a predictive model, deploying the model, and monitoring and evaluating the model's performance. Defining the objective is crucial as it determines the type of data that needs to be collected and analyzed. Collecting and preparing data involves cleaning, transforming, and formatting the data for analysis. Exploratory data analysis helps identify patterns and relationships in the data. Feature selection involves selecting the most relevant variables for the predictive model.

Building the predictive model involves selecting an appropriate algorithm and training the model. Deploying the model involves making predictions on new data. Finally, model monitoring and evaluation involves tracking the model's performance over time and updating it as needed.

In the business world, predictive analytics is often used to help companies make data-driven decisions (Kelleheret al., 2018). The study by Verma and Singh (2019) is a literature review of the usage of predictive analytics in the banking industry. The research found that predictive analytics is widely used in the banking industry for various purposes such as customer acquisition, retention, and risk management. They also found that banks use various techniques such as regression analysis, decision trees, and neural networks to build predictive models. The study highlights that the major challenges faced by banks in implementing predictive analytics are data quality, data security, and privacy concerns.

In the healthcare industry, predictive analytics can be used to identify patients at high risk for certain conditions, such as diabetes or heart disease. The study by Tharwat (2020) focused on the application of machine learning techniques for the early detection and prediction of breast cancer. The results of the study showed that the random forest model outperformed other machine learning models in predicting breast cancer with an accuracy of 97.9%. Singh et al., (2020) conducted a study on the use of machine learning for predicting the risk of heart disease. The results of the study showed that the support vector machine model performed the best in predicting the risk of heart disease, with an accuracy of 87%.

In the finance industry, predictive analytics is used to forecast stock prices, identify trends, and detect fraud. Zhang et al., (2019) in their study used a combination of machine learning algorithms to predict stock prices. Chen et al., (2020) conducted a study on the application of predictive analytics to identify trends in the financial market. They found that the best-performing algorithm was the long short-term memory (LSTM) neural network, which was able to achieve a prediction accuracy of 61.1%. Anandarajan et al., (2019) conducted a study on the use of predictive analytics for fraud detection in the insurance industry. The use of predictive analytics was also found to lead to significant cost savings for insurance companies, as it allowed them to identify and reject fraudulent claims more efficiently.

In sports, predictive analytics is used to gain insights into player performance and optimize team strategy. Albert and Bennett (2018) conducted a comprehensive review of the use of analytics in sports. They found that sports teams and organizations are increasingly turning to analytics to gain insights and improve performance. Tseng and Chen (2020) conducted a study on the use of predictive analytics for NBA games using a machine learning approach. The study also identified the key factors that had the greatest impact on predicting game outcomes, including the number of rebounds, assists, steals, and blocks.

In the field of human resources management, it is also desirable to use Big Data predictive analytics. For example, when analyzing fluctuations. A study by Gupta and Sagar (2022) found that predictive analytics can accurately predict employee turnover with an accuracy of 82.2%, which can help organizations take proactive measures to retain employees. Another study by Braganza and Bharati (2021) found that predictive analytics can help identify the factors that contribute to employee turnover, such as job satisfaction, work-life balance, and career growth opportunities. Companies have begun using predictive analytics to identify high-potential employees and predict future hiring needs (Boudreau, Cascio 2017).

The research presented in this paper showed that in terms of the application of Big data analytics in HRM systems, about one-fifth of companies surveyed apply predictive analytics to their employees extensively, while more than a third of companies apply it partially, suggesting that they are not yet fully utilizing this technology. About 16.8% of companies do not apply predictive analytics to their employees at all. A significant proportion of companies cannot assess whether they apply predictive analytics to their employees, indicating a potential lack of tracking or data collection in this area.

The questions in the survey were specific and measurable, which helped to ensure that the data collected from respondents were analyzed and used to interpret situations within the organization. The perception of data-driven approaches to HR is likely to be positive among organizations that have successfully implemented these approaches and seen positive results. However, there may also have been some uncertainty or concern among organizations that were hesitant to rely too heavily on data or that had encountered challenges in implementing these approaches.

According to the results, the usage of predictive analytics was not very common among Slovak companies, with only 17.2% of respondents reporting that they totally applied it. In fact, almost half of the respondents either did not use predictive analytics or could not assess whether they used it or not, suggesting a significant proportion of the respondents were not actively using predictive analytics in their strategies.

The questionnaire results provided valuable insight into the perception of predictive analytics among local companies. The positive response towards the use of predictive analytics, as reflected in the questionnaire results, served as confirmation of the importance of further research in this area. It suggested that local companies recognized the potential benefits of using predictive analytics and were willing to adopt this data-driven approach to improve their HR management practices. Although there was a clear interest in the use of predictive analytics in Slovak companies, there was still a lot of room for improvement and adoption of this approach in HR practices. Companies should consider the potential benefits of implementing predictive analytics in their strategies, as it can provide valuable insights and help improve decision-making processes. This opens up opportunities for further research to explore in-depth the implementation of predictive analytics in HR, identify potential challenges and limitations, and develop strategies to overcome them. The authors' findings also suggest that companies in Slovakia are increasingly recognizing the value of data-driven decision-making in HR and are willing to invest in these technologies in order to gain a competitive advantage.

The structural interviews aimed to understand how companies collect and use HR data, measure the success of HR initiatives and identify areas for improvement. It also investigated how companies balance the use of HR data with other factors such as employee feedback and intuition, and how they use data to inform retention strategies. Overall, it was observed that HR data collection and usage practices vary among companies, and there was a trend towards adopting more advanced HR systems to manage HR data. Companies use HR data for different purposes, such as predictive analytics on hiring needs, monitoring employee satisfaction, and performance evaluation.

Regarding areas for improvement, respondents identified recruitment, people analytics data generation, data management, performance management, and employee feedback tracking. Companies use various methods to collect employee feedback and HR data, such as surveys, one-on-one meetings, measurable goals, and analytics. The size of the company and the availability of tools and systems to collect and analyse HR data seemed to play a role in their approach to balancing the use of HR data with other factors such as employee feedback and intuition.

Regarding employee turnover, respondents identified factors that contributed to it, such as market competition, job design, career development, mismanagement of expectations, and lack of retention programs. Certain departments, such as sales and customer service, had higher turnover rates. Junior employees with under three years of work experience also tended to leave more frequently. Companies used various strategies to identify factors contributing to employee turnover and identify high-risk employees who may be considering leaving, such as exit interviews, performance evaluations, employee surveys, regular discussions with employees, and tracking employee attendance and work quality.

Finally, regarding retention strategies, responders had mixed answers regarding the use of data to inform retention strategies. While some mentioned not having any retention programs at the moment, others mentioned using data from stay-in interviews to identify issues and create action plans. Some companies are interested in implementing retention strategies in the future.

Overall, the authors confirmed that various types of companies were considering implementing a data-driven approach in their HR departments. However, there was a clear lack of comprehensive information on where this data could be sourced and how it could be utilized, with only one respondent mentioning a predictive approach. Nevertheless, the chosen topic is very relevant to the current market situation.

5. Summary and conclusion

Answer to RQ1 is: The study found that the application of predictive analytics in Slovak enterprises is relatively low. Only 19.2% of companies applied predictive analytics extensively to their employees, while 32.3% applied it partially. About 16.8% of companies did not apply predictive analytics at all, and a significant proportion (22.2%) could not assess whether they applied it or not. This suggests a potential lack of tracking or data collection in this area.

Answer to RQ2 is: The study indicated that there is a higher perceived future importance of predictive analytics compared to its current practical implementation. The mean score for the current application of Big Data analytics was 3.26, while the perceived importance for the future was 3.69. This shows that companies acknowledge the future potential and relevance of predictive analytics in HR but have not yet fully implemented it.

Companies use a variety of methods to collect employee feedback (Londonet al., 2023) and HR data, such as surveys, face-to-face meetings, measurable goals, and analytics. The size of the company and the availability of tools and systems for collecting and analyzing HR data appeared to have played a role in their approach to balancing the use of HR data with other factors such as employee feedback and intuition.

Although there was a clear interest in the use of predictive analytics in Slovak companies, there was still a lot of room for improvement and adoption of this approach in HR practice.

There are several limitations in the usage of the data approach. HR departments often lack the skills to perform analytics, and therefore, analytics teams should include people with experience in IT, finance, and data analytics (Mayo 2018). Companies have access to HR information in various systems, such as human resources information systems, pay systems, engagement surveys, performance management systems, and applicant tracking systems, among others. However, combining data from these systems can be challenging. For example, it may be difficult to compare engagement scores with employee performance data (Stanbery et al., 2023) or to compare HRIS and demographic information with absence systems (Ibrahim et al., 2023). Additionally, while companies may have data on the profiles of candidates attracted through the applicant tracking system, they may not have information on the performance of these applicants after one year in the organization (Jain et al., 2020). However, there are also some potential limitations and challenges associated with data-driven approaches to HR. For example, there may be concerns about the accuracy and reliability of the data being used (Conte, Siano 2023), or about the potential for data to be used in ways that are unethical or violate employees' privacy rights (Bender, Fish 2021; Marr, 2023).

The authors' findings also suggest that companies in Slovakia are increasingly aware of the value of data-driven decision-making in HR and are willing to invest in these technologies to gain a competitive advantage. The positive response to the use of predictive analytics, which is reflected in the results of the questionnaire, serves as a confirmation of the importance of further research in this area.

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