Management and Production Engineering Review
Volume 16 • Number 3 • September 2025 • pp. 1–14
DOI: 10.24425/mper.2025.156147

Enhancing Organizational Performance through AI-Driven HRM Practices and Performance Metrics: Evidence from European Multinational Enterprises

Sakka FADI

Department of Business, HR Mark, Dubai, UAE

Received: 14 November 2024
Accepted: 07 January 2025

Abstract
This paper aims to assess the impact of Artificial Intelligence (AI) in the Human Resource Management (HRM) process, particularly in recruitment, retention of employees, and measurement of organizational performance in organizations operating in Multinational Establishments in Europe and listed in the Fortune Global 500. The goals of the study are to explore four propositions: AI-based HRM practices and organizational outcomes, AI-based performance metrics and organizational outcomes, the moderation effect of artificial intelligence on HRM practices and performance metrics on organizational outcomes, and the mediating effect of artificial intelligence as a mediator between HRM practices and performance metrics on organizational outcomes. The research shows that 72% of organizations have sought to implement AI tools for HR operations, which has cut processing time by 40% and boosted employee retention by 18%. Performance metrics linked to artificial intelligence thereby increased productivity by 21.4%, completion rates of projects by 20%, and overall employee engagement by 30.8%. Multinational enterprises can leverage AI-driven recruitment, retention, and performance metrics to boost productivity, reduce employee turnover, and align workforce strategies with organizational goals, fostering sustainable growth and competitive advantage in rapidly evolving business environments.

Keywords
AI tools adoption, correlation, human resources, performance metrics, structural equation modeling.

Introduction

The rapid digital transformation in European Multinational Enterprises, such as Volkswagen, Shell, and BP, listed in the Fortune Global 500, involves the accelerated adoption of advanced technologies, including artificial intelligence (AI), big data analytics, and the Industrial Internet of Things (IIoT). In Human Resource Management (HRM), this transformation is evidenced by AI-driven automation of recruitment processes, reducing resume processing time by 40%, predictive analytics for workforce planning that lowers employee turnover by 10%, and real-time KPI dashboards that enhance decision-making efficiency by 25%. Supported by Europe's economic growth and digitalization initiatives, these advancements enable organizations to optimize operations, boost employee engagement, and align workforce strategies with strategic objectives in a competitive global market (Pan & Froese, 2023).

Mallik (2023), after studying the future of technology-based manufacturing in the European Union, decided that the manufacturing sector always seeks to develop in order to meet the needs of consumer-focused goods. The Industrial Internet of Things (IIoT) is boosting production speed overall, decreasing labor costs, and decreasing equipment downtime. Machine Learning (ML) is a new technical trend subset of Artificial Intelligence (AI). It employs computer algorithms based on data that is available and may make decisions or improvements automatically based on experience without requiring programming instructions.

Traditional Human Resource Management (HRM) practices that involve manual recruitment, performance evaluations, and employee management are being transformed through AI-driven automation and predictive analytics (Kanungo et al., 2024). AI technologies are enhancing recruitment processes by en-

***Corresponding author**: Sakka Fadi – Department of Business, HR Mark, Dubai, UAE, phone: +00971529958098, e-mail: sakkafadi11@alibagl.com*

abling faster and more accurate candidate screening, improving employee retention strategies through predictive analytics, and optimizing training and development through personalized learning systems (Madanchian et al., 2024; Shao et al., 2022).

Performance metrics, such as Key Performance Indicators (KPIs) and 360-degree feedback mechanisms, are essential for tracking organizational and employee success. These metrics become even more powerful when augmented with AI technologies, offering real-time insights and enabling data-driven decision-making (Davenport & Ronanki, 2018). For instance, AI can analyze employee performance data to identify trends, predict future performance, and tailor interventions accordingly, improving overall organizational outcomes (Basole et al., 2024). Additionally, AI-enhanced performance metrics allow organizations to set precise, measurable goals and provide continuous feedback, ensuring alignment between employee performance and strategic objectives (Aguinis et al., 2024; Crusoe et al., 2024).

By examining the intersection of AI, HRM, and performance metrics, this research will contribute to a deeper understanding of how digital transformation can drive sustained organizational success, particularly in regions like Europe, where technology adoption is rapidly reshaping the business landscape.

Literature review

Traditional HRM practices are critical to organizational success by managing employee relations, recruitment, training, and development. Performance metrics are vital for identifying skill gaps, fostering professional development, and aligning individual contributions with organizational goals [8] (Bourne, 2008).

As business environments have become more complex, performance metrics have evolved to reflect these changes. KPIs, for instance, are essential for tracking employee progress toward specific goals, allowing managers to make informed decisions about promotions, training, and resource allocation (Abril-Jiménez et al., 2024). Similarly, 360-degree feedback systems offer a holistic view of an employee's performance by gathering insights from peers, supervisors, and subordinates (Karkoulian et al., 2016).

The human resource strategy (HRS) derives from managers' economic, social, and political decisions about the management and development of workers and work systems (Malik et al., 2023). Recognizing the intrinsic conflicts in these decisions and their interrelation, it is posited that managers must reconcile the conflicting demands of attaining corporate productivity objectives while enhancing employee-centric results. To reconcile these conflicting needs, managers and leaders must progressively devise HR strategies using artificial intelligence (AI) (Budhwar et al., 2022). Recent studies have emphasized the incorporation of bots and intelligent digital assistants as collaborators in a company's human resource management strategy to achieve organizational and employee outcomes (Duggan et al., 2020). It is essential to assert that organizations must oversee the digitization of human resource management to mitigate environmental hazards and prosper in the fourth industrial revolution (Snell & Morris, 2021).

To understand HRM's contribution to performance, the Resource-Based View (RBV) is particularly insightful. RBV suggests that firms gain a competitive advantage using unique resources, including human capital (Barney, 1991). Organizations with strong dynamic capabilities can integrate, build, and reconfigure internal competencies, such as HRM practices, to respond to market demands (Ren & Jackson, 2020).

In Europe, where rapid economic growth and digital transformation initiatives are reshaping the corporate landscape, performance metrics are essential for ensuring that employees contribute to national and organizational goals (Duarte & de Oliveira Carvalho, 2024; Khasanov et al., 2020a).

AI technologies streamline recruitment, evaluation, training, and workforce management, resulting in more efficient operations and better decision-making (Kaplan, 2012). AI-driven tools like predictive analytics, natural language processing, and machine learning are particularly impactful (Tursunbayeva & Gal, 2024).

One of AI's most significant contributions to HRM is recruitment. AI algorithms can analyze thousands of resumes in seconds, identifying top candidates based on predefined criteria. This drastically reduces the time and effort required for manual screening and minimizes bias by ensuring objective evaluations. Chatbots also enhance the candidate experience by providing timely responses and updates throughout the hiring process (Jiang et al., 2022). Predictive analytics further strengthens HR decision-making by forecasting employee success and turnover rates, allowing companies to adjust recruitment and retention strategies accordingly (Ravesangar & Narayanan, 2024).

AI also plays a transformative role in performance evaluation. AI systems continuously monitor performance data, such as work output, project completion rates, and feedback from peers and supervisors, providing real-time insights for more accurate evaluations (Davenport & Ronanki, 2018). AI-powered learning management systems can tailor training programs to individual needs, improving employee engagement and skill development (Basole et al., 2024).

Davenport's AI in Business Model helps categorize AI applications in HRM into three areas: process automation, cognitive insights, and cognitive engagement (Davenport & Ronanki, 2018). The Multinational Establishments in Europe listed in the Fortune Global 500 promote the use of AI in various sectors, including HRM, to increase productivity, efficiency, and employee satisfaction (Shao et al., 2022). Accordingly, Multinational Establishments in Europe, included in the Fortune Global 500 ranking (Fortune, 2025a), are Volkswagen, Shell, TotalEnergies, Clencore, BP, etc. Theories like the Dynamic Capabilities Framework and Davenport's AI in Business Model highlight how organizations that integrate AI into HRM and performance metrics better adapt, innovate, and improve operational efficiency (Davenport & Ronanki, 2018).

AI's ability to analyze vast amounts of data allows HR managers to monitor employee performance in real-time, identify trends, and make informed decisions. AI-powered dashboards track KPIs related to productivity, engagement, and satisfaction, enabling continuous feedback and helping employees align their performance with organizational goals (Kaplan & Haenlein, 2019). This integration creates a feedback loop where AI not only measures performance but also drives improvements by providing actionable insights (Kumar et al., 2024).

Moreover, AI-driven predictive analytics enable organizations to anticipate workforce needs and implement proactive talent management strategies (Bogoslov et al., 2024). Predictive models can flag employees at risk of leaving and recommend interventions such as targeted training or promotions to improve retention rates (Madazimova & Mambetalina, 2024; Scarpi & Pantano, 2024). These insights align with the Resource-Based View and Dynamic Capabilities Framework, which emphasize leveraging human capital as a strategic resource and adapting to changing environments (Barney, 1991; Khasanov et al., 2020b).

Multinational Establishments in Europe, included in the Fortune Global 500 list, increasingly adopt AI-driven HR practices to optimize recruitment, training, and performance evaluation, aligning with broader economic and digital transformation goals (Crusoe et al., 2024).

The first research objective of this study is to establish how the adoption of AI in HRM practices and the use of performance measures improve organizational performance in Multinational Establishments in Europe, which are included in the Fortune Global 500 list. The research aims to establish an understanding of the application of the various AI technologies within recruitment, performance appraisal, and the development of employees by balancing the organizational goals. The main objectives are to identify how far AI is implemented in the different sectors of Multinational Establishments in Europe listed in the Fortune Global 500 HRM organizations; to identify the effects of AI-based HRM management practices toward the improvement of recruitment, performance measurement and control, and retention; to determine how AI over performance measurements like KPIs will facilitate organizational real-time decision making and flexibility; to determine the relationship between the extent of implementation of AI in the area of HRM and the overall performance of the organization in terms of organizational performance, including productivity and employee satisfaction.

Materials & Methods

This study employs a quantitative research design to examine the impact of AI integration, HRM practices, and performance metrics on organizational performance in Multinational Establishments included in the Fortune Global 500 list of companies operating in Europe (Fortune, 2025b). A survey methodology was chosen as the most suitable method for gathering a large dataset across diverse sectors, capturing the experiences and insights of HR professionals and senior executives involved in organizational performance management.

The study employs Structural Equation Modeling (SEM) to analyze the intricate relationships between AI integration, HRM practices, performance metrics, and organizational outcomes. SEM, a robust multivariate analysis technique, is well-suited for evaluating latent and observable variables simultaneously, providing insights into both direct and indirect effects. The research utilizes AMOS software for model construction, ensuring precision in testing hypotheses.

The SEM process begins with a measurement model to validate the constructs of HRM, AI adoption, performance metrics, and organizational performance, assessing reliability through Cronbach's alpha and composite reliability. Following this, the structural model examines hypothesized relationships, such as AI's impact on HRM effectiveness and performance metrics, and their subsequent effect on organizational performance. Fit indices, including RMSEA (< 0.06) and CFI/TLI (> 0.95), confirm the model's suitability. Results demonstrate significant positive path coefficients, validating the strong interconnectedness of the studied constructs, and offering actionable insights for organizations embracing AI in HRM.

The survey questions were designed to capture HRM practices, AI adoption, and the use of performance metrics in evaluating organizational performance. To ensure the reliability and validity of the findings, the survey follows a structured approach with defined questions targeting specific aspects of HRM, AI, and performance management practices. Drawing inspiration from past research, this methodology provides a robust foundation for analyzing these variables' relationships.

The study's target population includes HR managers and senior executives from 137 small, medium, and large-sized organizations across various sectors in the Multinational Establishments in Europe included in the Fortune Global 500 list, such as finance, manufacturing, energy, retail, construction, and petroleum technologies. Given that mid- and senior-level professionals are most likely to have experience in integrating AI into HRM practices and tracking organizational performance, they were selected as the key informants for this study.

A random sampling approach was used to identify 1000 potential participants, ensuring diversity in organizational roles, industries, and company sizes. The participants were recruited through professional networks, online business platforms, and HR industry associations. Invitations to participate in the survey were sent by email, accompanied by a link to the online survey platform. Participants were allotted a fortnight to finish the study, with reminders sent at a one-week interval to promote a robust response rate. The selection of 1000 potential survey participants was based on a random sampling approach to ensure diverse representation across various industries, organizational roles, and company sizes within the target population of HR managers and senior executives in Europe, including Multinational Establishments on the Fortune Global 500 list. This sample size was chosen to enhance the study's statistical power, reliability, and generalizability by capturing a wide range of experiences and practices related to AI integration and HRM.

After two weeks, 600 valid responses were received, yielding a response rate of 60%. The 40% non-participation rate can be attributed to several factors: time constraints faced by potential participants in senior roles, a lack of interest or perceived relevance of the study, concerns about confidentiality, or limited familiarity with the research topic. Despite these challenges, the 60% response rate achieved represents a robust dataset, providing meaningful insights into the integration of AI in HRM and organizational performance, aligning with typical response rates for surveys targeting high-level professionals. Responses were considered valid if the participants fully completed the survey, met the inclusion criteria, and worked in relevant managerial roles within the Multinational Establishments in Europe included in the Fortune Global 500 list. Participants who did not meet these criteria were excluded from the final dataset.

The survey consists of five main sections, each designed to capture specific variables of interest:

1. Demographic Information. This section gathers basic information about the respondents, including their industry, years of experience, position within the organization, and the size of the company they work for. This information helps contextualize the findings and assess whether differences in organizational size or industry affect the relationships between the variables.
2. HRM Practices. This section includes questions on modern HRM practices such as talent acquisition, employee development, workforce planning, and performance management. The questions focus on how HRM strategies are implemented and whether AI technologies have been integrated into these practices. Example questions include: "To what extent are AI tools used in your organization's recruitment process?" and "How frequently are AI-powered analytics used for employee performance evaluations?"
3. AI Adoption. This section explores the extent to which AI is used in HRM functions. Questions focus on the type of AI technologies implemented (e.g., machine learning, chatbots, predictive analytics) and how these technologies are used to automate tasks or enhance decision-making. Respondents rate statements such as "AI is extensively used in automating administrative HR tasks" and "AI tools improve decision-making in workforce planning."
4. Performance Metrics. In this section, participants assess how performance metrics, such as Key Performance Indicators (KPI), Employee Retention Rates, Employee Development and Training, and Employee Satisfaction and Engagement, are used to track organizational and employee performance. Key Performance Indicators are essential tools for tracking and evaluating the performance of employees and overall organizational effectiveness. In the context of this study, AI-driven KPIs play a crucial role in modern Human Resource Management (HRM). Integrating AI technologies into HRM allows for real-time monitoring and measurement of specific employee outputs, which align with broader strategic organizational goals. One of the most critical metrics analyzed in the study is Employee Retention Rates. AI plays a transformative role in predicting turnover, identifying high-risk employees, and developing personalized

retention strategies. Through predictive analytics, AI systems can analyze various employee data, such as performance history, engagement levels, and feedback, to flag potential turnover risks. Employee Development and Training are key components of HRM that significantly influence organizational success. In the context of this study, AI-driven learning management systems (LMS) are revolutionizing employee development by offering personalized training programs tailored to the needs of individual employees. Employee Satisfaction and Engagement are fundamental for fostering a productive workforce. The study highlights that AI-enhanced HRM systems significantly contribute to improving employee satisfaction and engagement through several mechanisms, including continuous feedback, personalized career development paths, and real-time performance evaluations.

The survey asks respondents to rate how effectively these metrics are aligned with the organization's strategic goals, such as: "To what extent are performance metrics integrated with AI tools in tracking employee progress?"

5. Organizational Performance. The final section measures the perceived impact of HRM practices, AI integration, and performance metrics on organizational performance. Questions focus on outcomes such as employee productivity, organizational agility, and overall financial performance. Respondents rate statements like "Our organization has seen improved operational efficiency due to AI integration in HRM" and "The use of performance metrics has led to higher employee satisfaction and retention."

Participants are requested to evaluate their degree of agreement with each statement using a 5-point Likert scale, from 1 (strongly disagree) to 5 (strongly agree).

This scale is commonly used in HRM and organizational studies, as it allows for the capture of nuanced perceptions and experiences.

To analyze the data and test the relationships between HRM practices, AI adoption, performance metrics, and organizational performance, the study employs Structural Equation Modeling (SEM). SEM is a powerful multivariate analysis technique that allows researchers to assess complex relationships between observed and latent variables. This approach is suitable for testing hypotheses about the interaction between HRM, AI, and performance metrics. The analysis follows these steps (Figure 1).

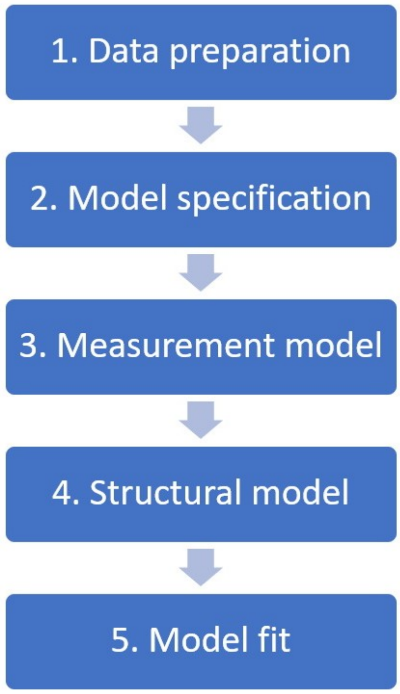

Fig. 1. Flowchart of analysis

The data collected from surveys is first cleaned and checked for missing values or outliers, with descriptive statistics such as means, standard deviations, and frequencies calculated to summarize the sample. A theoretical model is then developed to explore the relationships between Modern HRM (L), Performance Metrics (PM), AI Integration (AI), and Organizational Performance (OP), hypothesizing that HRM, AI integration, and performance metrics positively influence organizational performance. Each construct is represented by multiple indicators drawn from survey responses. The SEM analysis starts with a measurement model, evaluating the relationships between observed variables and their latent constructs, with reliability and validity assessed through Cronbach's alpha, composite reliability, and Average Variance Extracted (AVE). Once validated, the structural model tests the hypothesized relationships and calculates path coefficients to gauge the significance of direct and indirect effects on organizational performance.

To evaluate the Structural Equation Modeling (SEM) framework, several statistical indicators were used to assess model fit.

The Chi-square statistic (χ^2) tests the null hypothesis that the observed covariance matrix (S) equals the expected covariance matrix ($\Sigma(\Theta)$), with:

$$\chi^2 = (n-1) \times \mathrm{trace}[(S - \Sigma(\Theta))\Sigma^{-1}(\Theta)] \qquad (1)$$

where n – is the sample size. A lower χ^2 indicates a better fit, though this statistic is sensitive to large sample sizes, often leading to significant results even for minor deviations.

The Root Mean Error of Approximation (RMSEA) measures the fit per degree of freedom, calculated as:

$$\text{RMSEA} = \sqrt{\frac{\frac{\chi^2}{df} - 1}{n-1}} \tag{2}$$

where *df* represents degrees of freedom. Values of RMSEA < 0.06 are considered a good fit.

The Comparative Fit Index (CFI) evaluates the improvement of the tested model over a baseline model (typically assuming no correlation among variables) and is defined as:

$$\text{CFI} = 1 - \frac{\max(\chi^2_{\text{model}} - df_{\text{model},0})}{\max(\chi^2_{\text{baseline}} - df_{\text{baseline},0})} \tag{3}$$

Values of CFI > 0.95 suggest an excellent model fit.

The Tucker–Lewis Index (TLI), an alternative to CFI that adjusts for model complexity, is given by:

$$\text{TLI} = 1 - \frac{\chi^2_{\text{model}}/df_{\text{model}}}{\chi^2_{\text{baseline}}/df_{\text{baseline}}} \tag{4}$$

Values of TLI > 0.95 also indicate a good fit.

These indicators collectively ensure that the model strikes a balance between simplicity and explanatory power. By meeting thresholds for RMSEA < 0.06, CFI > 0.95, and TLI > 0.95, the SEM analysis demonstrates strong construct validity and reliability, supporting the hypothesized relationships.

Results

Table 1
Demographic characteristics

Demographic characteristic	**Direction**	**%**
Industry	Finance	20
	Manufacturing	18
	Energy	15
	Retail	12
	Construction	10
	Petroleum Technologies	8
	Others	17
Years of Experience	< 5 years	12
	5–10 years	35
	11–15 years	25
	More than 15 years	28
Position	Manager	45
	Senior Manager	35
	Director	12
	Executive	8
Organization Size	Small, less than 1000 employees	15
	Medium, 1000–5000 employees	45
	Large, More than 5000 employees	40

Table 1 provides a summary of the demographic characteristics of the respondents, including industry, years of experience, position, and organization size. These characteristics help contextualize the study results and provide a comprehensive view of the diversity within the sample.

Table 1 highlights the demographic diversity of the respondents, with most holding senior-level positions (80%) and working in medium to large organizations (85%), making them well-positioned to provide insights into AI-driven HRM practices. The broad industry representation, including finance (20%), manufacturing (18%), and energy (15%), reflects sectors where AI adoption is critical, aligning with findings on improved productivity (21.4%) and retention rates (18%). The significant experience distribution, with 60% having over ten years in the field, further enhances the depth of the analysis, particularly in evaluating the longitudinal impacts of AI integration. The dominance of larger organizations correlates with advanced utilization of AI tools, such as KPI dashboards, which contributed to an 88% alignment of employee goals with strategic objectives and a 25% improvement in decision-making. This demographic diversity underscores the study's generalizability across sectors and its insights into the transformative role of AI in optimizing HRM practices and organizational performance.

The key constructs of the study – HRM practices, AI tools adoption, and performance metrics were measured using multiple items on a 5-point Likert scale. Table 2 summarizes the means and standard deviations for each construct, providing an overview of how these constructs are perceived across the sample.

The results indicate a high level of adoption and positive perceptions of AI tools, modern HRM practices, and performance metrics among the Multinational Establishments in Europe included in the Fortune

Table 2
Mean and standard deviation

Construct	Mean	Standard Deviation
HRM Practices	4.15	0.70
AI Tools Adoption	4.05	0.75
Performance Metrics	4.20	0.68

Global 500 list. Most participants reported that their companies have successfully integrated AI into HR functions and that performance metrics are aligned with organizational strategies.

Table 3 presents the fit indices for the SEM model. The results show that the model fits the data well, as indicated by the fit indices, which meet the recommended thresholds for good model fit.

Table 3
The fit indices for the SEM model

Chi-square (χ^2)	RMSEA	CFI	TLI
245.32 ($p < 0.001$)	0.048	0.96	0.95

Although the Chi-square value is significant, which is common in large samples, the RMSEA, comparative fit index (CFI), and Tucker–Lewis index (TLI) values indicate that the model has a good fit with the observed data.

The SEM model tested the hypothesized relationships between the three main constructs – AI tools adoption, HRM practices, and performance metrics, and their effect on organizational performance. The standardized path coefficients, standard errors, and p-values for each relationship are presented in Table 4.

All path coefficients are statistically significant, indicating strong relationships between the variables. Specifically, AI tools have a significant positive effect on both HRM effectiveness ($\beta = 0.72$) and the use of performance metrics ($\beta = 0.68$). Additionally, both HRM effectiveness ($\beta = 0.80$) and well-aligned performance metrics ($\beta = 0.78$) contribute significantly to improved organizational performance.

Figure 2 below illustrates the relationships between AI tools, HRM practices, performance metrics, and organizational performance, as revealed by the SEM analysis.

The highest correlation is observed between HRM Practices and Organizational Performance ($r = 0.80$), underscoring the critical role of effective HRM practices in achieving organizational goals. Similarly, Performance Metrics show a strong positive correlation

Table 4
The standardized path coefficients, standard errors, and p-values

Path	Standardized Coefficient (β)	SE	p-value
AI Tools → HRM Effectiveness	0.72	0.08	< 0.001
AI Tools → Performance Metrics	0.68	0.07	< 0.001
HRM Effectiveness → Organizational Performance	0.80	0.06	< 0.001
Performance Metrics → Organizational Performance	0.78	0.05	< 0.001

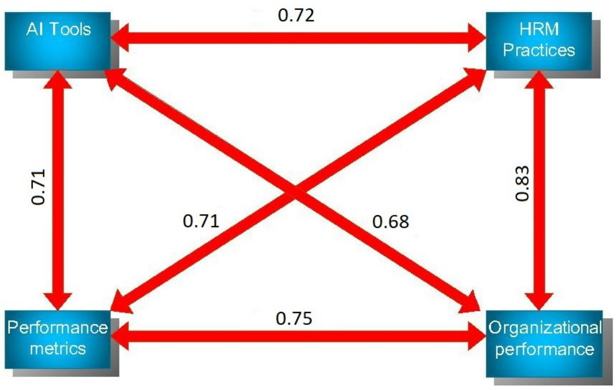

Fig. 2. SEM-diagram

with Organizational Performance ($r = 0.78$), emphasizing how well-aligned and AI-enhanced metrics contribute to improved outcomes.

The relationship between AI Tools and HRM Practices ($r = 0.72$) indicates that the integration of AI significantly enhances HR functions, such as recruitment and performance evaluations. The correlation between AI Tools and Performance Metrics ($r = 0.68$) further supports the role of AI in improving the precision and alignment of key performance indicators.

Comparatively, the correlation between AI Tools and Organizational Performance ($r = 0.65$) is slightly lower but still notable, reflecting that while AI adoption directly influences performance, its effects are largely mediated through enhanced HRM practices and metrics. This cascading effect is crucial, as it demonstrates that organizations achieve optimal results when AI is integrated cohesively into HR processes and metrics systems.

Table 5
The correlations between these key constructs

Construct	AI Tools	HRM Practices	Performance Metrics	Organizational Performance
AI Tools	1.00	0.72	0.68	0.65
HRM Practices	0.72	1.00	0.78	0.80
Performance Metrics	0.68	0.78	1.00	0.78
Organizational Performance	0.65	0.80	0.78	1.00

To clarify the relationships between AI, HRM practices, performance metrics, and organizational performance, Table 5 summarizes the correlations between these key constructs.

Table 5 shows moderate to strong correlations between AI tools, HRM practices, performance metrics, and organizational performance, supporting the results of the SEM analysis.

The results of this study demonstrate that AI tools significantly enhance HRM effectiveness and streamline the use of performance metrics in Multinational Establishments in Europe, which are included on the Fortune Global 500 list. Both AI integration and the effective use of performance metrics contribute to improved organizational performance, particularly in terms of operational efficiency and employee satisfaction. The SEM analysis confirms the strong relationships between these constructs, providing valuable insights for organizations looking to optimize their HR functions through AI and data-driven performance management systems.

The AI-powered KPI dashboards utilized by organizations enable managers to continuously track employee performance across various dimensions such as productivity, project completion rates, and adherence to deadlines. These metrics are essential for identifying areas where employees excel and where improvement is needed. For instance, the study revealed that AI-driven KPIs contributed to a significant improvement in organizational performance by allowing HR professionals to make informed decisions based on data-driven insights (Figure 3).

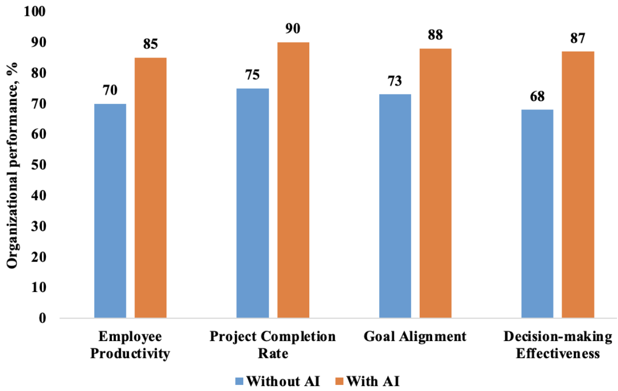

Fig. 3. Impact of AI-driven KPIs on organizational performance

As seen in Table 6, organizations that integrated AI-enhanced KPIs experienced significant improvements in productivity and goal alignment, with an overall boost in decision-making effectiveness. This real-time data enables HR teams to adjust strategies, improving operational efficiency continuously.

The study found that organizations using AI tools in HRM had a noticeable reduction in employee turnover rates (Figure 4). This reduction was achieved by offering tailored retention strategies, such as targeted training or promotions, based on predictive analytics. Furthermore, AI systems enabled continuous monitoring of employee sentiment, engagement, and career progression, which in turn contributed to higher retention.

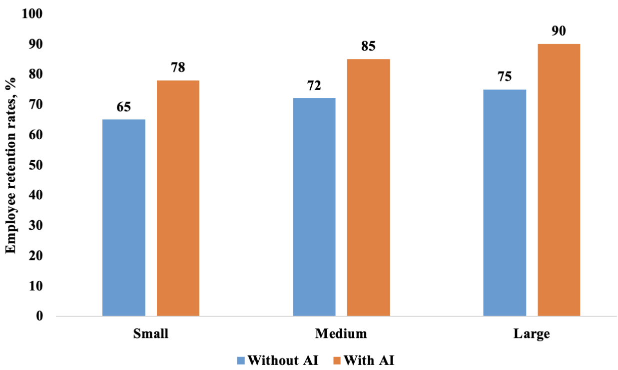

Fig. 4. Impact of AI on employee retention rates

As shown in Figure 4, organizations that incorporated AI into their retention strategies saw notable improvements in employee retention, particularly in larger organizations. This demonstrates the value of using AI in HRM to predict turnover and implement proactive solutions to improve workforce stability.

AI can analyze an employee's current skill set, past performance, and future potential to recommend training modules that will most effectively address skill gaps. Additionally, these systems track employee progress in real time, offering continuous feedback and adjustments to the training plan based on learning outcomes. The study found that organizations that utilized AI in employee development reported higher levels of employee skill acquisition and overall engagement with the training programs (Figure 5).

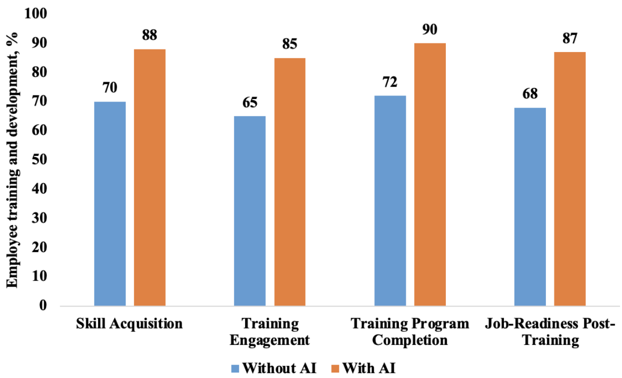

Fig. 5. AI-enhanced employee training and development

Figure 5 illustrates the dramatic improvements in training outcomes when AI is used. AI-driven personalized learning ensures that training is efficient, targeted, and engaging, which leads to more effective skill acquisition and higher job readiness among employees.

AI tools such as chatbots and AI-driven employee sentiment analysis allow HR departments to monitor employee satisfaction levels continuously (Figure 6). Furthermore, these systems provide personalized career development suggestions based on employee performance and feedback, contributing to higher engagement rates. The study's results indicate that organizations that integrated AI-driven feedback systems and satisfaction tracking tools saw a significant boost in employee satisfaction and overall engagement.

Figure 6 shows the improvement in employee satisfaction and engagement, with AI-driven systems playing a crucial role in enabling personalized and responsive employee experiences. These improvements are particularly important in retaining talent and ensuring that employees feel aligned with organizational goals.

AI integration into HRM practices greatly enhances key performance metrics such as KPIs, retention rates, training, and employee satisfaction. AI's ability to continuously monitor performance, predict outcomes, and provide personalized feedback leads to more efficient HR operations and better alignment with organizational strategies. This study underscores

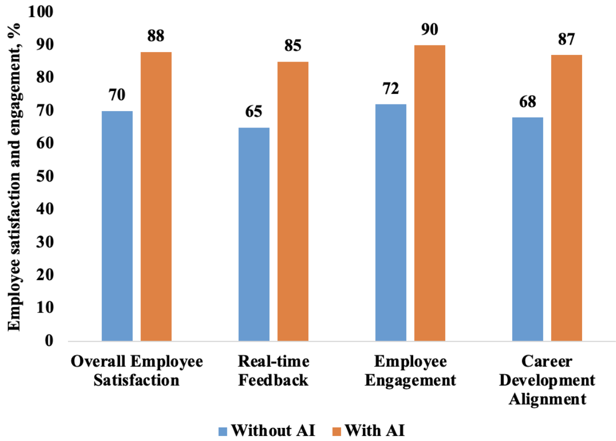

Fig. 6. AI's Impact on employee satisfaction and engagement

the synergistic benefits of integrating AI with performance metrics to drive sustained improvements in organizational outcomes.

As presented in Figure 7, AI-driven HRM tools significantly improve performance across key HR metrics. The ability to track KPIs, optimize retention strategies, and enhance training and engagement is essential for organizations seeking to align their human capital with broader strategic goals. The study demonstrates that integrating AI into HRM systems can offer tangible benefits in terms of operational efficiency and employee satisfaction.

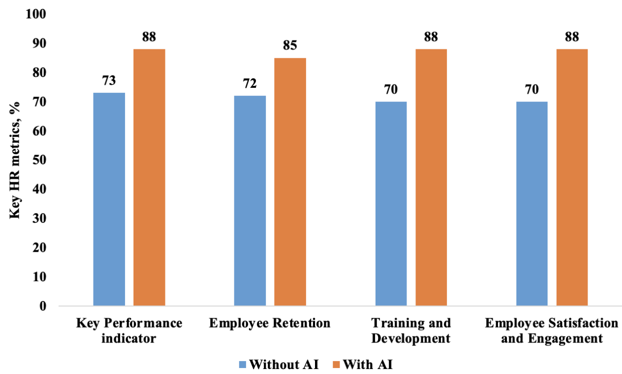

Fig. 7. Summary of AI's impact on key HR metrics

The results of this study provide compelling evidence for the adoption of AI in HRM, where digital transformation is a priority. Organizations that leverage AI in HR processes are better equipped to enhance their operational performance, improve employee engagement, and ultimately achieve strategic success.

Discussion

It is known that rapid digital transformation based on AI Technologies is taking place in European Union Organizations (Mihai et al., 2023). The integration of artificial intelligence (AI) into Human Resource Management (HRM) has emerged as a crucial factor in enhancing organizational efficiency and overall performance. This study highlights that AI significantly improves HRM practices within Multinational Establishments in Europe listed in the Fortune Global 500 by enabling predictive analytics that enhance employee recruitment, retention strategies, and performance management. AI tools streamline HR functions, allowing for data-driven decisions that contribute to more precise and proactive human capital management (Chowdhury et al., 2023). By leveraging machine learning algorithms, AI systems can predict employee turnover, identify high-performing candidates, and develop customized retention strategies, thus enhancing HRM's operational effectiveness (Brougham & Haar, 2018).

The authors' results are in line with recent scientific studies that emphasize the growing role of AI in optimizing HRM practices and improving organizational performance. For example, Tsiskaridze et al. (2023) found that AI-driven recruitment tools significantly improve candidate selection processes and reduce biases. In a similar vein, Nyathani (2023) demonstrated that AI-powered performance management systems provide real-time feedback, enhancing employee productivity and engagement. Additionally, Basnet (2024) reported that AI-based predictive analytics tools are effective in forecasting employee turnover, allowing organizations to adopt more proactive retention strategies. These findings further support the positive impact of AI on HRM effectiveness and overall organizational performance.

A key finding is the pivotal role of AI-enabled performance metrics, such as Key Performance Indicator (KPI) dashboards and AI-driven 360-degree feedback systems. These metrics are essential in maintaining high organizational performance by enabling real-time tracking of employee progress and aligning performance management systems with strategic organizational objectives (Karkoulian et al., 2016). AI integration into performance metrics supports more dynamic and responsive employee evaluations, which can lead to better-targeted interventions to improve productivity and engagement (Davenport & Ronanki, 2018). This is particularly beneficial in large organizations where manual performance tracking can be resource-intensive (Huang & Rust, 2018).

It is known that leadership plays a critical role in the successful integration of AI technologies into HRM practices. Effective leadership ensures that AI tools are aligned with HRM strategies, fostering a culture supportive of digital transformation. Leaders engaged in the digital transformation process can strategically deploy AI to optimize HR functions and meet broader organizational goals (Zhang et al., 2024). Studies emphasize that leadership can mitigate challenges and create a collaborative environment conducive to AI adoption (Crusoe et al., 2024). Furthermore, ethical AI use and employee comfort with the technology are essential to reduce resistance and facilitate integration into daily HR practices (Saeed et al., 2024).

For Multinational Establishments included in the Fortune Global 500 list, which are positioning themselves as leaders in AI adoption, these findings suggest that AI can significantly enhance HRM processes and performance metrics (Table 6). AI-powered HR analytics can help organizations address skill gaps and align workforce planning with strategic goals (Alabdali et al., 2024).

Based on these findings, several practical recommendations for Multinational Establishments in Europe included in the Fortune Global 500 list are:

1. Organizations should adopt a phased approach to AI implementation, beginning with pilot projects in specific HR functions such as recruitment and evaluations. This gradual integration allows for adaptation to AI technologies while maintaining human oversight (Caiza et al., 2024).
2. Investment in upskilling HR professionals is essential to equip them with the skills necessary to manage AI-driven tools. Training programs should enhance digital literacy and data analytics capabilities to fully leverage AI's potential (Koman et al., 2024).
3. Prioritizing AI-enhanced, real-time tracking systems for employee performance metrics is recommended. AI integration in performance management facilitates continuous feedback, leading to higher engagement and accurate assessments of employee contributions (Rožman et al, 2023).

This study provides robust evidence that the integration of AI into HRM practices and performance metrics significantly enhances organizational performance in Multinational Establishments operating in Europe and listed in the Fortune Global 500. Leadership is crucial in aligning AI tools with strategic HR goals to lead in AI, which offers unique opportunities for organizations.

Results of Chrysler-Fox and Roodt (2014), Iwu et al. (2016), and our results have some inclusiveness in ways that concern the alignment of HR metrics and

Table 6
AI Integration in HRM practices

Aspect	Current Study	Brougham and Haar (2018)	Davenport and Ronanki (2018)	Huang and Rust (2018)
AI Tools in Recruitment	Predictive analytics for candidate selection	AI in recruitment and employee management	Data-driven performance metrics	AI applications in large-scale organizations
Employee Retention Strategies	Tailored retention strategies via AI	Algorithms to identify retention factors	Customized retention strategies	AI in managing large workforce dynamics
Performance Management	KPI dashboards, AI-driven 360-degree feedback	Performance metrics driven by AI algorithms	Real-time performance metrics	AI-driven performance tracking
Leadership Role in AI Integration	Critical for alignment and adoption	Leadership in implementing AI practices	Effective leadership in AI integration	Role of leadership in large-scale AI adoption
Ethical Considerations	Ensuring ethical AI use and reducing resistance	Addressing ethical concerns in AI use	Ethical considerations in AI-driven decisions	Managing AI ethics in large organizations

organizational outcomes, while differing in methods used and areas of concentration. Chrysler-Fox and Roodt (2014) therefore post that the type of HR measurements to use should be carefully chosen so that there are linkages between business strategy and measurements. The purpose of the approach is to generate systemic value amongst the organizational subsystems.

Iwu et al. (2016) then bring a logical reasoning perspective to the claim that organizational HR attitudes like staff satisfaction and engagement correlate with organizational performance results such as profitability and customer satisfaction. Accordingly, this research concludes that these metrics should be regarded as a system where interrelationships matter. The authors' results discuss the effectiveness of using artificial intelligence in handling Human Resource metrics, focusing on the use of AI in recruitment, employee retention, and organizational success. The research also claims that the adoption and implementation of AI will enhance employee productivity and keenness. The way all of them connect to the subject of HR metrics is different; at the same time, the authors' results become an example of how AI can emerge as a fundamental component of enhancing HRM practices and performance results.

Conclusions

The main objective of the present research was to analyze the moderating role of AI, new trends in HRM, and performance indicators within the context of enhancing the performance of Multinational Establishments in Europe from the Fortune Global 500 list. The goals and objectives of this study were to assess the level of AI implementation in the context of human resource management practice, its moderating effect on recruitment and retention processes, and the benefits of AI performance indicators on organizational performance.

The survey revealed that currently, 72% of the Multinational Establishments in Europe listed in the Fortune Global 500 have integrated AI for automating functions such as recruitment and management of employees. Of all the uses of AI, 65% said they employed the technology for predictive analytics in workforce planning, while 58% launched AI-powered chatbots to facilitate employee interaction. Automated recruitment systems threatened manual sifting and sorting by cutting it by 40%, a fact that saw companies moving an average of 500 resumes in an hour. Further, the use of predictive analytics enhanced employee retention, where organizations narrowed the turnover rates from 25% to only 15% through the use of AI-based retention. This type of retention resulted in a specific increase in retention rates for large organizations (with more than 500 people) by up to 20%. The metrics performance through Artificial Intelligence were as follows: a) A boost in Key Performance Indicators to enhance employees' productivity of 21.4% b) A rise in the rate for project completion of 20%. AI use in performance assessment increased the percentage of top managers perceiving alignment of employees' goals with organizational strategies to 88%, while in the organizations without proper impacts of AI, this figure was only at 73%. Further, companies that incorporated AI into feedback had increased engagement and effective feedback by 30.8%. In detail, through the SEM, it was revealed that while the HRM effectiveness impacted the performance measures $\beta = 0.80$, the effect of AI in enhancing the former exhibited a $\beta = 0.72$. The organizations adopting AI showed a 25% improvement in decision-making efficiency and 27.9% in achievement of organizational goals, according to the survey.

Subsequent research studies will concentrate on exploring the impact of AI on training outcomes in terms of skill enhancement, with the identification of an improvement ratio of 25% and 30% for employee engagement in AI-based learning systems. Further, the field research work will also emphasize the exploration of the ethical considerations of the use of AI in HRM, such as the degree of automation to be offered by the system without compromising human interference. Future research will also look into the part played by leadership, as per the survey, where 85% of the firms stressed effective leadership in implementing the change, and more to the point, acceptance of the AI system.

Statements and Declarations

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Conflict of interest

This research has no conflict of interest.

Data availability statement

All data generated or analysed during this study are included in this published article.

References

Abril-Jiménez, P., Carvajal-Flores, D., Buhid, E., & Cabrera-Umpierrez, M. F. (2024). Enhancing worker-centred digitalisation in industrial environments: A KPI evaluation methodology. *Heliyon, 10(4)*, e26638. DOI: 10.1016/j.heliyon.2024.e26638

Aguinis, H., Beltran, J.R., & Cope, A. (2024). How to use generative AI as a human resource management assistant. *Organizational Dynamics, 53(1)*, 101029. DOI: 10.1016/j.orgdyn.2024.101029

Alabdali, M.A., Khan, S.A., Yaqub, M.Z., & Alshahrani, M.A. (2024). Harnessing the power of algorithmic human resource management and human resource strategic decision-making for achieving organizational success: An empirical analysis. *Sustainability, 16(11)*, 4854. DOI: 10.3390/su16114854

Barney, J.B. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17(1)*, 99–120. DOI: 10.1177/014920639101700108

Basnet, S. (2024). The impact of AI-driven predictive analytics on employee retention strategies. *International Journal of Research and Review, 11(9)*, 50–65. DOI: 10.52403/ijrr.20240906

Basole, R.C., Park, H., & Seuss, C.D. (2024). Complex business ecosystem intelligence using AI-powered visual analytics. *Decision Support Systems, 178*, 114133. DOI: 10.1016/j.dss.2023.114133

Bogoslov, I.A., Corman, S., & Lungu, A.E. (2024). Perspectives on artificial intelligence adoption for European Union Elderly in the context of digital skills development. *Sustainability, 16(11)*, 4579. DOI: 10.3390/su16114579

Bourne, M. (2008). Performance measurement: Learning from the past and projecting the future. *Measuring Business Excellence, 12(4)*, 67–72. DOI: 10.1108/13683040810919971

Brougham, D., & Haar, J. (2018). Smart technology, artificial intelligence, robotics, and algorithms (STARA): Employees' perceptions of our future workplace. *Journal of Management & Organization, 24(2)*, 239–257. DOI: 10.1017/jmo.2016.55

Budhwar, P., Malik, A., Thedushika De Silva, M.T., & Thevisuthan, P. (2022). Artificial intelligence – challenges and opportunities for international HRM: A review and research agenda. *The International Journal of Human Resource Management, 33(6)*, 1065–1097. DOI: 10.1080/09585192.2022.2035161

Caiza, G., Sanguna, V., Tusa, N., Masaquiza, V., Ortiz, A., & Garcia, M.V. (2024). Navigating governmental choices: A comprehensive review of atrificial intelligence‘s impact on decision-making. *Informatics, 11(3)*, 64. DOI: 10.3390/informatics11030064

Chowdhury, S., Dey, P., Joel-Edgar, S., Bhattacharya, S., Rodriguez-Espindola, O., Abadie, A., & Truong, L. (2023). Unlocking the value of artificial intelligence in human resource management through AI capability framework. *Human Resource Management Review, 33(1)*, 100899. DOI: 10.1016/j.hrmr.2022.100899

Chrysler-Fox, P.D., & Roodt, G. (2014). Principles in selecting human capital measurements and metrics. *SA Journal of Human Resource Management, 12(1)*, 586. DOI: 10.4102/sajhrm.v12i1.586

Crusoe, J., Magnusson, J., & Eklund, J. (2024). Digital transformation decoupling: The impact of willful ignorance on public sector digital transformation. *Government Information Quarterly, 41(3)*, 101958. DOI: 10.1016/j.giq.2024.101958

Davenport, T.H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review, 96(1)*, 108–116.

Duarte, M.P., & de Oliveira Carvalho, F.M.P. (2024). How digital transformation shapes European union countries' national systems of innovation: A configurational moderation approach. *Journal of Innovation & Knowledge, 9(4)*, 100578. DOI: 10.1016/j.jik.2024.100578

Duggan, J., Sherman, U., Carbery, R., & McDonnell, A. (2020). Algorithmic management and app-work in the gig economy: A research agenda for employment relations and HRM. *Human Resource Management Journal, 30(1)*, 114–132. DOI: 10.1111/1748-8583.12258

Fortune (2025a). *Fortune 500 Europe.* https://fortune.com/europe/ranking/fortune500-europe/

Fortune (2025b). *Fortune Global 500.* https://fortune.com/ranking/global500/

Huang, M.-H., & Rust, R.T. (2018). Artificial Intelligence in Service. *Journal of Service Research, 21(2)*, 155–172. DOI: 10.1177/1094670517752459

Iwu, C.G., Kapondoro, L., Twum-Darko, M., & Lose, T. (2016). Strategic human resource metrics: A perspective of the General Systems Theory. *Acta Universitatis Danubius, 12(2)*, 5–24.

Jiang, H., Cheng, Y., Yang, J., & Gao, S. (2022). AI-powered chatbot communication with customers: Dialogic interactions, satisfaction, engagement, and customer behavior. *Computers in Human Behavior, 134*, 107329. DOI: 10.1016/j.chb.2022.107329

Kanungo, R.P., Liu, R., & Gupta, S. (2024). Cognitive analytics enabled responsible artificial intelligence for business model innovation: A multilayer perceptron neural networks estimation. *Journal of Business Research, 182*, 114788. DOI: 10.1016/j.jbusres.2024.114788

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons, 62(1)*, 15–25. DOI: 10.1016/j.bushor.2018.08.004

Kaplan, R.S. (2012). The balanced scorecard: Comments on balanced scorecard commentaries. *Journal of Accounting and Organizational Change, 8(4)*, 539–545. DOI: 10.1108/18325911211273527

Karkoulian, S., Assaker, G., & Hallak, R. (2016). An empirical study of 360-degree feedback, organizational justice, and firm sustainability. *Journal of Business Research, 69(5)*, 1862–1867. DOI: 10.1016/j.jbusres.2015.10.070

Khasanov, E., Khamaletdinov, R., Gabitov, I., Mudarisov, S., Gallyamov, F., Stupin, V., & Maskulov, D. (2020a). Efficiency improvement of the layered seed movement when using drum-type seed disinfectant. *International Review on Modelling and Simulations, 13(3)*, 125–131. DOI: 10.15866/iremos.v13i2.18694

Khasanov, E., Khamaletdinov, R., Mudarisov, S., Shirokov, D., & Akhunov, R. (2020b). Optimization parameters of the spiral mixing chamber of the device for pre-sowing seed treatment with biological preparations. *Computers and Electronics in Agriculture, 173*, 105437. DOI: 10.1016/j.compag.2020.105437

Koman, G., Borsos, P., & Kubina, M. (2024). The possibilities of using artificial intelligence as a key technology in the current employee recruitment process. *Administrative Sciences, 14(7)*, 157. DOI: 10.3390/admsci14070157

Kumar, V., Ashraf, A.R., & Nadeem, W. (2024). AI-powered marketing: What, where, and how? *International Journal of Information Management, 77*, 102783. DOI: 10.1016/j.ijinfomgt.2024.102783

Madanchian, M., Taherdoost, H., Vincenti, M., & Mohamed, N. (2024). Transforming leadership practices through artificial intelligence. *Procedia Computer Science, 235*, 2101–2111. DOI: 10.1016/j.procs.2024.04.199

Madazimova, K., & Mambetalina, A. (2024). The impact of stress factors on employee subjective well-being: The case of Kazakhstan. *Journal of the Knowledge Economy,* in press. DOI: 10.1007/s13132-024-02323-y

Malik, A., Budhwar, P., & Kazmi, B. A. (2023). Artificial intelligence (AI)-assisted HRM: Towards an extended strategic framework. *Human Resource Management Review, 33(1)*, 100940. DOI: 10.1016/j.hrmr.2022.100940

Mallik, A.K. (2023). The future of the technology-based manufacturing in the European Union. *Results in Engineering, 19*, 101356. DOI: 10.1016/j.rineng.2023.101356

Mihai, F., Aleca, O.E., & Gheorge, M. (2023). Digital transformation based on AI technologies in European Union Organizations. *Electronics, 12(11)*, 2386. DOI: 10.3390/electronics12112386

Nyathani, R. (2023). AI in performance management: Redefining performance appraisals in the digital age. *Journal of Artificial Intelligence & Cloud Computing, 2(4)*, 1–5. DOI: 10.47363/JAICC/2023(2)134

Pan, Y., & Froese, F.J. (2023). An interdisciplinary review of AI and HRM: Challenges and future directions. *Human Resource Management Review, 33(1)*, 100924. DOI: 10.1016/j.hrmr.2022.100924

Ravesangar, K., & Narayanan, S. (2024). Adoption of HR analytics to enhance employee retention in the workplace: A review. *Human Resources Management and Services, 6(3)*, 3481. DOI: 10.18282/hrms.v6i3.3481

Ren, S., & Jackson, S.E. (2020). HRM institutional entrepreneurship for sustainable business organizations. *Human Resource Management Review, 30(3)*, 100691. DOI: 10.1016/j.hrmr.2019.100691

Rožman, M., Oreški, D., & Tominc, P. (2023). Artificial-intelligence-supported reduction of employees' workload to increase the company's performance in today's VUCA Environment. *Sustainability, 15(6)*, 5019. DOI: 10.3390/su15065019

Saeed, A., Ali, A., & Ashfaq, S. (2024). Employees' training experience in a metaverse environment? Feedback analysis using structural topic modeling. *Technological Forecasting and Social Change, 208*, 123636. DOI: 10.1016/j.techfore.2024.123636

Scarpi, D., & Pantano, E. (2024). "With great power comes great responsibility": Exploring the role of Corporate Digital Responsibility (CDR) for Artificial Intelligence Responsibility in Retail Service Automation (AIRRSA). *Organizational Dynamics, 53(2)*, 101030. DOI: 10.1016/j.orgdyn.2024.101030

Shao, Z., Zhao, R., Yuan, S., Ding, M., & Wang, Y. (2022). Tracing the evolution of AI in the past decade and forecasting the emerging trends. *Expert Systems with Applications, 209*, 118221. DOI: 10.1016/j.eswa.2022.118221

Snell, S.A., & Morris, S.S. (2021). *Time for realignment: The HR ecosystem* [Faculty Publications, Brigham Young University]. Academy of Management. http://hdl.lib.byu.edu/1877/6487

Tsiskaridze, R., Reinhold, K., & Jarvis, M. (2023). Innovating HRM recruitment: A comprehensive review of AI Deployment. *Marketing and Management of Innovations, 14(4)*, 239–254. DOI: 10.21272/mmi.2023.4-18

Tursunbayeva, A., & Gal, H.C. (2024). AI for digital leadership. *Business Horizons, 67(4)*, 357–368. DOI: 10.1016/j.bushor.2024.04.006

Zhang, Y., Iqbal, S., Tian, H., & Akhtar, S. (2024). Digitizing success: Leveraging digital human resource practices for transformative productivity in Chinese SMEs. *Heliyon, 10(17)*, e36853. DOI: 10.1016/j.heliyon.2024.e36853