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EXPLORING THE SYNERGY BETWEEN ARTIFICIAL INTELLIGENCE AND HUMAN RESOURCES: A QUALITATIVE REVIEW OF BUSINESS MANAGEMENT LITERATURE

Aura GIRLOVAN
Bucharest University of Economic Studies, Romania

Alexandra HOROBET
Bucharest University of Economic Studies, Romania

Cosmin-Alin BOTOROGA
Bucharest University of Economic Studies, Romania

Lucian BELASCU
Lucian Blaga University of Sibiu, Romania

Paul LUCIAN
Lucian Blaga University of Sibiu, Romania

Abstract:

This paper portrays the role of the interplay between artificial intelligence and human resources as evidenced by an extensive review of academic literature. The study investigated 402 abstracts of scholarly articles published in the Business Management and Accounting domain of the Scopus database spanning from 2000 to 2023. Using QDA Miner 2024, a novel approach based on content, link, and proximity analysis was employed to conduct the literature review. Three major findings were revealed by our investigation. First, while codes such as 'AI' and 'employees' dominate the academic discourse, there is an evolving trend toward more sophisticated analyses of AI-human resources interactions, including their impact on business strategies and performance. Second, research methods show significant diversification over time, going from more descriptive approaches to sophisticated quantitative and qualitative methodologies. Third, several areas appear to lack research focus, such as the connection between employee recruitment and future career paths with AI and business progress. The findings contribute to understanding how the technological revolution shapes business operations, particularly workforce management, while highlighting the need for structural reforms in organizational approaches to AI adoption, and provide valuable insights for both scholars and practitioners interested in the integration of AI in human resource management.

Keywords: *artificial intelligence, human resources, qualitative research, content analysis, link analysis, proximity analysis*

1. Introduction

The impact of technology on the global economy is growing exponentially, allowing us to see both unprecedented advances in any industry and considerable changes in human resource management (HRM). Increasingly, we observe the speed with which repetitive and time-consuming human tasks such as documentation, programming, equipment inspection, data collection, etc. are being taken over by artificial intelligence (AI) (Jaiswal et al., 2022). As AI continues to evolve and shape the business world, the incorporation of AI technologies becomes crucial for maintaining long-term competitiveness and performance. Digitization has reduced transaction costs and given rise to innovative business models, which, in turn, shape how human resources are managed within organizations (Horobet et al., 2022). A sub-discipline of artificial intelligence concerns the creation of computers or machines that learn automatically and move toward statistical learning. Machine learning aims to create algorithms that can manage real-time information and improve the data management experience without being explicitly personalized (Tariq et al., 2021). There is a range of levels of AI, starting from task-specific specialized AI, evolving to general AI with extensive capabilities, and culminating in superintelligent AI that surpasses human intelligence.

The digital economy is defining a new role for human resources (HR) and human capital, with people becoming essential to the success of companies (Hasnaoui & Hasnaoui, 2022). Digital businesses and managers need to integrate digital competencies with traditional managerial knowledge and skills. Analytical skills, creativity, familiarity with technology, quick thinking, team collaboration, cross-disciplinarity, online communication skills, and health maintenance skills are just a few of these skills (Mazurchenko & Maršíková, 2019). Therefore, to successfully implement digital business models and meet the demands of a changing world, digital economy professionals need to possess both digital and traditional skills. Traditional human resource management systems are being transformed into talent management, training, and employee development, supporting the achievement of sustainable competitive advantages (Ogrean et al., 2009). This is because, despite all the advances in business process automation, people with their intuition, skills, and capabilities remain essential to the success of a digital enterprise (Muxamedraximovich, 2024). Moreover, research suggests that green human resource increases profitability (Afzal et al., 2024).

The study of van den Bosch et al. (2019) describes a case study in which a hybrid team of humans and AI agents collaborate in an adaptive, dynamic, and personalized way on a project. AI agents, like humans, need to have mental models that contain information about the context of the task, their own role, and the role of others. They must also have the ability to improve and modify their mental models through experiences and feedback. Although AI agents can share information, creating a common database for the whole team, not all functions and knowledge are stored by AI agents in these databases.

The transformations brought about by digitization in HRM highlight the shift to an era where digital technologies are integrated into HRM practices. This integration has brought efficiency, accessibility, and data-driven decision-making to the recruitment and hiring processes (Strohmeier, 2020). The advent of online job portals and applicant tracking systems has revolutionized the recruitment process, while digital platforms for onboarding new employees into companies have provided access to important information such as company policies and procedures, benefits, training programs, and other relevant resources, contributing to faster and more efficient onboarding. The implementation of human resources information systems has facilitated the management and monitoring of employee performance (Prokopenko et al., 2023). These digital transformations represent a significant advance in human resource management, providing organizations with powerful tools to address their HR needs more effectively in an increasingly digitalized environment.

The body of literature investigating the integration of artificial intelligence across diverse business sectors, including information systems and human resource management, is progressively becoming more comprehensive and intricate in its analysis of the impacts, methodologies, and results associated with this technological advancement (Lee et al., 2023). However, due to the different levels of analysis, disciplines, and organizational functions addressed, research is often fragmented and conclusions about the actual effects of artificial intelligence in the workplace can be inconsistent. This research paper adds a new perspective to the literature by analyzing the co-evolution of artificial intelligence, business strategies and organizational performance, and human resource management within companies as reflected in academic studies in the business and management literature. In this framework, the purpose of this study is to analyze the main trends in topics and research objectives in the literature on the interplay between AI, human resources, and business strategy and performance by examining the abstracts of relevant articles in the scholarly literature. With this purpose, the study proposes several novel contributions to the scholarly literature. First, it employs an innovative methodological approach using QDA Miner software for content, link, and proximity analysis, able to offer a comprehensive understanding of research patterns in the field. Second, it categorizes and analyzes the evolution of research topics and sub-topics across three distinct categories: AI, human resources processes, and business performance outcomes. Third, it identifies specific relationships between these categories, revealing insightful patterns in their interaction. Finally, the study maps the objectives and methodological diversification in this research area, demonstrating its increased maturity and sophistication from descriptive to more complex analytical approaches.

The study is organized into four primary sections. The first section conducts a literature review that situates our research into existing theoretical frameworks and synthesizes current debates in the field. The second section outlines the methodology employed in the research. The third section presents the key findings and discusses their significance. Lastly, the conclusion section offers a comprehensive summary of the study, emphasizing its contributions and proposing potential avenues for future research.

2. Literature review

The fourth industrial revolution is characterized by a significant increase in the adoption of advanced technologies, including AI, big data analytics, machine learning, mobile technology, the Internet of Things (IoT), geolocation, virtual reality, voice recognition, and biometrics. The implementation of these advanced technologies is redefining the way business is conducted locally and globally, with a significant impact on workplace design, employee engagement, and work process change (Budhwar, et al., 2022). The Technology Acceptance Model (TAM) proposed by Davis (1989) offers the theoretical framework for understanding how users come to accept and finally use technology, suggesting that perceived usefulness and perceived ease of use are the two main factors that influence technology adoption. In the context of AI and human resources, TAM can help explain how employees and businesses adapt to and further implement technological solutions in their existing structures. Recent research has extended TAM to incorporate additional variables specific to AI adoption, such as trust in AI systems, perceived job security, and organizational support in private and public settings (Çetin, 2024; Huang and Mizumoto, 2024; Malik et al., 2020). These studies demonstrate that successful AI implementation in HR processes and management, ranging from recruiting employees to assessing their performance, essentially depends, as TAM suggests, on users' perceptions and attitudes besides technology's capabilities.

` In recent years, organizations have demonstrated a notable expansion in the utilization and exploration of AI applications. Within the literature, scholars underscored the benefits and advantages of AI implementation and its potential to reshape organizations, industries, and society in the foreseeable future (Jarrahi, 2018; Tong, et al., 2021). However, AI can be perceived as a disruptive technology with the potential to fundamentally reshape our lives and work. Implementing AI is a complex and lengthy process, requiring between 18 and 36 months to be fully operational, with some systems taking up to five years to be fully integrated into an organization. Its adoption therefore involves significant investment and risk, requiring careful analysis of the impact, outcomes, and potential changes (Olan et al., 2022).

Huang and Rust introduced in 2018 the "Theory of AI Job Replacement" which advocates that AI's impact on the workforce results in a reconfiguration of jobs, presenting both innovative opportunities and potential threats (Huang & Rust, 2018). According to this theory, four types of intelligence - mechanical, analytical, intuitive, and empathic - are central to employees' roles, prompting companies to choose between retaining a human workforce or integrating AI solutions. The theory suggests that AI primarily automates routine mechanical tasks initially, expanding to encompass more complex responsibilities over time. For instance, as AI assumes analytical tasks requiring logical and rule-based thinking, the significance of human analytical skills diminishes. Eventually, AI could undertake intuitive and empathetic tasks, paving the way for innovative approaches to integrating humans and AI agents in service delivery. However, this also raises concerns about potential job displacement for humans (Choi & Leigh, 2024). Consequently, the future growth and efficiency of companies are expected to hinge on employees' capacity to adapt and upgrade their skills. Rather than facing job loss, employees may find their roles evolving, with a greater emphasis on intuitive capabilities over purely analytical thinking (Morandini et al., 2023). In university programs designed to train specialists in the field of AI, the issues of implementing AI systems and managing the problems that can arise with organizational change are often not addressed in detail. Therefore, creating a qualitative, inclusive educational system focused on skill acquisition allows students to explore, make mistakes, learn, relearn, and develop their skills so that they can deeply understand business problems and convert them into algorithmic information, and vice versa, to effectively communicate technical details to company managers (Boțoroga et al., 2022). Employees in managerial roles, characterized by higher levels of education and professionalism, tend to exhibit fewer concerns regarding the integration of work automation technologies and AI in the workplace when compared to those engaged in manual tasks, individuals with lower educational attainment, and workers in the service sector. Even though there are differences between professions today, experts predict that automation and AI technologies will likely affect a vast array of professions in the future (Dekker et al., 2017).

A survey conducted by the IBM Institute for Business Value (IBM, 2022) among 5,000 businesses worldwide revealed that 93% of companies are contemplating the implementation of artificial intelligence. However, a significant portion (60%) expresses apprehension regarding potential liability issues, while 63% cite a shortage of human resources and expertise to effectively manage AI technologies. Leaders acknowledge the potential of AI to enhance operational efficiency (59%), expedite decision-making processes (50%), substantially cut costs (45%), and enhance both customer (40%) and employee (37%) experiences. Senior employees are also worried about the speed at which artificial intelligence adoption is required to sustain competitiveness in the workplace. Therefore, there is a concerted focus on leveraging AI to alleviate employee workloads and identify avenues for enhancing employee engagement and performance, thereby bolstering overall company performance.

The use of AI in the organizational environment presents various ethical and practical challenges. One of these is the risk of algorithmic bias, which can lead to discriminatory outcomes and harm to certain groups of individuals (Kumar & Suthar, 2024). There are also concerns about unexplained decisions generated by AI learning algorithms, which can be difficult to justify due to their complexity (Bewersdorff et al., 2023). In addition, the dilution of liability boundaries in the context of using AI for decision-making is another challenge, and clarifying responsibilities and legal liability is paramount for managing this issue (Benbya et al., 2020).

Exploring the scholarly literature on AI's interplay with human resources processes and management provides a thorough understanding of the reshaping of workplace dynamics by AI, at the same time revealing the challenges of implementing AI-driven solutions for the various business functions related to human resources, from recruiting employees to offering development paths and assessing their performance. Several recent systematic reviews and bibliometric analyses have attempted to map the intellectual developments in this field of research, identifying key research sub-topics, developing trends, and signaling gaps in current knowledge. For example, Votto et al. (2021) have investigated the literature on the interaction of AI with tactical HRM, including recruitment, employee performance evaluation and satisfaction, benefit analysis, and employee training. Pereira et al. (2023) reviewed the literature on the nexus between AI and workplace outcomes by cross-relating 60 papers from 30 leading international journals between 1995 and 2020, showing that the impact of AI influence can be better captured when the drivers of AI use are understood, alongside the outcomes of AI implementation on human resources and employees. In their review, Qamar et al. (2021) explored 59 articles on the extent to which AI intersects with human resources using content and structural concept analysis. Another review, this time of the "multidisciplinary management literature" was conducted by

Chowdhury et al. (2023); this review analysed works published in journals in the various fields with the aim of discovering the organisational resources needed to support AI integration into human resources management. By analyzing 863 articles from the Web of Science, Ogrean (2023) identifies Sustainable Development Goal 8 as especially significant for HR in AI-driven workplaces. This goal underscores sustained, inclusive economic growth, full and productive employment, and decent work for all. Achieving these objectives requires employee upskilling, fair labor practices, and responsible AI use to enhance productivity and growth.

As outlined above, content analysis was employed in the previous reviews due to its flexibility which serves well in studies on information, either as a stand-alone method or in collaboration with other methods (White & Marsh, 2006). Content analysis allows researchers to easily wade through large volumes of data systematically and is versatile enough to be applied to textual, visual, and audio data (Stemler, 2015). This study employs word coding, which involves assigning specific codes to keywords to identify and analyze particular aspects of content. By using this approach, textual data is organized and interpreted, facilitating the analysis and extraction of pertinent information.

QDA Miner is a software platform for qualitative data analysis, and its most important functions are co-occurrence counting, keyword or key segment searching, and analysis based on a coded sequence (Derobertmasure & Robertson, 2014). Several studies have used content analysis on Artificial Intelligence using QDA Miner. Thus, Belda-Medina and Calvo-Ferrer (2022) developed a study to identify the role of chatbots as conversational AI partners in language learning, indicating that they could be beneficial in educational environments. Perkins and Roe's study (2023) on generative AI policies for academics highlighted the importance of transparency in the use of AI tools in academic research and the need to maintain and consult human intelligence in the academic writing process. Kinnett and Steinbach (2022) conducted a content analysis of consumer relationship management (CRM) curricula to identify the skills needed for the role of sales manager, concluding that developing digital skills, non-technical skills (effective communication, problem-solving, teamwork, creativity, and decision-making ability), and those related to project management are crucial to excellence in this role.

Limitations of content analysis in the context of using QDA include the risk of generating redundant codes and the tendency to place too much emphasis on word frequency, thus requiring careful supervision by the user to avoid possible distortions in the interpretation of results (Marathe & Toyama, 2018). Interpreting statistical methods and setting parameters in QDA Miner requires a deep understanding of the domain and a careful analysis of the source data, suggesting the use of paragraphs for counting to gain a more comprehensive perspective on narrative segments (LaPan, 2013). Keeping these issues in mind, we chose to keep the number of categories at a lower level for optimal coding error management, mirroring the approach of Horobet et al. (2024).

3. Methodology

The present research analyses scientific articles that have been collected from the Scopus database that link AI and human resources. The Scopus database was preferred over other options such as Web of Science, Google Scholar, Dimensions or OpenAlex due to its wide coverage of scholarly journals (43,465 in 2024) that are peer-reviewed and have to comply with high-level quality criteria. Moreover, Scopus has many operating functionalities that facilitate the conduct of systematic or bibliometric reviews (Agarwal et al., 2016).

The first step consisted of selecting keywords such as ”artificial intelligence”, ”employees”, ”personnel”, ”job requirements”, ”working conditions”, ”digital skills”, ”employees”, ”organizational culture” and ”competencies” that have been searched both in the title of articles, keywords, and their abstracts. Thus, 11,997 documents were obtained. The next step involved the selection of documents from 2000 – 2023, obtaining 10,695 documents. We decided to apply a time filter because from the 2000s people’s access to the Internet accelerated, which coincided with the peak period of the speculative bubble in the technology sector ”dot com” (Goodnight & Green, 2010). Also, 2023 was chosen for the end of the analysis period because it highlights the period after the technological growth that occurred during the COVID-19 pandemic (Xiang et al., 2021). The 24-year analysis offers, therefore, a comprehensive insight into the evolution of AI and how it has changed the way people work over the past two decades. The next filter applied focused on the domain, selecting journals categorized under "Business Management and Accounting." This field provides valuable insights into technological change and the impact of AI on work dynamics, highlighting how recent advancements automate repetitive tasks, thereby alleviating human workload (Manyika & Sneader, 2018). Applying this filter resulted in 1,121 documents. To focus the dataset on high-quality and relevant sources, a series of filters were systematically applied. The next filter targeted the document type, retaining only peer-reviewed articles, which reduced the dataset to 611. To ensure linguistic consistency and accessibility, a language filter was then applied, selecting only English-language articles, further narrowing the dataset to 580 documents. To enhance relevance to the research objectives, a keyword filter was employed. The selected keywords, designed to capture critical themes related to artificial intelligence (AI) and its impact on the workforce, included: ”Artificial Intelligence”, ”Personnel”, ”Human Resource Management”, ”Artificial Intelligence (AI)”, ”Personnel Training”, ”Employment”, ”Automation”, ”Digital Transformation”, ”AI”, ”Digitalization”, ”Chatbots”, ”Human”, ”Future of Work”, ”Digital Technologies”, ”Employee Engagement”, ”Organizational Culture”, ”Human Resources Management”, ”Human Resources”, ”Artificial Intelligence Technologies”, ”Productivity”, ”Workplace”, ”Job Insecurity”, ”Human Capital”, ”Employee”, ”Competence”, ”Working Conditions”, ”Performance” and ”ChatGPT”. This step reduced the dataset to 439 documents. Finally, to ensure the inclusion of only completed and finalized research, a publication stage filter was applied, restricting the dataset to fully published articles. This final step produced a dataset of 402 articles deemed suitable for detailed analysis. Following the filtering process, the final dataset comprising 402 articles was exported in CSV format. The exported data included key elements such as the article titles, publication years, abstracts, authors’ keywords, and keywords provided by the journals. The next stage involved manually reviewing the abstracts of all 402 articles to ensure their relevance to the research objectives. Additionally, a new column was created to document the research methods employed by the authors of each article.

The 402 articles were analyzed using the QDA Miner 2024 software program developed by Provalis Research (Provalis Research, 2024), which is a program for qualitative data analysis. QDA Miner provides robust features for frequency analysis and statistical evaluation, making it a versatile tool for both qualitative and quantitative data analysis. Its user-friendly interface allows researchers to perform coding with minimal technical expertise, which has contributed to its popularity in academic research (LaPan, 2013). In recent years, there has been a growing trend in the integration of quantitative approaches in qualitative data analysis. This trend spans diverse applications, including online product review analyses (Islam et al., 2021), entrepreneurship studies (Zaharia & Hassan, 2021), and retail journal evaluations (Anderson et al., 2007). By leveraging this methodological versatility, QDA Miner enables researchers to combine qualitative insights with quantitative rigor, making it a valuable tool for comprehensive academic inquiry.

Consistent with the research problem approached, as well as with the objective of the study, but also based on the analysis of the 402 abstracts (an abstract is a case in QDA Miner), 5 major themes were defined: Artificial Intelligence, Performance in Business and Strategy, Human Resources, Research Methods, and Research Goals. These 5 major themes received associated codes that were applied to the content of abstracts of articles. The authors used 36 codes (see Table 1), most of which were associated with research methods (13). The encodings made according to the keywords in the second column of Table 1 were applied to sentences. To ensure the correctness of the code assignment, the authors manually checked the sentences where the words in the second column of Table 1 were assigned, thus validating the attribution process.

The analysis of the codes was carried out based on frequency (how often the words mentioned in the second column of Table 1 were mentioned in the abstracts), both individually and jointly, but also based on similarity. The similarity that appears between the codes illustrates the co-occurrence between the two codes. Co-occurrence is the situation where two codes appear in sentences at the same time, determining this by using existing total cases.

In the similarity analysis, the Jaccard coefficient was used, which shows the ratio between the intersection of two sets (A and B) divided by the union of the two sets (A and B) (Bag et al., 2019), thus assessing the degree of similarity between elements. The Jaccard coefficient has the following formula:

$$Jaccard\ coefficient\ \ J\ (JC)\ (A, B) = \frac{|A \cap B|}{|A \cup B|} \qquad (1)$$

The Jaccard coefficient can have values between 0 and 1 (0 ≤ J (A, B) ≤ 1), where a value closer to 1 suggests that there is a high similarity between the two sets and a value closer to 0 illustrates that there are few elements to be found in both sets.

Table 1. Categories, codes, and words searched in the document

Categories and codes	Words searched
ARTIFICIAL INTELLIGENCE	
AI	Artificial neural network, ANN, neural network, genetic algorithm
CHATBOT	Chatbot, chat-bot
ROBOTS	Robotics, robot, sensor
DATA ANALYTICS	Data analytics, analytics (after coding with Data analytics)
IOT AND CLOUD	IoT, Internet. cloud
BIG DATA	Big data, bigdata
DIGITALIZATION	Digital, digitalization, ICT
MACHINE LEARNING	Machine learning, machine-learning
SUPPORT VECTOR MACHINE	Support vector machines, SVM
COMPUTING	Computing, computer
BUSINESS PERFORMANCE AND STRATEGY	
EFFICIENCY	Efficiency, efficient
PRODUCTIVITY	Productivity, productive
PROFITABILITY	Profitability, profit
OPTIMIZATION	Optimization, optimize, optimizing
PLANNING	Planning, plan
COMPETITIVE ADVANTAGE	Competitive advantage, competitive advantages, competitive (in uncoded segments)
STRATEGY	Strategic, strategy
DECISION	Decision
HUMAN RESOURCES	
EMPLOYEES	Employee, Personnel, Workforce, Human resource
SKILLS	Skill, Competence, Talent, Expertise
CAREER PATH	Career, recruitment
TRAINING	Training, trained
RESEARCH METHODS	
QUANTITATIVE RESEARCH	Quantitative research, quantitative, empirical study, empirical studies
QUALITATIVE RESEARCH	Qualitative research, qualitative
REGRESSION ANALYSIS	Regression analysis, regression, ordinary least squares, OLS, panel data, hierarchical linear modeling
STRUCTURAL EQUATION MODELING	Structural equation modeling, structural equation model, SEM
EXPERIMENTAL STUDIES	Experiment, experimental study, experimental studies
NEURAL NETWORKS	Artificial neural network, ANN, neural network, genetic algorithm
DATA MINING	Data mining
DEEP LEARNING	Deep learning, DL
SURVEY	Survey, questionnaire
INTERVIEW	Interview
FOCUS GROUP	Focus group
CASE STUDY	Case study, case studies, case-based reasoning
SYSTEMATIC LITERATURE REVIEW	Systematic literature review, systematic review, literature review, review
RESEARCH GOALS	
RESEARCH OBJECTIVES	objective, goal, purpose, aim, examine, investigate, explore, seek, focus

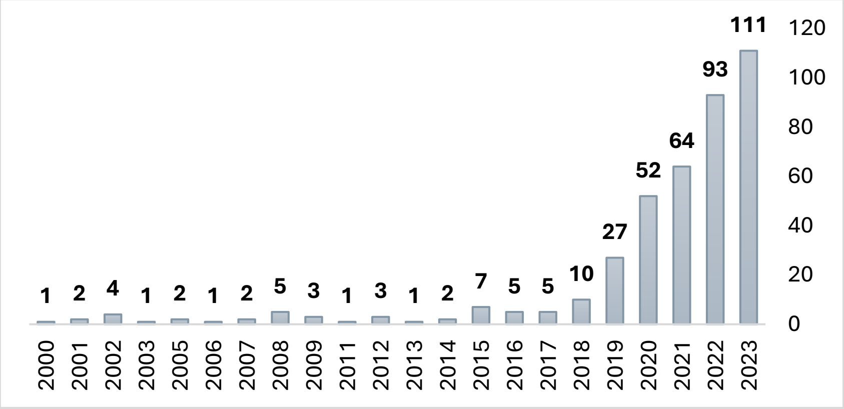
The similarity analysis was mainly conducted using link analysis and proximity analysis in the QDA Miner software. Link analysis explores the co-occurrence of codes within sentences, and permits the identification of significant associations between the different sub-topics in the research encompassing AI and human resources. Moreover, the strength of these associations, based on the Jaccard coefficient, is visualized through a network shape. Proximity analysis, on the other hand, considers the physical distance between coded segments, assuming that codes that appear closer together in the text are more strongly related. Both techniques are highly valuable for identifying patterns and relationships in abstracts, in our case, supporting an improved understanding of how scholars frame their research on the topic of interest.

4. Results and discussion

First, we show in Figure 1 the evolution of publications on AI and human resources after 2000, with a clear upward trend, particularly after 2020. At the beginning of the period (2000-2015), publication activity was very low albeit stable, with only 1-5 articles published annually. A noticeable increase appeared around 2018, with 10 articles published, but the growth accelerated significantly from 2019 onwards. The number of publications reached 27 articles in 2019 and almost doubled to 52 in 2020, then it increased to 64 in 2021, followed by a substantial increase to 93 in 2022. In 2023 there were 111 publications on the topic. This almost exponential increase in research output over the past five years reflects the growing academic interest in understanding the link between AI and human resources, in an era driven by the rapid advancement and adoption of AI technologies in workplace settings.

At the same time, the pattern is similar to many other topics, which is the result of a publication spree determined by the “publish or perish” paradigm (Madikizela-Madiya, 2023), or even “publish and flourish” (Yeo et al., 2022), and the increased use of open access publication solutions (Zhang, 2024).

Figure 1. Number of articles published on the research topic, 2000-2023

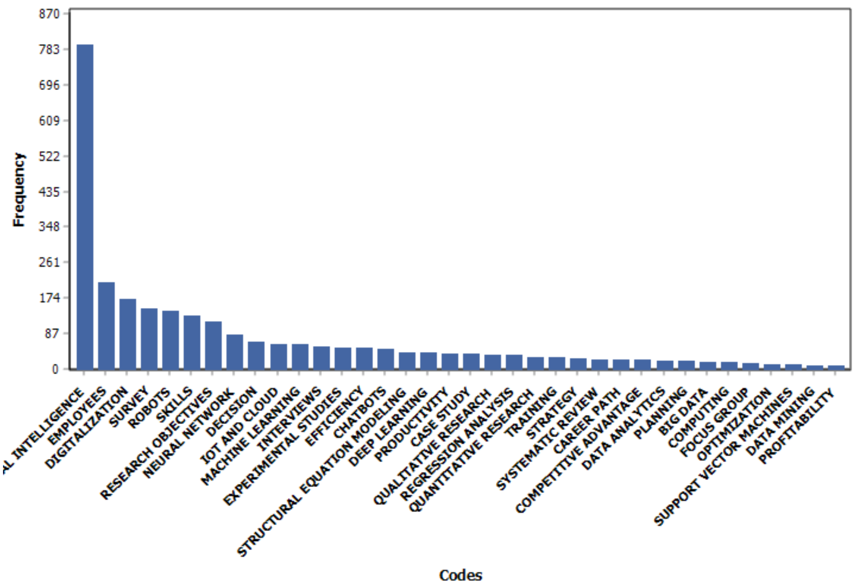


Source: Authors’ representation based on Scopus data

The distribution of codes in the abstracts and in cases is presented in Figures 2 and 3, respectively. The bar chart in Figure 2 shows the “Artificial intelligence” code as having the highest frequency among all codes with 784 occurrences, followed by “Employees” and “Digitalization” with approximately 175 occurrences each. This suggests that AI, as expected given the researched topic, is a key concept mentioned in abstracts, while more specific topics appear less frequently in the abstracts. Also, codes related to human resources, again as expected, are among the most frequent codes, although at a substantial distance to AI.

For what concerns the distribution of codes in cases (abstracts), illustrated in Figure 3, again AI is most frequently encountered (in 301 cases or 74.9% of total cases), followed by “Research objectives” (in 98 or 24.4% of total cases). For the latter, their presence in such a low proportion of cases is concerning, as this indicates less attention awarded by scholars to the writing of abstracts.

Figure 2. Distribution of codes (frequency)

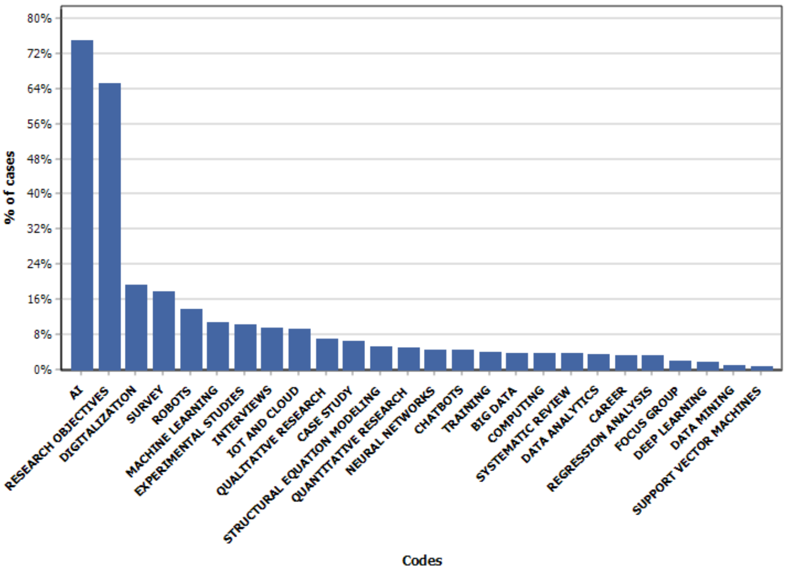


Source: QDA Miner output

It should be noted that abstracts are one of the most important components of a scholarly paper as they represent a concise and comprehensive summary of the study and, as Kumar (2018) notes, are a window to any research article. Moreover, research articles with better quality and more readable abstracts tend to attract more attention and citations (Jin et al., 2021). All the other codes received less attention in abstracts, but this is not uncommon given the particular research interests portrayed in each abstract.

The difference between the four main categories of codes – we excluded “Research goals” due to only one code – in terms of their presence in cases is demonstrated in Figure 4, which shows the minimum, maximum, and mean percentage of total cases where codes in these categories are encountered.

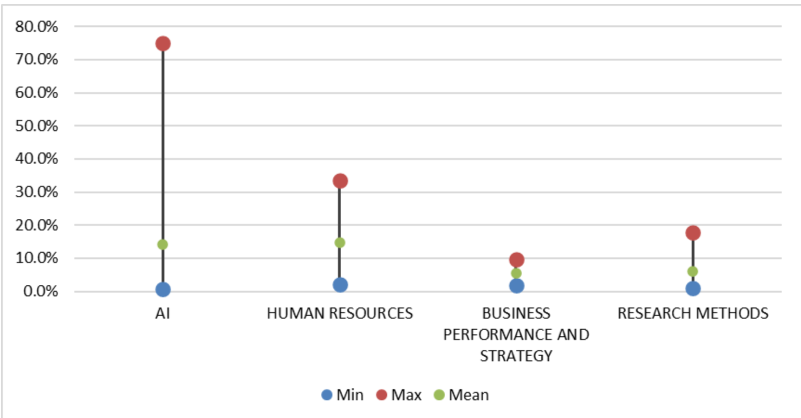
Figure 3. Distribution of codes in cases (% in cases)



Source: QDA Miner output

AI and Human resources categories are most present, with AI and Employees as codes at maximum levels of 74.9% and 33.6%, respectively, while the code Decision under the category Business performance and strategy is the most present in cases (9.7%). The means of codes within each category confirm the dominance of AI and Human resources categories, followed by Research methods and Business performance and strategy.

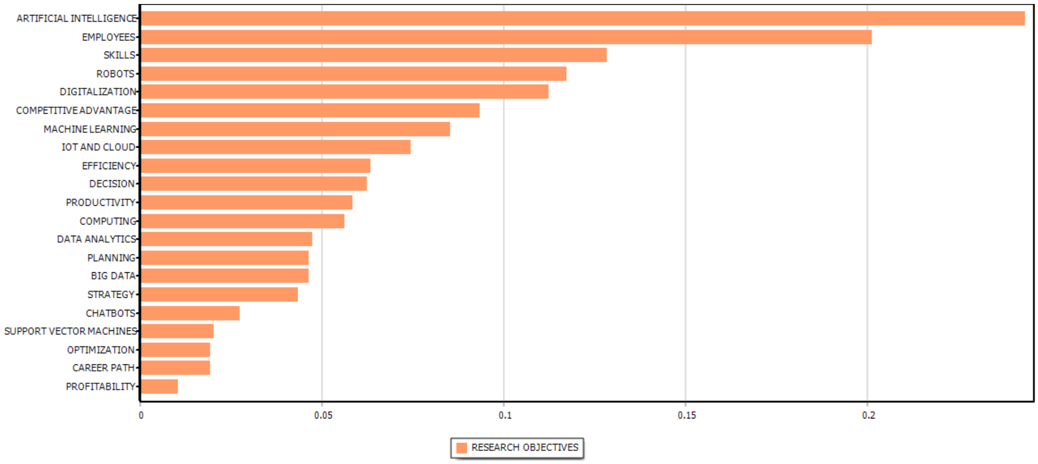
Figure 4. Minimum, maximum, and mean occurrences of categories (% in cases)



Source: Authors' representation based on QDA Miner output

The second step of our analysis refers to the research objectives claimed and research methods adopted by scholars when investigating AI and human resources. The proximity plot for the code "Research objectives" – which includes sentences with the words objective, goal, purpose, aim, examine, investigate, explore, seek, focus –, presented in Figure 5, shows that "Artificial Intelligence" and "Employees" have the highest proximity (around 0.2), indicating they are frequently discussed together in the abstracts. "Skills," "Robots," and "Digitalization" follow, with Jaccard coefficients around 0.15, implying these are also important themes mentioned by scholars concerning research objectives. At the lower end of the plot, codes such as "Chatbots," "Support Vector Machines," "Career Path," and "Profitability" have weaker proximity coefficients (below 0.05), pointing to a lower association with research objectives.

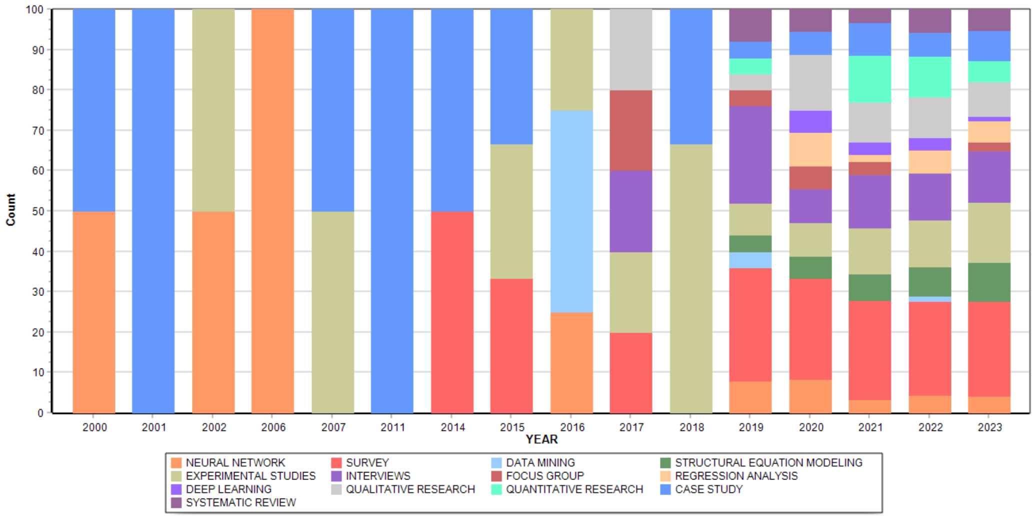
Figure 5. Proximity plot of research objectives



Source: QDA Miner output

The stacked bar chart in Figure 6 depicts the evolution of research methods employed in AI and human resources studies from 2000 to 2023, as reflected in abstracts.

Figure 6. Research methods evolution between 2000 and 2023

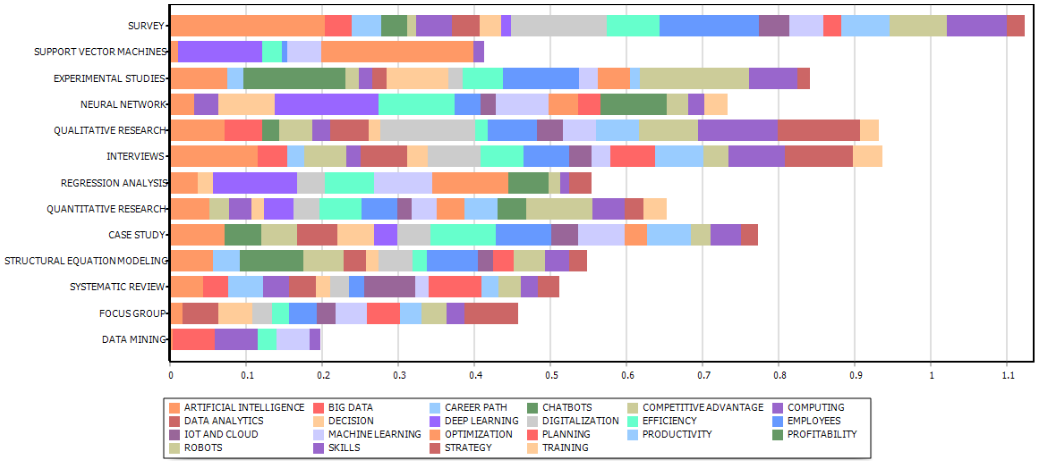


Source: QDA Miner output

Multiple interesting patterns are noticed: (i) the first part of the period (2000-2015) was dominated by several methods: case studies, surveys, experimental studies and neural networks; however, one should recall from Figure 1 that only a few papers were published yearly on the topic of interest; (ii) in more recent years we see a higher methodological diversity, accompanied by the increased presence of systematic reviews, a growth in deep learning applications and the introduction of more sophisticated quantitative methods, such as regression analysis or Structural Equation Modeling. This evolution is a reflection of the research field maturation, as scholars explored more varied and complex approaches to study the impact of AI on human resources, but also a move from more descriptive methods toward a mix of qualitative and quantitative tools that encourage a better understanding of the research topic.

Figure 7 shows the relationship between research methods (on the vertical axis) and research sub-topics in the AI and human resources literature. The proximity coefficients are represented on the horizontal axis and indicate how closely different sub-topics are associated with each research method. The most represented research method across sub-topics is the survey, suggesting that it is the preferred method in the studies that investigate AI and human resources. Surveys are followed by Qualitative Research, Interviews, and Experimental studies, other widely used research methods across sub-topics. Other interesting observations refer to Neural Networks that show stronger proximity with technical topics (AI, Machine learning), Structural Equation Modeling that is particularly linked to organizational sub-topics, and Case Studies that demonstrate a rather balanced use in technical and managerial topics.

Figure 7. Proximity plot of research methods

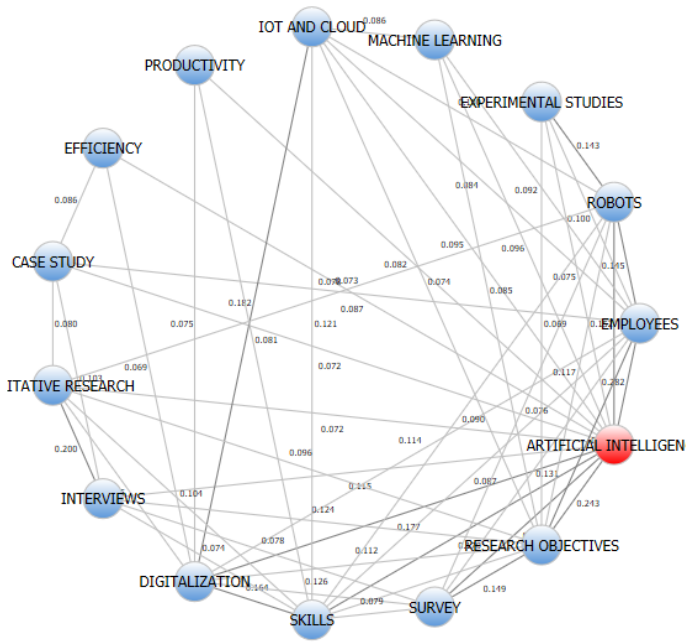


Source: QDA Miner output

Further, we portray in Figure 8 the network of links between all codes (represented as nodes), including Research objectives and research methods. “Artificial intelligence” appears as the central node marked in red, which indicates its role as a key sub-topic. The lines connecting the nodes are the Jaccard coefficients between codes that describe the strength of the relationship between them. These links show strong connections between

“Artificial intelligence” and “Employees” (coefficient of 0.282), “Artificial intelligence” and “Research objectives” (coefficient of 0.243), and between “Qualitative research” and “Interviews” (coefficient of 0.200). All the other coefficients have values below 0.200. At the same time, the network suggests a complex web of connections between sub-topics, with an important cluster seemingly formed around “Artificial intelligence”, “Employees”, and “Robots”, on the one hand, and “Research objectives” and “Experimental studies”, on the other hand.

Figure 8. Link analysis of all codes

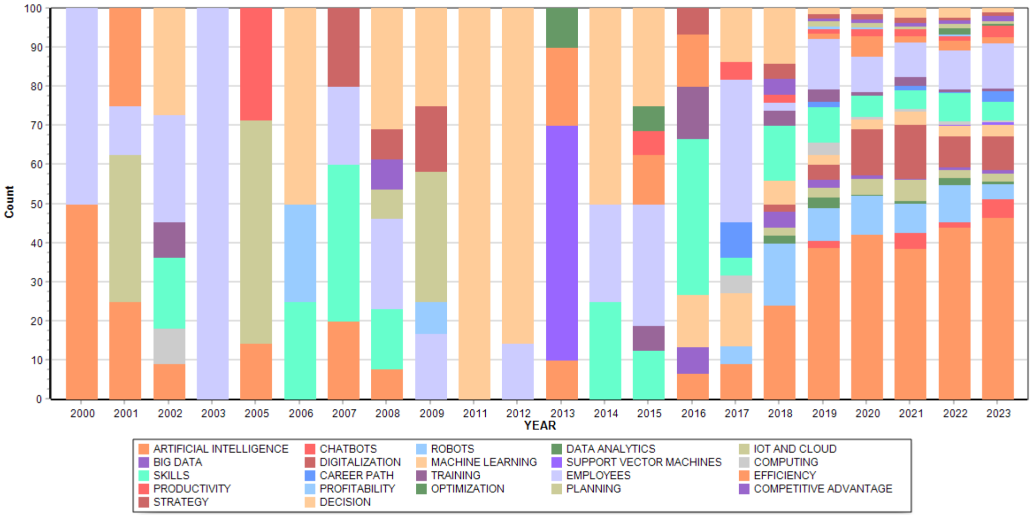


Source: QDA Miner output

This cluster points to the relatively more important appearance of these sub-topics in the abstracts compared to the other sub-topics and a leading role of “Employees” and “Robots” as sub-topics connected to “Artificial intelligence”.

In the last step of our analysis, we focus on the evolution over time and the connections between AI and human resources sub-topics, also including sub-topics from the Business strategy and performance category. Figure 9 shows the progression of these sub-topics from 2000 to 2023 and several insights are very interesting. First, AI topics (found in the codes “Artificial intelligence”, “Machine Learning”, “Robots”, “Chatbots”, “Bug Data”, “Digitalization” etc. – please refer to Table 1) dominated research until 2006 but also saw a resurgence after 2014 when more sophisticated AI solutions became the center of this research domain. Human resources topics (“Employees”, “Training”, “Skills”, “Career path”) were present in research from the beginning of the period but gained prominence after 2007 and more importance after 2015, with “Training”, and “Career path” gaining increased interest in 2018-2023. However, both AI and Human resources topics were accompanied in research by Business Strategy and Performance topics (“Efficiency”, “Productivity”, and “Competitive Advantage”), which saw steady growth in importance after 2015. This signals that scholars related the interplay between AI and human resources to its effect on business operations, highlighting practical business outcomes and potential competitive gains. Overall, the evolution of these topics indicates a clear move from research focused mostly on AI to a more balanced approach that incorporates employee-related and business aspects - the recent years (2018-2013) reveal a more diversified distribution of research across the three main categories, showing a more maturing understanding of AI’s role in human resources processes and management in scholarly research.

Figure 9. Evolution of topics over time (2000-2023)



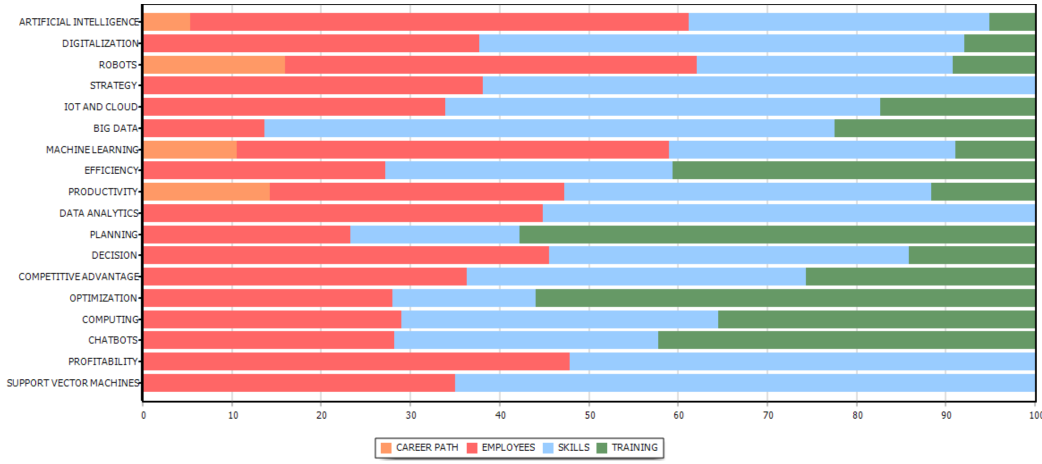
Source: QDA Miner output

Figure 10 displays the connections between Human resources topics, on the one hand, and AI and Business strategy and performance topics, on the other hand, as a percentage of total proximity (100%). By far, studies have mostly linked “Employees” and “Skills” to all codes under AI and Business strategy and performance categories, although “Training” was prominent in relation to “Planning”, “Optimization” and “Efficiency”, suggesting that personnel development was advanced by scholars as a key element of business progress and increased viability. It is also noteworthy that “Career path” was connected only to “AI”, “Robots”, “Machine learning” and “Productivity”, potentially upholding that research on recruitment of employees and their further careers has more to offer in the future when connected to technological developments and business performance.

A similar approach to Figure 10 is taken for Business strategy and performance sub-topics, which are linked to AI and Human resources topics in Figure 11. While most sub-AI and/or Human resources codes are connected in existing research to many (even all) of the Business strategy and performance sub-topics (“Machine learning”, “Artificial intelligence”, “Computing”, “Skills”, “Employees”, “IoT and cloud”, “Big data”, “Robots”), other show a preference for only one or two codes in the Business strategy and performance category:

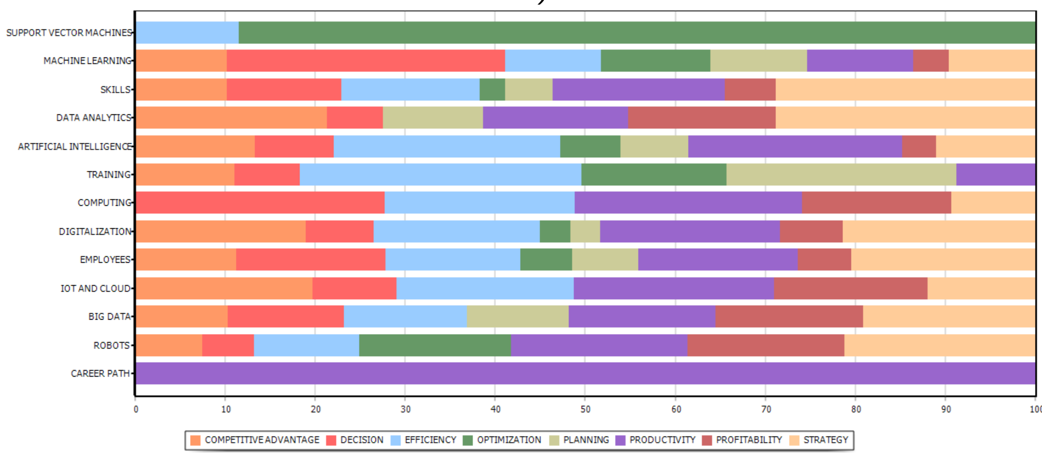
"Support Vector Machines" - "Efficiency" and "Optimization", and "Career path" – "Productivity". This hints at the diverse ways in which approaches to AI, human resources and business growth were being integrated into scholarly research after 2000 but also advocates for specific further research focus on less investigated connections.

Figure 10. Proximity analysis of Human resources topics (percentage of total)



Source: QDA Miner output

Figure 11. Proximity analysis of Business strategy and performance topics (percentage of total)



Source: QDA Miner output

5. Conclusions

This study investigated the evolution and current state of research on artificial intelligence's interaction with human resources management through a qualitative analysis of 402 scholarly article abstracts published between 2000 and 2023 and collected from Scopus. Using QDA Miner 2024, we employed content, link, and proximity analyses to understand how this research field has developed and identify key patterns in the academic discourse. The findings highlight three key aspects: (1) the dominance of AI and employee-related topics in the literature, suggesting these are central to understanding the AI and human resources relationship; (2) the growing complexity of research methods used by scholars to study this relationship, reflecting the field's increasing sophistication; and (3) the distinct patterns in the interaction between AI adoption, human resources processes and management, and business performance and strategic options, also indicating areas that deserve further investigation.

Several limitations should be noted, however. First, the use of article abstracts may not capture the full complexity of research findings on the interplay between AI and human resources. Second, the literature review added business strategy and performance to the analysis, but other themes may be of interest in the exploration of AI and human resources – for example, risk and change management, sustainability, the transformation of organizational culture diversity and inclusion, or cross-cultural implications. Additionally, the intersection of AI with organizational learning, workforce dynamics, inter-generational perspectives, and the complex aspects of the collaboration between human resources and AI tools and solutions represent promising avenues for future research.

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