The Impact of Artificial Intelligence on Job Performance: A Systematic Review

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ABSTRACT

The rapid diffusion of artificial intelligence (AI) technologies across organizational functions has intensified scholarly interest in their implications for employee job performance. While existing studies highlight both productivity gains and emerging challenges associated with AI adoption, the intellectual structure, thematic evolution, and research frontiers of this growing body of literature remain fragmented. The goal of this study is to organize the scholarly contribution to the impact of artificial intelligence on job performance. The study was carried out by examining 1,747 publications that were indexed in the Scopus database. The data were analyzed to give an overview of the domain using the PRISMA sampling approach and VOSviewer software. We then reported tables, graphs, and maps to highlight the key performance metrics for the creation of articles and their citations. The findings demonstrate the frequent usage of phrases like “job performance,” “artificial intelligence,” “organization performance,” “human resources management,” “performance management,” and “machine learning,” among others. Furthermore, some of the more recent study subjects are revealed by the density map, including “digital education technology,” “innovation performance,” “emotional intelligence,” “big data analysis,” “deep learning algorithms,” “data augmentation,” “smart technologies,” and “knowledge specificity." The study offers valuable insights for managers and policymakers who aim to utilize AI to improve job performance while minimizing negative impacts on employees.

Keywords: Artificial intelligence, Bibliometric Analysis, Job Performance, VOSviewer

I. INTRODUCTION

The recent landscape of Human Resource Management (HRM) is being dynamically reinvented globally by emerging technology (Ancarani et al., 2019; Vrontis et al., 2021). The dynamics among customers, businesses, and employees are undergoing profound changes due to the rapid advancements and widespread adoption of artificial intelligence (AI) and other innovative technologies. Consequently, the administrative facets of human resource management (HRM) are progressively transitioning towards automation (Marler & Parry, 2016). Although technology has played a role in HRM since the Industrial Revolution, its evolution has primarily impacted the accessibility of mental or physical services.

Yet, in activities traditionally reliant on human collaboration and communication, contemporary advancements are progressively presenting substitutes for human involvement in the workforce (Luo et al., 2019). This is altering organizational structures as well as the nature of work (Vrontis et al., 2021). For instance, the industry is becoming more and more interested in humanoid service robots and artificial intelligence bots (Go & Sundar, 2019; Larivière et al., 2017). These clever "beings" have completely changed the way that traditional HRM duties are performed. These advancements offer Human Resource Management (HRM) fresh opportunities and advantages, yet they also raise notable concerns, such as the potential obsolescence of certain roles (Larivière et al., 2017). Nonetheless, due to their capacity to enhance coordination and collaboration, “smart devices,” “the Internet of Things,” and “deep learning algorithms” prove particularly beneficial for multinational companies (Cooke et al., 2019).

Similarly, the emergence of electronic “HRM information systems” and other advanced technologies present numerous opportunities to enhance HRM operations while reducing costs, including tasks such as employee performance assessments and candidate evaluations (Bondarouk et al., 2015; Cooke et al., 2019; Vrontis et al., 2021). In addition, scholars emphasize how information technologies are revolutionizing HRM processes through the introduction of “e-competence management,” “e-recruitment,” and “e-training,” consequently enhancing the quality of HRM services in both domestic and international organizations (Bondarouk & Brewster, 2016).

These technologies provide diverse opportunities and support various HRM practices by bringing new elements like “social robots” into HRM practices (Bondarouk et al., 2015; Vrontis et al., 2021). From this viewpoint, several studies demonstrate how automation enhances performance and speed by automating numerous tasks across “computerized design,” manufacturing,” and “process planning”(Park, 2016). Mostly, a growing corpus of research focuses on HRM's role as a catalyst for innovation and technological development on a worldwide scale through work reorganization, including training programs for employees and improved working conditions (Vrontis et al., 2021).

Artificial intelligence (AI) is popping up everywhere in workplaces, and research on it has exploded in recent years. Yet when it comes to understanding exactly how AI affects job performance, the picture is still pretty messy. Some studies paint AI as a powerful tool that boosts productivity, others see it as a way to keep closer tabs on employees, a helpful teammate, or even something that piles on more work and stress. Because researchers are looking at it from so many angles, the results are all over the place—we're left wondering whether AI actually helps people do their jobs better, and if so, under what circumstances.

Previous reviews have done a great job exploring related topics, like digital HR systems, big data in management, or how companies adopt AI in general (Bondarouk et al., 2016; Garcia-Arroyo & Osca, 2021; Vrontis et al., 2021). But they haven't really zoomed in on job performance as the main focus. We still don't have a clear map of how different fields have defined and measured performance in the context of AI, or how those ideas have evolved over time.

One big issue is that no one has fully laid out the big-picture structure of this research—who the key players are, which journals matter most, how the main themes cluster together, and what's just starting to emerge. Without that kind of overview, researchers can end up reinventing the wheel, missing important gaps, or struggling to build on what others have already discovered. A bibliometric approach—using data-driven tools to analyze thousands of publications—feels like the perfect way to uncover those hidden patterns and bring some order to the chaos.

Different theories help explain what's going on. For example, classic ideas about job design and motivation—like how much autonomy people have, clear goal-setting, or the give-and-take in workplace relationships—shed light on how AI's instant feedback, automation, or decision helpers shape the way we work (Landers et al., 2015; Park, 2016). From the human-computer interaction side, concepts like treating AI as almost "human" (anthropomorphism) or feeling a real social connection with chatbots and virtual assistants explain why some interactions boost performance while others fall flat (Araujo, 2018; Go & Sundar, 2019).

All these different lenses highlight just how complex the topic is, and they make a strong case for a thorough bibliometric review that can organize everything and spotlight the foundational ideas driving the field.

To fill these gaps, this study uses bibliometric techniques to map out the entire body of research on AI's impact on job performance. Our specific goals are to:

1. Track how the field has grown over time and spot key publication trends;
2. Pinpoint the most influential authors, journals, institutions, and countries shaping the conversation;
3. Reveal the intellectual structure through analyses of citations, co-citations, and how keywords appear together;
4. Uncover the major themes and emerging hot topics around AI and job performance;
5. Point out gaps in theory, methods, and contexts to guide future research.

The rest of the paper is organized like this: Section 2 reviews the existing literature on AI, human resource management, and job performance. Section 3 explains our bibliometric methods, including where we got the data and how we analyzed it. Section 4 shares the results—trends, influential works, and thematic maps. Section 5 discusses what it all means for theory and practice. Finally, Section 6 wraps things up with the main takeaways, limitations, and ideas for where the research should go next.

II. LITERATURE REVIEW

The concept of artificial intelligence is well known and gain confidence on its applicability in modern organization. Most organizations intend to pursue the highest rate of return consider artificial intelligence as an important tool for their business success. Application of artificial intelligence therefore compels organizations to have a deeper understanding of the concept its and the ways it can be used to venture business performance. Scholars have provided various definitions of artificial intelligence.

Mikalef and Gupta (2021) defines artificial Intelligence as the ability of a system to identify, interpret, make inferences, and learn from data to achieve predetermined organizational and societal goals. Koo et al. (2021) defines artificial intelligence as field within computer sciences where human-like tasks are performed by machines to enhance business prosperity. Consequently, echoes that the basic utility of artificial intelligence is improvements of various organizational key performance indicators (Mikalef & Gupta, 2021).

Subsequently, Ramachandran et al. (2022), considers that artificial intelligence plays diverse roles in business, such as improving employee and customer engagements; identifying patterns in large data sets; automating tedious tasks and enhances employee success and productivity

Job performance is described as a measure of employee productivity in a manufacturing setting, based on the quantity of quality units produced within a set timeframe (Makanthi & Hussain, 2016). Said et al. (2022) defined job performance as consisting of five indicators such that work quality, work quantity, punctuality, efficiency and autonomy.

Based on the definitions provided, understanding the core to job performance is paramount for business growth. Therefore, creating a motivating atmosphere, offering growth opportunities, and rewarding accomplishments are crucial for organizations to improve job satisfaction and boost job performance. High levels of job satisfaction can positively affect overall organizational performance, while job dissatisfaction can result in negative behaviors and have a detrimental impact on organizations.

The connection between artificial intelligence (AI) and how well people perform at work ties into bigger conversations about digital tools, automation, and the way technology is reshaping jobs. Early research on technology in the workplace focused mostly on making things more efficient, standardizing tasks, and giving managers more control (Chow et al., 2006; Zanko et al., 2008). But as AI arrived on the scene—systems that can learn, make decisions, and even interact with people—the discussion shifted dramatically. Now we're talking about tools that fundamentally change how jobs are designed, supervised, and measured (Loebbecke & Picot, 2015; Newell & Marabelli, 2015).

When we think about job performance, it usually breaks down into three parts: getting your core tasks done (task performance), going the extra mile and helping colleagues (contextual performance), and adapting to new situations (adaptive performance). AI affects all of these—sometimes by augmenting what humans do, sometimes by taking over tasks entirely, and often by completely redesigning roles (Fleming, 2019; Park, 2016). The good news? Modern thinking has moved away from the scary idea that AI will just wipe out jobs. Instead, most researchers see it as a partner that changes the skills we need, the freedom we have, and what "good performance" even looks like (Colbert et al., 2016). That shift explains why there's been such a boom in studies linking AI to job performance—and why a bibliometric review makes perfect sense for mapping it all out.

HR research gives us a solid starting point for understanding AI's role. Back when "electronic HRM" was the hot topic, studies looked at how digital systems sped up HR processes and improved employee outcomes (Bondarouk et al., 2016; Parry & Tyson, 2008, 2011). The big lesson? Just throwing technology at HR doesn't automatically make things better—it has to fit the company's strategy and feel useful to employees (Bondarouk et al., 2015; Marler & Parry, 2016).

More advanced tools, including AI, are now transforming everything from hiring to training and performance reviews (Stone et al., 2015). Think automated resume screening: it shapes performance indirectly by helping companies hire people who are a great fit (Buckley et al., 2004). Recent reviews show that AI-powered analytics and decision tools are increasingly tied to better results for both individuals and organizations (Garcia-Arroyo & Osca, 2021; Vrontis et al., 2021).

That said, there's a darker side. Constant monitoring and algorithmic management can boost metrics but erode trust and autonomy (Abraham et al., 2019). These mixed effects explain why findings on AI and performance vary so much—and why a bibliometric map could help us spot the main themes and disagreements.

A lot of research explores how AI changes the very nature of work—things like autonomy, task complexity, and the skills people need. For instance, automation can either free employees to contribute more creatively or box them in, depending on how it's rolled out (Ancarani et al., 2019; Park, 2016).

Fleming (2019) pushes back against doom-and-gloom predictions of mass job loss, reminding us that politics, culture, and organizational choices all shape what actually happens. This fits nicely with studies on innovation and human agency (Crossan & Apaydin, 2010; Seeck & Diehl, 2017). In bibliometric terms, you'll see optimistic productivity-focused clusters sitting right next to more critical work on power and resistance.

AI's influence shows up clearly in remote and virtual teams. Tools that handle scheduling or power collaboration platforms can make teams more effective, but they can also make communication feel flat or impersonal (Dulebohn & Hoch, 2017; Schaubroeck & Yu, 2017).

Individual factors—like how confident someone feels using tech or how well they self-regulate—play a huge role in whether digital setups help or hurt performance (Pellas, 2014). The pandemic supercharged this area: studies found that good real-time digital communication kept people engaged, though not everyone had equal access or skills (Wang & Zou, 2021). Bibliometric trends show AI, remote work, and performance research increasingly overlapping.

AI also works through more social and motivational channels. Using social media at work can build connections and improve performance by growing social capital—especially now that algorithms shape what we see and who we interact with (Ali-Hassan et al., 2015). Gamification is another great example: AI-driven leaderboards and instant feedback tap into goal-setting psychology to motivate people (Landers et al., 2015). These angles remind us that AI doesn't just automate—it can change behavior and cognition in subtle ways. Bibliometric maps often group these studies around engagement and motivation themes.

How AI affects performance isn't the same everywhere. Adoption varies based on national regulations, company capabilities, and local culture (Cooke et al., 2019; Pisani, 2009; Pisani et al., 2017). Innovation research adds that AI's real impact depends on strong human and organizational foundations (Crossan & Apaydin, 2010; Seeck & Diehl, 2017). A bibliometric view can reveal how the topic spans individual, team, organizational, and global levels.

III. METHODOLOGY

3.1 Bibliometric Approach and Systematic Literature Review

In accordance with the recommendations of Crossan and Apaydin (2010) and Tranfield et al. (2003), we carried out a bibliometric assessment in order to identify research trends and identify potential directions for future investigations pertaining to "the impact of AI on job performance." Since a transparent and easily replicable technique is used, a bibliometric method was determined to be appropriate to enhance the general efficacy of the review (Crossan & Apaydin, 2010; Tranfield et al., 2003). Through the use of a "systematic literature review approach," we were able to map, critically analyze, and synthesize the available research by determining the primary themes.

This study looks at the changes that have occurred in studies on "the impact of AI on job performance" within the last thirty-five years, namely from 1989 to 2024. Due to artificial intelligence's contemporary significance and relevance—especially with regard to the Scopus database entries (Nyabakora, 2023b), we chose it as the research's focal point. On this topic, a comprehensive review of 1,747 articles was carried out. Using VOSviewer (Benziane et al., 2022; Nyabakora, 2023a), anunrestricted program for creating and visualizing bibliometric networks, the results of the parameters that were evaluated (co-citation, co-occurrence of phrases, citations, etc.) were graphically shown.

In order to create clusters based on quotations, co-citations, and co-occurrences, VOSviewer can handle data about researchers, publications, themes, journals, and countries (Benziane et al., 2022; Nyabakora, 2023a). The information is then displayed graphically to improve comprehension (Nyabakora, 2023b; Priyan et al., 2023b). This application displays the pertinent facts in a map format by using data from the Scopus database. "The impact of AI on job performance" is examined in this study from 1989 until 2024. It is possible to follow the change in perception regarding the domain by conducting a long-term analysis of the notion.

The PRISMA framework was utilized to create the inclusion criteria prior to the initiation of data collection (Moher et al., 2009; Nyabakora, 2023b). The evidence-based PRISMA ("Preferred Reporting Items for Systematic Reviews and Meta-Analyses") set of tools helps writers describe a diversity of systematic assessments, which are typically used to weigh the benefits and drawbacks of a healthcare intervention. According to Priyan et al. (2023a), PRISMA places a strong emphasis on techniques that help writers make sure this kind of research is reported truthfully and openly.

3.2 Selection of Articles

The notion that higher-quality sources are correlated with the Web of Science's narrow scope was disputed by Hallinger and Kovačević (2019), who contended that discipline-specific verification of this is necessary. This was a reaction to Mongeon and Paul-Hus(2016), who, based on their empirical research, concluded that the Scopus index was a more comprehensive information source for searching and collecting papers in the social sciences. Furthermore, Scopus has more sophisticated exporting features than Google Scholar (Benziane et al., 2022). Furthermore, Scopus offers a standardized method for work indexing (Hallinger & Nguyen, 2020). Archambault et al. (2009) did an interdisciplinary study that revealed a substantial correlation between articles published in the Web of Science and Scopus.

3.3 Data Searching Criteria

We performed our preliminary exploration using the previously defined search string on February 8, 2024, on the Scopus database. We utilized the "TITLE-ABS-KEY" tool in conjunction with the PRISMA technique (Crossan & Apaydin, 2010; Nyabakora, 2023a; Pisani et al., 2017) to search the Scopus Database and gather only double-blind, peer-reviewed literature. We limited the scope of our search to English final papers published by February 8, 2024. We limited our results by using inclusion and exclusion criteria, yielding 7,263 publications. After that, we followed a four-step procedure to choose just the publications that were relevant to this study (Figure 1). There were 5,278 hits when the search was limited to papers in the domains of computer science, business, management, accounting, economics, social sciences, econometrics, and finance.

After that, we reduced the number of articles to only those that were about "the impact of AI on job performance" using keywords, leaving 3,498. 1,747 articles remained to be included in our bibliometric review after we went through the papers and removed 33 that were not in English.

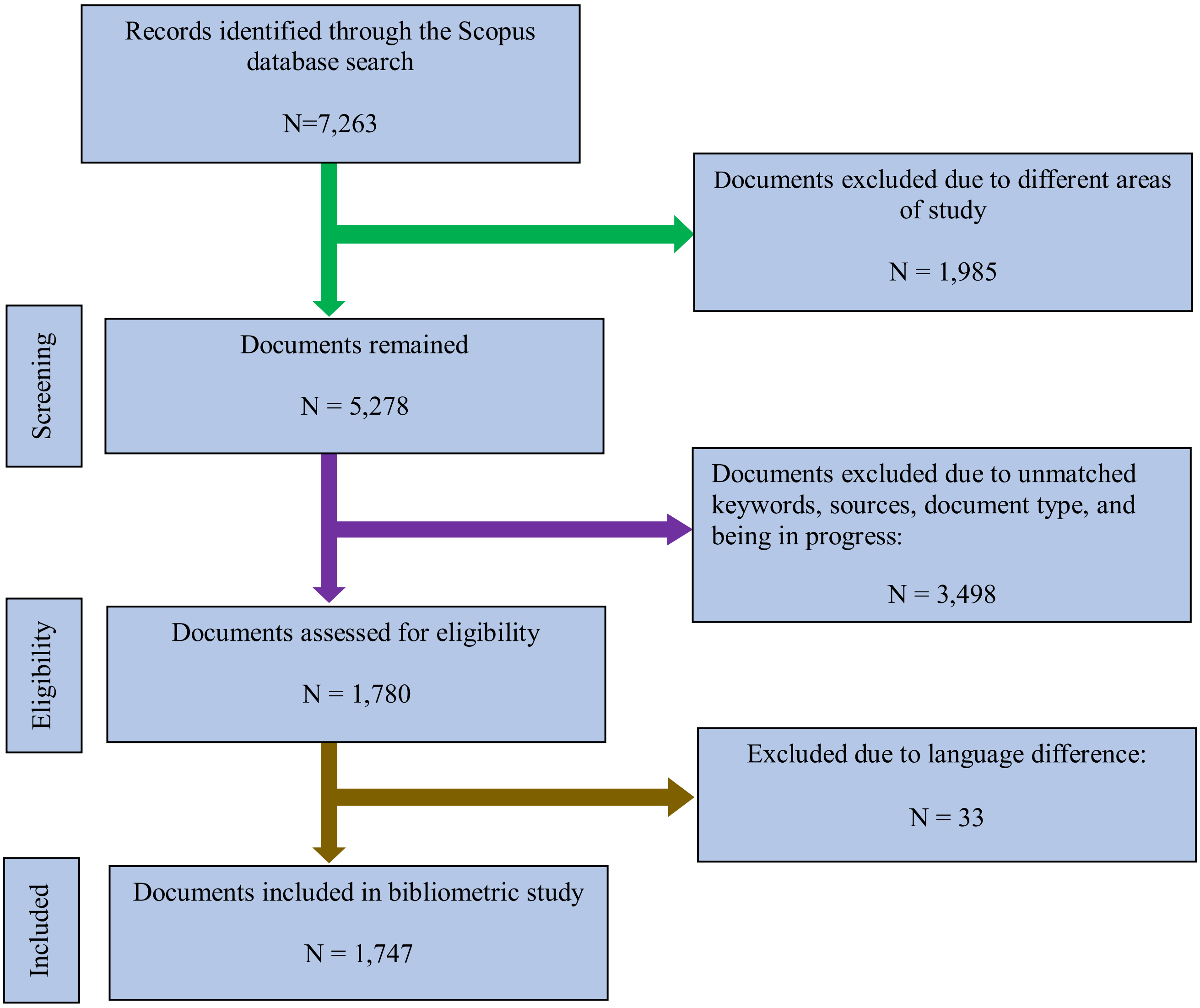

Figure 1
The PRISMA Digram on Data Sampling Process (Moher et al., 2009; Nyabakora, 2024)

The PRISMA technique (Hallinger & Nguyen, 2020; Priyan et al., 2023a, 2023b) served as the search criteria, and brackets were used to guarantee precision. The search terms could be narrowed or broadened by adding an asterisk ("*") or a question mark ("?") accordingly. A single search technique was made possible by the application of common Boolean operators (Pisani et al., 2017).

The phrases search algorithm ((impact* OR influenc* OR effect*) AND ("artificial intelligenc*" OR "automat* intelligence" OR AI OR "machine* intelligence" OR "digital intelligence") AND ("job* perform*" OR "work* efficienc*")) was employed to refine the search in the Scopus database to locate pertinent records. 7,263 documents were found in the first results of the search; however, the total number was reduced to 1,747 after removing papers that did not meet the requirements or were deemed not important enough (Figure 1).

3.4 Data Analysis

The 1,747 documents' bibliographic information was retained for use in later procedures. A bibliometrics technique was used to analyze the results in greater detail. This involved presenting a visual illustration of the similarities between author co-citation and phrase co-occurrence evaluation, as well as considering citation and co-citation evaluation (Benziane et al., 2022; Nyabakora, 2023a, 2023b).

A bibliometric investigation was carried out using VOSviewer, bibliometric software, Excel, Tableau, and Scopus analytics (Benziane et al., 2022; Nyabakora, 2023a, 2023b). The results of an investigation into the impact of artificial intelligence knowledge bases are presented in this section. The following is the order in which the following four research queries were evaluated.

IV. FINDINGS & DISCUSSION

4.1 Findings

4.1.1 Direction of Research Growth in the Impact of AI on Job Performance

The expansion of the impact of AI on job performance has demonstrated the evolution of our understanding of this domain. 1,747 articles about “the impact of AI on job performance” have been published since 1989, according to a search of the Scopus database. Table 1 exhibits the documents’ authors, titles, journals they were published in, and countries of affiliation. A review of 1,747 publications was done in order to assess this tendency, and the results indicated that between 2018 and 2024, the papers had a regular growing trend. 1,425 of these publications, or eighty-one percent, were released in the last six years (2018–2023). This suggests a highly promising future for the field of study because it shows that researchers into “the influence of AI on job performance” are becoming more and more interested in this area (Figure 2).

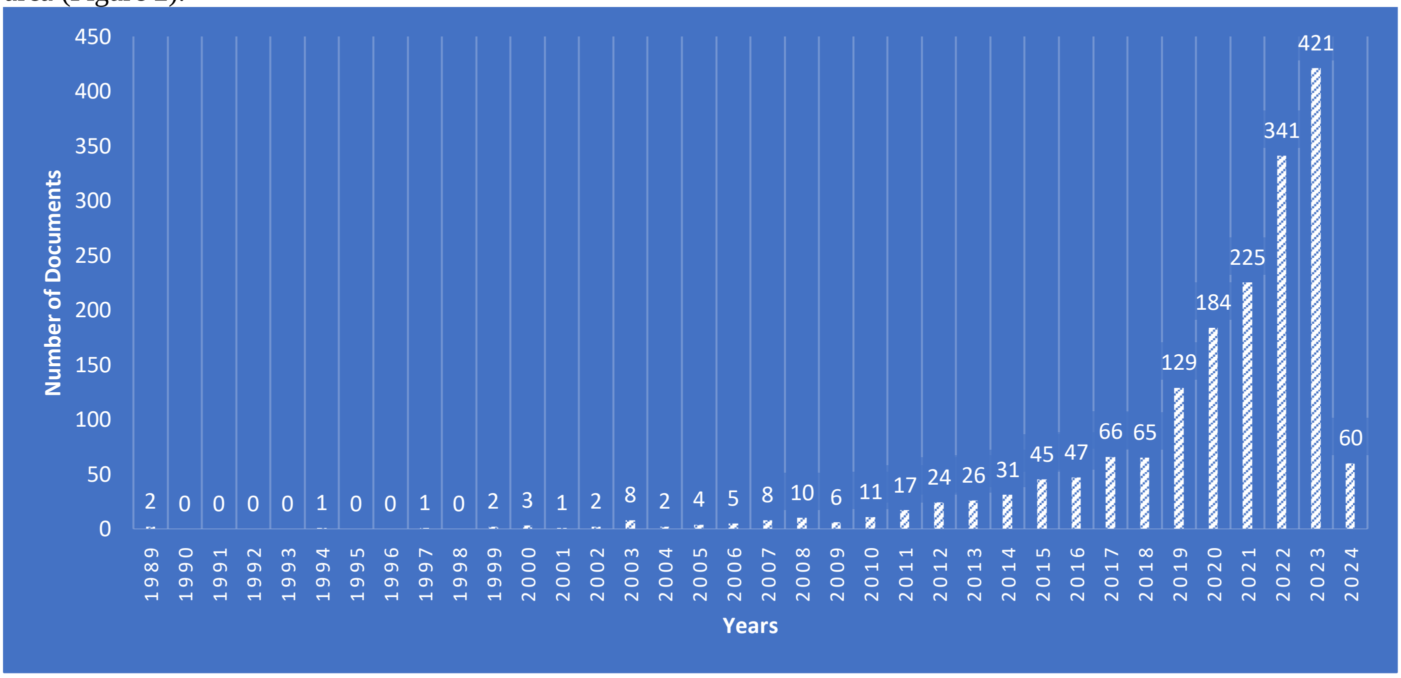

Figure 2
Direction of Research Growth in the Impact of AI on Job Performance (1989-2024)

The frequency of occurrences and correlation between keywords in papers published between 1989 and 2024 were measured using the VOSviewer in order to get insight into the evolution of perspectives on “the impact of AI on job performance.” The total number of keywords dropped from 2,846 to 349 by imposing the requirement that a keyword appear in at least five articles (Figure 3). To achieve the objectives outlined in this paper, it is imperative to identify the impact of artificial intelligence on job performance subjects that are most commonly addressed.

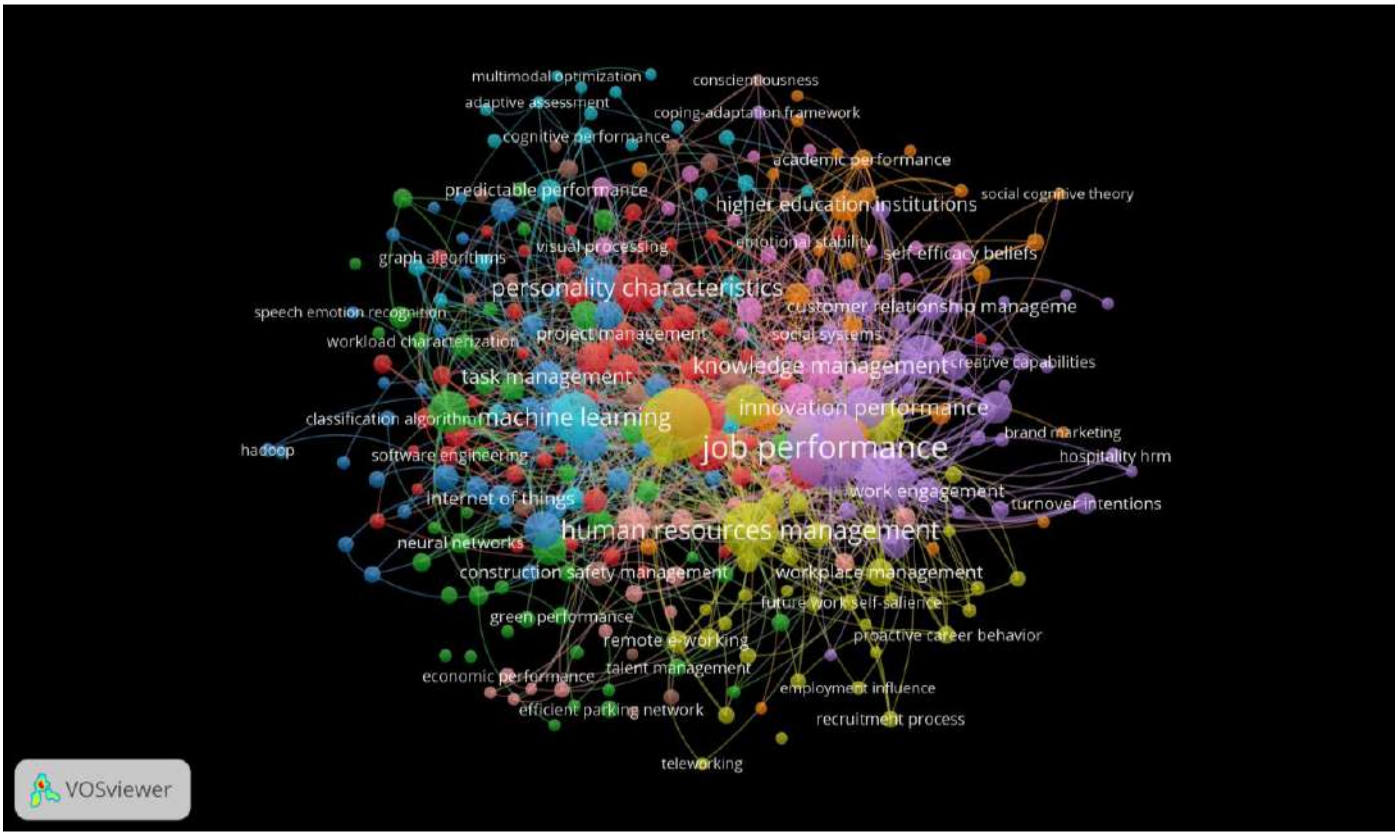

Figure 3

Co-occurrence of Keywords for the Impact of AI on Job Performance (1989-2024)

To investigate the subjects covered in the literature on “the impact of AI on job performance,” we performed a keyword analysis. When we first began our analysis, we used VOSviewer to see which terms were most frequently used. “Job performance” (212), “artificial intelligence” (166), “organization performance” (110), “human resources management” (105), “performance management” (98), “machine learning” (86), “personality characters” (79), “social media analysis” (66), “knowledge management” (63), and “knowledge sharing behavior” were mentioned 63 times (Figure 3's density map).

The keyword analysis showed that “the impact of AI on job performance,” which is our primary focus, is still less common. The fact that it is still new in the HRM domain is true due to its first appearance in the top fifteen trends in the period between 2018 and 2021.

A "chronological keyword map" (Figure 3) with at least five co-occurrences was created using VOSviewer to establish this. To find the primary keywords that could connect the others, there weren't any significant node discrepancies. The documents were split into three groups for examination, and this map looked at how the keywords were distributed among them according to when they were published (Table 1).

According to the study, there was a substantial correlation between “job performance” and “artificial intelligence.” Approximately 9.93 percent of the keywords that satisfied the requirement of having at least five co-occurrences during the first sub-period, which ran from 1989 to 2017, had some connection to it. “Knowledge management” accounted for 7.67 percent of the keyword occurrences, while “performance management” comprised 4.97 percent overall. The remaining keywords, along with their descriptions, can be seen in Table 1.

Table 1
Keywords Growth on Artificial Intelligence and Job Performance

ID	Label	1989-2024		Label	1989-2017		Label	2018-2021		Label	2022-2024	
		occ	%		occ	%		occ	%		occ	%
1	Job performance	212	4.40	Job performance	44	9.93	Job performance	71	6.48	Job performance	126	6.56
2	Artificial intelligence	166	3.45	Knowledge management	34	7.67	Artificial intelligence	60	5.47	Artificial intelligence	108	5.62
3	Organization performance	110	2.29	Performance management	22	4.97	Performance management	34	3.10	HRM	74	3.85
4	HRM	105	2.18	Organizational performance	20	4.51	HRM	33	3.01	Organization performance	57	2.97
5	Performance management	98	2.04	Personality characteristics	18	4.06	Organizational performance	30	2.74	Machine learning	55	2.86
6	Machine learning	86	1.79	Productivity assessment	14	3.16	Personality characteristics	30	2.74	Knowledge management	52	2.71
7	Personality characteristics	79	1.64	Human performance	12	2.71	Social media analysis	30	2.74	Digital education technology	41	2.13
8	Social media analysis	66	1.37	Artificial intelligence	11	2.48	Knowledge specificity	28	2.55	Deep learning algorithm	37	1.93
9	Knowledge management	63	1.31	Decision performance	11	2.48	Machine learning	27	2.46	Innovation performance	36	1.87
10	Knowledge sharing behavior	63	1.31	Emotional intelligence	11	2.48	Knowledge management	24	2.19	Social media analysis	34	1.77
11	Innovation performance	61	1.27	Social networking	11	2.48	Smart technologies	21	1.92	Emotional intelligence	26	1.35
12	ICT	59	1.23	Software development	11	2.48	Data augmentation	20	1.82	Employee performance	26	1.35
13	Emotional intelligence	58	1.21	Team performance	10	2.26	Deep learning	20	1.82	ICT	26	1.35
14	Deep learning algorithm	57	1.18	Collaborative technologies	9	2.03	ICT	19	1.73	Big data analysis	25	1.30
15	Digital education technology	54	1.12	Motivation	9	2.03	Social networking	18	1.64	Personality characteristics	25	1.30

HRM = human resources management, ICT = information and communication technology, OCC = Occurrence

According to the study, 6.48 percent of the terms that satisfied the requirement of having at least five co-occurrences related to “job performance” were associated with “the impact of AI on job performance” in the articles published between 2018 and 2021 (the second sub-period). Table 1 lists the top fifteen keywords associated with “the impact of AI on job performance,” along with their corresponding percentages. These are the most commonly used keywords. In comparison to the preceding time, this list of terminology has been revised and now contains phrases like “artificial intelligence,” “social media analysis,” “knowledge specificity,” “machine learning,” “smart technologies,” “data augmentation,” “deep learning,” and “information and communication technology.”

Even though the 2022–2024 period's publishing period was shorter than the previous sub-periods' study, the increase in published papers makes this data essential to include in the evaluation. Table 1 shows that research at the time indicated a direct connection between AI and “job performance.” Job performance was responsible for 6.56 percent of the keywords related to “the impact of AI on job performance” literature. Roughly 6 percent of the total terms are related to “artificial intelligence.” The fifteen most popular keywords, together with the percentage of usage, are shown in Table 1. “Digital education technology,” “innovation performance,” “emotional intelligence,” “employee performance,” and “big data analysis” are new additions compared to the prior periods.

The third sub-period research showed that there was an increase in the occurrence of keywords associated with “the influence of AI on job performance” for all three sub-periods: “job performance” (44, 71, 126), “artificial intelligence” (0, 60, 108), “human resources management” (0, 33, 74), and “organization performance” (20, 30, 57), among others. This indicates that there is still significant growth in domain issues (Table 1).

4.1.2 The Growing Trend of the Top Five Current Themes in *the Domain Literature*

Understanding the growth history adds to our comprehension of the main topics that are most important to “the influence of AI on job performance” research and to the readers' understanding of it as well. There was “job performance” in each of the three subperiods. 9.9 percent of all occurrences were attributed to “job performance” in the first period, while in the second, this figure dropped to 6.5 percent. However, it was the most common keyword in the third sub-period, making up around 6.6 percent of all co-occurrences. Overall, “job performance” grew at a pace of almost 4.4 percent and emerged as the most popular keyword across all sub-periods (Table 1). The concept has become more common as a result of the growth of studies on the use of AI in the HRM domain. As a result, additional study is required to fully understand the connections between artificial intelligence and job performance.

The top fifteen articles from the first period did not address the rate of growth of “artificial intelligence.” It debuted on the list for the first time with 5.4 percent at the beginning of the second period. Remarkably, in the third period, it surged to 5.6 percent and emerged as the second-top keyword. With an average growth rate of 3.45 percent, it is clear that “artificial intelligence” is a second significant phenomenon overall (Table 1). This is still a very important subject; thus, it is necessary that scholars look at it more.

“Organization performance” appears in each of the three subperiods. 4.5 percent of all occurrences were attributed to “organization performance” in the first period, while in the second, this figure dropped to 2.7 percent. However, it was the fourth most common keyword in the third sub-period, making up around 3 percent of all co-occurrences. Overall, “organization performance” grew at a pace of almost 2.3 percent and emerged as the third most popular keyword overall (Table 1). Due to the phrase's low growth rate, it still needs to be studied because it is unknown. As a result, additional study is required to fully understand the connections between artificial intelligence and organization performance.

The top fifteen articles from the first period did not address the rate of growth of “human resources management.” It debuted on the list for the first time with 3 percent at the beginning of the second period. Remarkably, in the third period, it surged to 3.85 percent and emerged as the third-top keyword. With an average growth rate of 2.18 percent, it is clear that “human resources management” is a fourth significant phenomenon overall (Table 1). This is still a very important subject; thus, scholars must look at it more.

Over time, research into “performance management” has gradually increased; it started off growing at a pace of more than 5 percent when it was first introduced as a new word in the first period (Table 1). The next period, it dropped to 3.1 percent, though it scored the third most occurring term. However, it stopped appearing in the fifteen most frequently occurring terms in the third period. Because the influence of artificial intelligence on job performance is expected to continue growing at a rapid pace in the upcoming years, additional research is required to fully investigate the impact of artificial intelligence on job performance.

4.1.3 Logical Structure of *the Domain* Literature

Scholars can learn more about the state of “the impact of AI on job performance” research now by looking at its "intellectual structure" (Nerur et al., 2008). They can accomplish this by applying methods for scientific mapping and review. By looking at the authors' co-citation analysis, a VOSviewer-generated network map may be utilized to visualize the conceptual structure of the domain knowledge bases (Hallinger & Nguyen, 2020). This method can assist in identifying the field's most and least researched subjects.

Scholars have found that authors with similar scholarly ideas are frequently mentioned together in the same publications (Hallinger & Kovačević, 2019). In order to illustrate this, the VOSviewer program can provide a network map that shows the common ideas among the writers cited in our database (Priyan et al., 2023a).

The co-citation map produced by VOSviewer, Fig. 4, shows 107 academics who have been cited in at least 100 other publications. The larger the bubbles, the more influential scholars are; the size of the nodes specifies the rate with which each scientist is mentioned by other researchers. Furthermore, due to their co-citation associations, the colored clusters of bubbles (Fig. 4) categorize scholars into four fields of study. A thorough investigation of Fig. 4 discloses that the relationships between writers indicate the rate of their joint citations.

The map provides information on four different philosophical stances. The knowledge base's interdependence is also shown by the four clusters and the linkages that link them. This suggests that the most substantialbubbles on the network map were Wang, Y., in the red cluster; Bakker, A. B., in the blue cluster; Hair, J. F., in the green cluster; and Judge, T. A., in the yellow cluster. The individuals situated at the core of the clusters demonstrate their capacity to reconcile concepts from the four schools (Figure 4).

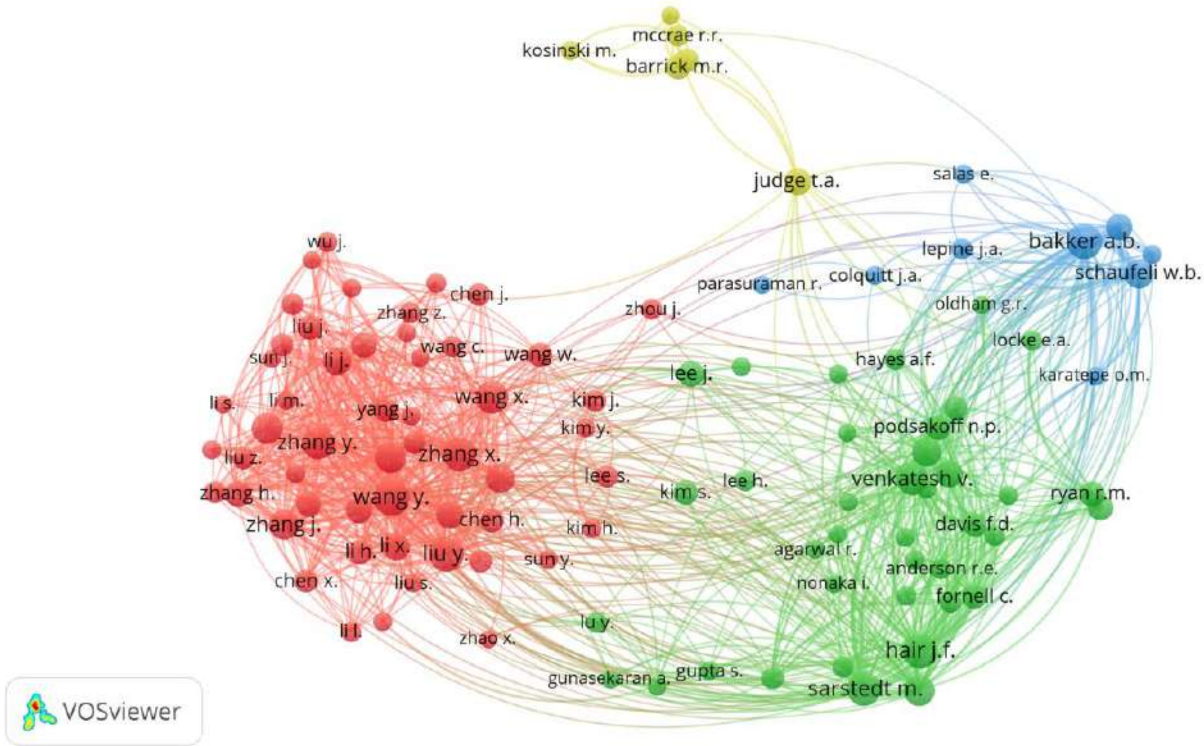

Figure 4
Co-citation Network Map of the Influence of AI on Job Performance (n = 107 authors)

4.1.4 Topical Concentrations of the Domain Knowledge Base

A multitude of stakeholders can benefit from gaining an understanding of the fundamental themes and subjects covered in the literature on “the effect of AI on job performance.” It can offer a framework for understanding present research, hint at possible future directions, assist practitioners in identifying study subjects that may be of interest to them, and help researchers identify significant themes and areas that have not yet been investigated (Nyabakora, 2023b).

A historical keyword map with at least five co-occurrences was created using VOSviewer (Figure 3). This kind of analysis assesses the frequency with which specific keywords appear in documents according to their publication date. In order to investigate the subjects covered in the domain of “the impact of AI on job performance,” we carried out a keyword analysis. With 212 co-occurrences, “job performance” is the most commonly used phrase (Figure 3), followed by “artificial intelligence” with 166 co-occurrences. With 110, 105, and 98 mentions, respectively, “organization performance,” “human resources management,” and “performance management” rank third, fourth, and fifth in terms of frequency of usage. With 61, 59, 58, 57, and 54 instances, respectively, innovation performance,” “information and communication technology,” “emotional intelligence,” “deep learning algorithms,” and “digital education technology” are the least mentioned.

The fact that the referenced author co-occurred demonstrated that all of the clusters were related to the core theme, even though the theme (“the effect of AI on job productivity”) was expressed in diverse ways. The frequently appearing keywords, which have the likelihoodofaffecting or beingaffected by the impact of “artificial intelligence” on “job performance,” made this clear. We created a "chronological keyword map" (Figure 3) with at least five co-occurrences using VOSviewer to investigate the distribution of the keywords in more detail (Priyan et al., 2023b). This study of the chronological co-words (Figure 3) sheds light on the distribution of the keywords.

4.1.5 The Most Contributory Players in the Domain

Knowing the major writers and publications on the subject of “the influence of AI on job performance” can help one get perspective on the state of knowledge at the moment and identify possible directions for future study and innovation. Moreover, it can help scholars choose which nations, publications, writers, and papers are the most significant and have to be reviewed for more thorough information.

4.1.5.1 Fruitful Countries in the Domain Knowledge Base

Researchers can learn which nations are actively studying “artificial intelligence in HRM,” keep up with the latest developments in the field, and comprehend the norms for “artificial intelligence in HRM” practices by investigating the most productive nations in terms of “artificial intelligence in HRM.” Furthermore, a closer look at the locations of these papers' authors can reveal where most scholarly attention is being directed towards the topic of “AI in job performance.”

The fact that the work in Fig. 5 was produced in sixty different nations demonstrates how fascinating the topic of “the effect of AI on job performance” is on a worldwide scale. Researchers from China (374), the United States (360), the United Kingdom (144), India (105), Germany (91), Australia (79), Canada (67), Malaysia (66), Spain (59), and Italy (56) accounted for the majority of the study undertaken in this area. The main sources of information and research on the subject were these nations.

Furthermore, as Figure 6 shows, out of the ten countries that rank highest in terms of citation counts, researchers in China (9,799), the United States (5,304), the United Kingdom (3,483), India (2,494), Germany (2,328), Australia (1,972), Canada (1,919), Malaysia (1,379), Spain (1,346), and Italy (1,206) accounted for more than fifty percent of the domain quotes examined in this evaluation. In conclusion, the majority of studies on “the impact of AI on job performance” focus on rich and emerging nations, completely ignoring the work being done in underdeveloped nations. Academics are greatly impacted by this, with the previously stated nations having a significant impact and their studies having a substantial effect.

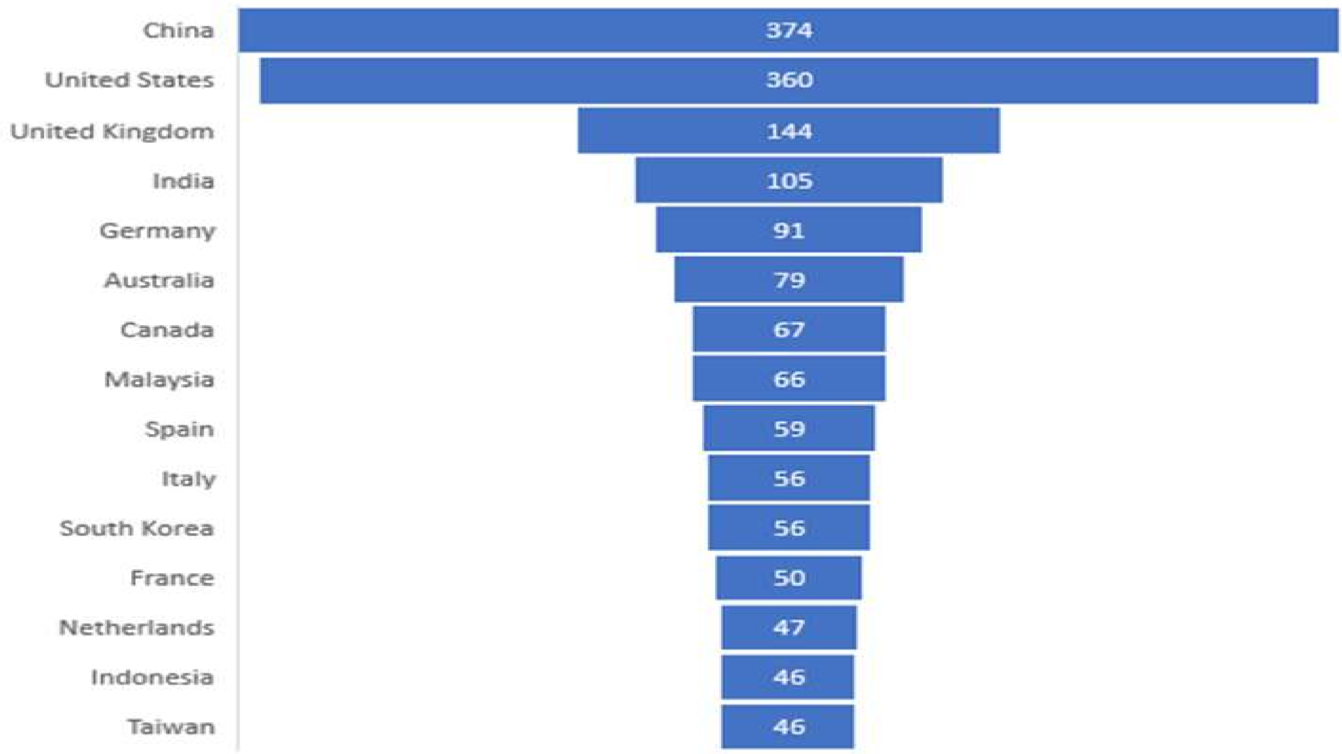

Figure 5
Most Contributing Countries by Documents Published

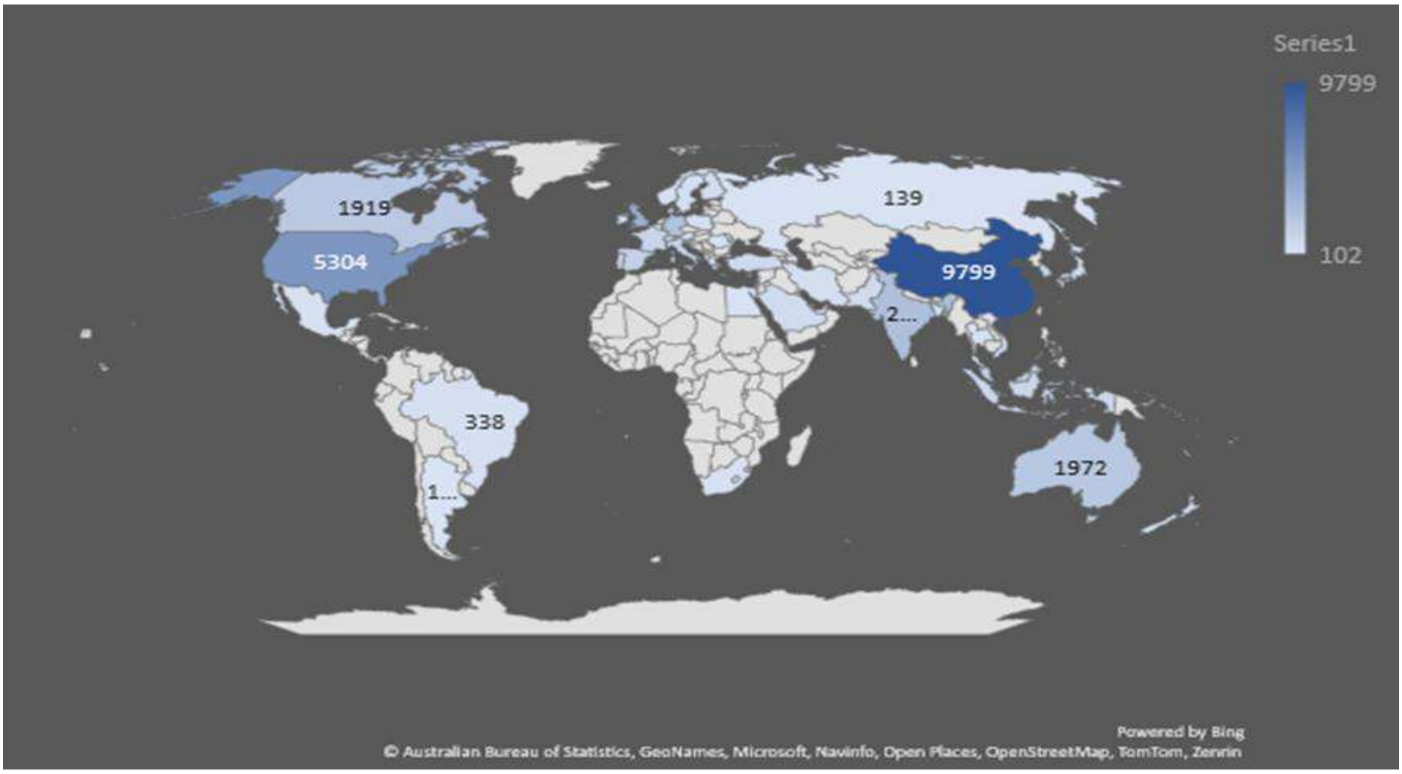

Figure 6
Most Prolific Countries by Citation Count

4.1.5.2 Evaluation of the Most Active Journals

To help academics and practitioners stay informed on the most recent findings and advancements in the domain, this analysis offers a thorough review of the most prestigious journals. It also identifies the journals that are most likely to approve the work submitted to them. There were 757 sources among the 1,747 papers under this evaluation. Even though only 37 percent of the sources had more than one publication, more than twenty percent of the corpus was made up of the top fifteen sources only (Figure 7).

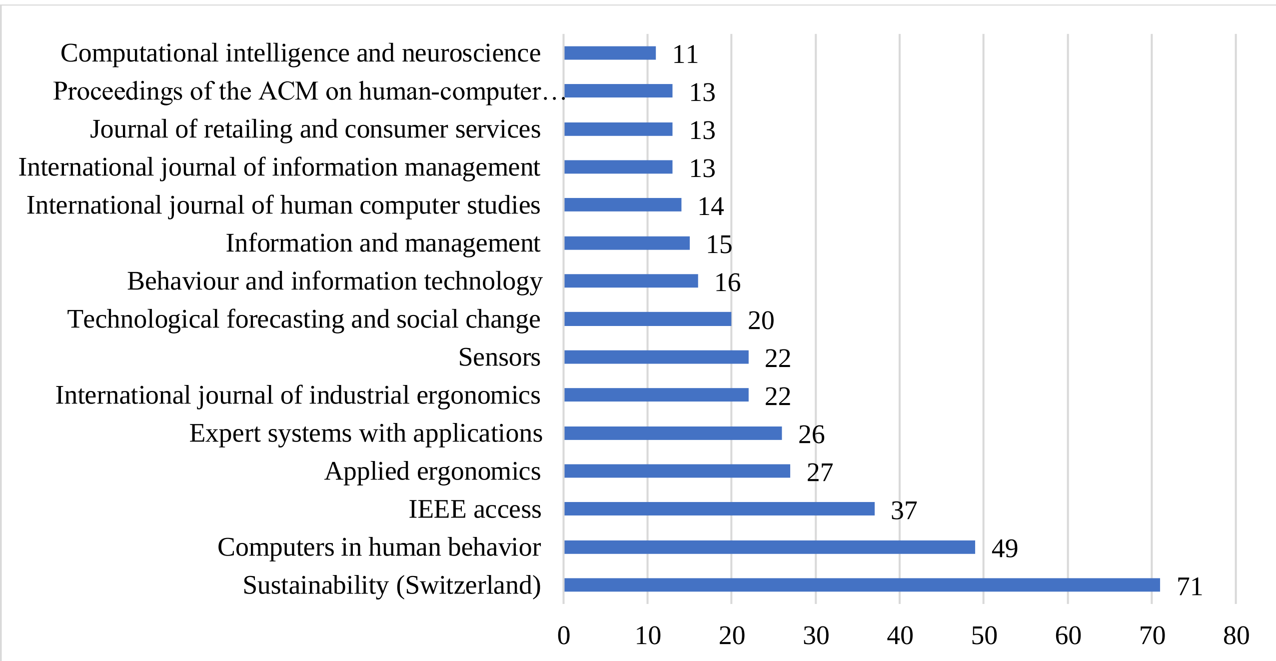

Figure 7
Top Sources by Number of Documents

The most active source was Sustainability (Switzerland), with 71 articles; nonetheless, the total number of citations from all 757 sources was 32,803. Of the total sources, 129 were found to have no citations (the list is not attached), and more than 36 percent of all citations were found in the top 15 sources (Table 2). With 2,710 citations from 71 documents, "Computer in Human behavior" was the most cited source (Table 2 lists the information from the other notable sources).

Table 2
Most Contributing Sources by Number of Documents Published

ID	Label	Citations	Documents
1	Computers in human behavior	2710	71
2	Expert systems with applications	1492	49
3	Applied ergonomics	877	37
4	Information and management	787	27
5	Sustainability (Switzerland)	689	26
6	Computers and education	687	22
7	IEEE transactions on information technology in biomedicine	653	22
8	International journal of information management	650	20
9	Journal of strategic information systems	563	16
10	IEEE access	546	15
11	International journal of human computer studies	498	14
12	Technological forecasting and social change	464	13
13	Mis quarterly: management information systems	444	13
14	Safety science	386	13
15	Management science	373	11

4.1.5.3 The Most Influential Authors on *the Impact of AI on Job Performance*

Two publications by Mantyjarvi, Jani, published in 2003 and 2006, received the greatest citation count (612) in total, according to Table 3. Ermes, Miikka, Korhonen, Iikka, and Parkka, Juha, who have 597 citations, came in after him. Since the h-index considers all academic works, not simply the papers they have produced on this theme, we did not use it as a metric (Priyan et al., 2023b). As a result, Table 3's citations accurately represent the authors' contributions to the domain.

Table 3
Top Authors by Citations

ID	Label	Documents	Citations
1	Mäntyjärvi, Jani	2	612
2	Ermes, Miikka	1	597
3	Korhonen, Ilkka	1	597
4	Pärkkä, Juha	1	597
5	Cheung, Ronnie	1	566
6	Vogel, Doug	1	566
7	Ahuja, Manju K.	1	373
8	Carley, Kathleen M.	1	373
9	Galletta, Dennis F.	1	373
10	Chow, Harry K.H.	2	368
11	Lee, W.B.	2	368
12	Zhang, Li	2	344
13	Landers, Richard N.	4	342
14	Ali-Hassan, Hossam	1	325
15	Nevo, Dorit	1	325

4.1.5.4 The Most Influential Documents on *the Effect of AI on Job Performance*

Based on the frequency of citations in the Scopus core collection, Table 4 displays the most cited works on the subject. The purpose of this examination was to assess the input of the academics' work in the field. The work by Ali-Hassan et al. (2015) is the most quoted in this field, with 325 mentions. Table 4 displays the additional significant documents together with their citations. Below is an explanation of how the top five documents have contributed to the work on the impact of AI on job performance.

Table 4
Most Contributing Relevant Articles on the Reviewed Domain

ID	Authors	Title	Source	Citations	Country
1	Ali-Hassan H. et al (2015)	Linking dimensions of social media use to job performance: The role of social capital	Journal of Strategic Information Systems	325	Canada
2	Chow H.K.H. (2006)	Design of a RFID case-based resource management system for warehouse operations	Expert Systems with Applications	288	Hong Kong
3	Landers R.N. (2017)	Gamification of task performance with leaderboards: A goal setting experiment	Computers in Human Behavior	255	United States
4	Vrontis D. et al. (2022)	Artificial intelligence, robotics, advanced technologies and human resource management: a systematic review	International Journal of Human Resource Management	239	Cyprus
5	Pellas N. (2014)	The influence of computer self-efficacy, metacognitive self-regulation and self-esteem on student engagement in online learning programs: Evidence from the virtual world of Second Life	Computers in Human Behavior	234	Greece
6	Rezvani A. et al (2016)	Manager emotional intelligence and project success: The mediating role of job satisfaction and trust	International Journal of Project Management	167	Australia
7	Acuña S.T. et al (2009)	How do personality, team processes and task characteristics relate to job satisfaction and software quality?	Information and Software Technology	156	Spain
8	Sedighi Maman Z. et al. (2017)	A data-driven approach to modelling physical fatigue in the workplace using wearable sensors	Applied Ergonomics	147	United States
9	Sykes T.A. (2015)	Support structures and their impacts on employee outcomes: A longitudinal field study of an enterprise system implementation	MIS Quarterly: Management Information Systems	131	United States
10	Cheng E.W.L. et al. (2012)	Exploring the perceived influence of safety management practices on project performance in the construction industry	Safety Science	114	Hong Kong

Through the intermediary role of social capital (structural, relational, and cognitive), Ali-Hassan et al. (2015) investigate how several aspects of social media use—social, hedonic, and cognitive—affect individual job performance—routine and inventive. The study employs a survey of workers in a global IT company to propose and test a model based on the uses and gratifications theory, affordances theory, and social capital theory. The study concludes that, depending on the usage environment and nature of performance, "social media" can have favorable and unfavorable influences on job performance.

Additionally, the study demonstrates how social capital is crucial in moderating the associations between employment performance and social media use. This work adds to the literature on social media, social capital, and job success. It also offers practical and research implications.

Chow et al. (2006) introduce RFID-RMS, a system that combines case-based reasoning, RFID technology, and a route optimization model to assist warehouse managers in choosing the optimal resource consumption packages for various orders. The system's objectives are to lower operational expenses and skew judgements while simultaneously increasing the productivity and efficiency of warehouse operations. The applicability and advantages of RFID-RMS are also illustrated in the essay through a real-world case study.

Landers et al. (2015) use goal-setting theory as a framework to investigate how leaderboards, a popular gamification tool, affect task performance. The experiment described in the study assesses the moderating effect of goal commitment by comparing leaderboards to varying degrees of goal difficulty. The study concludes that goal commitment amplifies the impact of leaderboards on performance and that leaderboards work similarly to hard objectives. The limitations and consequences of these findings for researchers and practitioners are also covered in the publication.

A thorough assessment of the literature on the effects of intelligent automation, including robots, artificial intelligence, and cutting-edge technology, on HRM may be found in Vrontis et al. (2021). It highlights the potential and difficulties of these technologies for HRM at the organizational and individual levels, as well as the three primary research subjects and their sub-themes. It also makes recommendations for future transdisciplinary research topics and puts forth a framework to connect intelligent automation with business success and the future of employment.

Pellas (2014) looks at how students' characteristics such as their self-esteem, computer self-efficacy, and metacognitive self-regulation affect their participation in online courses held in the Second Life virtual environment. In this study, a conceptual model based on a survey of 305 university-level online course participants is proposed and tested. According to the study, there is a negative correlation between behavioral engagement and “computer self-efficacy,” “metacognitive self-regulation,” and “self-esteem,” but a direct connection between the factors and intellectual and emotive involvement. In order to improve the quality of learning in virtual worlds such as Second Life, the study explores the educational implications of better understanding and utilizing students' personal aspects in the design and delivery of online courses.

4.2 Discussion of Findings

This review shows that research on how artificial intelligence (AI) affects job performance has grown quickly, especially in the last decade or so—a clear sign of how fast smart technologies are becoming part of everyday work (Loebbecke & Picot, 2015; Newell & Marabelli, 2015). Most influential papers appear in leading journals covering human resources, information systems, and organizational behavior, showing that job performance is now a major focus in discussions about digital change (Bondarouk et al., 2016; Garcia-Arroyo & Osca, 2021; Vrontis et al., 2021).

Early studies tended to emphasize automation and straightforward efficiency improvements (Chow et al., 2006; Zanko et al., 2008). Newer research, however, increasingly views AI as a tool that complements and enhances human abilities rather than simply replacing them (Colbert et al., 2016; Fleming, 2019). This evolution points to a more mature understanding: AI's effects aren't automatic—they depend on the situation (Crossan & Apaydin, 2010; Seeck & Diehl, 2017).

A major insight is how broadly job performance is now defined. It's not just about speed or output anymore; studies increasingly include adaptability, creativity, teamwork, and those voluntary extra efforts people make (Park, 2016). Themes that emerge strongly connect AI with greater job autonomy, better decision-making support, and ongoing skill growth (Ancarani et al., 2019; Landers et al., 2015). Overall, AI appears to boost performance when it empowers employees and helps them learn, but it can drag performance down when used mainly for tight control or constant monitoring (Abraham et al., 2019). This dual nature explains many of the contradictory results in the literature and stresses how important the way AI is implemented really is.

Psychological and social elements also play a big role. Research highlights trust in AI, attitudes toward it, and whether people see it as fair and transparent (Araujo, 2018; Go & Sundar, 2019). When AI tools—like chatbots or decision algorithms—are designed to be clear, helpful, and respectful of users, performance tends to improve (Ali-Hassan et al., 2015; Pellas, 2014). Studies on virtual and remote work further show how digital collaboration tools influence engagement and outcomes (Dulebohn & Hoch, 2017; Schaubroeck & Yu, 2017; Wang & Zou, 2021). On the flip side, systems that feel opaque or overly intrusive often lead to resistance, added stress, and less willingness to go above and beyond.

The review also uncovers some clear imbalances. Most studies come from developed countries and focus on knowledge-based jobs, leaving emerging markets, lower-skilled roles, and varied cultural contexts largely unexplored (Cooke et al., 2019; Pisani et al., 2017). There's also a tendency to look at short-term impacts, with far less attention to longer-term questions like skill degradation, career paths, or truly sustainable performance (Stone et al., 2015).

These patterns suggest future research should include more long-term studies, incorporate ethical considerations, and examine AI's effects across individual, team, organizational, and societal levels (Tranfield et al., 2003). Filling these gaps will help create a more complete and balanced view of how AI is shaping the future of work.

V. CONCLUSION & RECOMMENDATIONS

5.1 Conclusion

This work provides a foundation for assessing the current state of scientific knowledge on “the impact of AI on job performance.” Several bibliometric techniques, such as algorithmic procedures and software, were employed to evaluate the stream of facts in this domain. We have identified possible research areas, put together a thorough summary of what is already known about the issue, and established a strategy for further study that takes into account how the field is changing.

The vast amount of study on virtual environments that has been done since 1998, when the first pertinent academic publication was published in the Scopus database, is revealed by this analysis of studies. Most of the literature on this subject has emerged in the last ten years, probably as a result of “job performance,” “artificial intelligence,” “organization performance,” “human resources management,” “performance management,” “machine learning,” “personality characteristics,” “social media analysis,” “knowledge management,” and “knowledge sharing behavior” being among the frequently examined themes identified by the review.

“Digital education technology,” “innovation performance,” “emotional intelligence,” “employee performance,” “big data analysis,” “ICT,” “deep learning algorithms,” “data augmentation,” “smart technologies,” and “knowledge specificity” have all been the focus of recent studies in this sector. As a result, these are the areas that need the greatest focus from researchers because, as the data demonstrates, they are still relatively new not only in poor countries but also in the majority of wealthy countries.

By examining previous research, identifying recurring themes, and identifying themes that have hardly been fully researched and need more investigation, this study contributes to our current understanding of this domain. It might offer a thorough summary of the subject or a detailed examination of the reference system for researchers. This can help educators by highlighting the most investigated topics, keeping up with the most recent advancements, and figuring out the direction the field is taking in order to further the information that already exists associated with the influence of artificial intelligence on job performance.

In order to help academics and other stakeholders make well-informed decisions on research and publication in this field, this impact of artificial intelligence on job performance research has identified the nations and journals that have been the most productive and highly referenced.

This study gives an in-depth summary of the development and status of “the influence of AI on job performance.” It offers important sources of information, publications, and ideas for the future direction of the discipline, making it an invaluable resource for researchers in computer science, accounting, finance, economics, and business management. Furthermore, anyone interested in learning about this domain’s literature can benefit from this research.

The majority of current research on “the impact of AI on job performance” has focused on issues related to “digital education technology,” “innovation performance,” “emotional intelligence,” “employee performance,” “big data analysis,” “ICT,” “deep learning algorithms,” “data augmentation,” “smart technologies,” and “knowledge specificity." These have all been the focus of recent studies in this sector. As a result, these are the areas that need the greatest focus from researchers because, as the data demonstrates, they are still relatively new not only in poor countries but also in the majority of wealthy countries. (Tables 1 and 2).

The third sub-period research showed that there was an increase in the occurrence of keywords associated with the domain for all three sub-periods: “job performance” (44, 71, 126), “artificial intelligence” (0, 60, 108), “human resources management” (0, 33, 74), and “organization performance” (20, 30, 57), among others. This indicates that there is still significant growth in “the influence of AI on job performance” issues (Table 1).

5.2 Recommendations

Although there are advantages to using the Scopus database in this study, there are also drawbacks. One recurrent problem in bibliometric research is the possibility that records sourced from several databases, like ABI, Web of Sciences, and Inform/ProQuest, were disregarded. Other materials that can be pertinent when talking about “the influence of AI on job performance” should be taken into consideration in addition to the results of this search, such as editorials, conference papers, and national journals.

Co-citation, keyword searches, and co-occurrence evaluation were employed in this study. It could be beneficial to include bibliographic coupling to the findings. Nonetheless, the limitations mentioned point to possible directions for improving bibliometric research in the future.

Declaration of Interest

The authors declares that they do not have any known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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