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Impact of AI-focussed technologies on social and technical competencies for HR managers – A systematic review and research agenda

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ABSTRACT

Research on the application of Artificial Intelligence (AI)-based technologies in the HRM domain has attracted significant scholarly attention. Yet, few studies have consolidated key trends in adopting AI for HRM, especially on managerial competencies required for adopting AI-based technologies and identifying the key research directions for HR managers, including the development of an AI-focused competency framework for HR managers. A systematic literature review (SLR) and bibliometrics analysis were conducted to identify the current research direction for managers adopting AI in HRM. Several themes of managerial capabilities required for adopting AI in HRM were identified, utilizing the Dynamic Capabilities View (DCV). The SLR identified applications of various AI tools and techniques in HR functions, recruitment and selection was one with the broadest use of AI applications. Managerial cognitive capability, managerial human capital, and managerial social capital of DCV were considered the initial coding categories under which various managerial competencies are required for the adoption of AI in HRM. This study utilized SLR, Bibliometric, and directed content analysis as three distinct but interrelated sets of methodologies for extracting novel insights into the adoption of AI for HRM. It highlights the associated managerial capabilities that need mapping for its adoption.

1. Introduction

Technological advancements in Artificial Intelligence (AI) continue to disrupt and impact all functional domains of business, such as HRM, including through the use of generative AI applications for Human Resource Management (HRM) (Budhwar et al., 2023). The application of generative and other AI applications have been evident in a range of contexts, including AI-assisted autonomous decision-making systems for retail business (Sharma et al., 2022; Talwar et al., 2021), AI-enabled voice assistants in hospitality and tourism (Talwar et al., 2022), customer services (Malodia et al., 2021). Still, other applications focus on improving service quality (Nguyen and Malik, 2022a, 2022b), augmenting C-suite leaders' decision-making (Kondapaka et al., 2023), and facilitating AI-mediated knowledge-sharing social exchange between employees (Malik et al., 2022b). Within the HRM function, there is an increasing range of AI technology applications are emerging globally (Pan et al., 2021; Shet and Pereira, 2021). Among the recent technologies, AI is most influential in automating administrative components of HRM (Vrontis et al., 2022), enhancing employee experience through AI-mediated knowledge-sharing social exchanges (Malik et al., 2022a, 2022b; Nguyen and Malik, 2022a), and is increasing HRM effectiveness. Thus, organizations must identify managers' desired capabilities and competencies to effectively adopt and manage the implementation of AI in HRM (Malik et al., 2020, 2021a, 2021b, 2023b; Prikshat et al., 2023a, 2023b).

The applications of AI in HRM can be found across the entire employee life cycle, starting from workforce planning, job design, recruitment, selection, performance, and rewards management, learning and development, and personalized employee experience (Allal-Chérif et al., 2021; Jaiswal et al., 2022; Kaushal et al., 2023; Prikshat et al., 2023b; Votto et al., 2021). For example, AI-based video recruitment has been perceived to be objective, fair, and consistent in evaluation, with a greater probability of producing outcomes that overcome biases in human decision-making (Allal-Chérif et al., 2021;

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Kim and Heo, 2021). Similarly, employee communication, experience, and engagement have been normalized by using chatbots, providing employees with round-the-clock ease of access to information (Pillai et al., 2023). With the changing technological demands, employee health and well-being, self-service, coaching, and counselling are prominent HR touchpoints that are finding traction in AI-based HR technologies (Kaushal et al., 2023; Pan and Froese, 2022; Pillai et al., 2023). AI-based technologies like the use of personal assistants, chatbots, robots, and automated systems have are on the rise, wherein organizations looking for speed, precision, convenience, and adaptability of system skills to achieve profitable goals (de Visser et al., 2018). Other digital technologies like QR codes, mobile-based applications, internal and social networking, and augmented and virtual reality have further digitalized the HR environment, aiding HR to be a part of the digital transformation milieu (Robert et al., 2020).

The implications of AI-based technologies show a noticeable impact on HRM practices, thus signifying the importance of its adoption. AI technologies also face ethical and human rights challenges relating to data privacy, dealing with biases and discrimination, employees' psychological safety, and data security (Stahl et al., 2023). From being a technology black box, explainable AI (XAI) is considered by managers to help build the required trust, fairness, transparency, understandability, and usability of AI systems (Haque et al., 2023).

Adopting AI for HRM requires an interdisciplinary approach to effectively study the human-machine interface (Pan and Froese, 2022; Prikshat et al., 2023b; Di Vaio et al., 2020; Johnson et al., 2022; Vrontis et al., 2022). A relatively few studies (e.g., Votto et al., 2021) have attempted to consolidate the diverse perspectives and understand the current research landscape for adopting AI-based technologies in HRM (Budhwar et al., 2022; Malik et al., 2023a, 2023b). Further, while several studies have reiterated the implications of AI for the workplace (Bahoo et al., 2023; Truong and Papagiannidis, 2022; Pietronudo et al., 2022), a key implication is to augment managers' tasks and skills for enabling innovation and developing AI-specific competencies (Giraud et al., 2022). Others have noted that the adoption of AI-based technologies requires developing managerial capabilities and competencies to work to effectively deliver human-machine teamwork and collaboration (Pereira et al., 2023; Prikshat et al., 2023a; Vrontis et al., 2022). Thus, from the above, it is evident that the research gap has widened, and further inquiry is required to understand the managerial capabilities needed for adopting AI to deliver sustained levels of individual, team, and firm performance (Giraud et al., 2022; Leyer and Schneider, 2021; Pereira et al., 2023; Vrontis et al., 2022). To address the stated research gaps, the study attempts to answer the following research questions:

1. What is the direction of research towards the application and adoption of AI by HR managers?
2. What managerial capabilities are required to adopt AI in HRM?

While the first research question examines the various applications and adoption of AI in HRM, the second research question seeks to understand the managerial capabilities and competencies that must be mapped to multiple technologies used for AI adoption in HRM. Systematic literature review (SLR) and bibliometric analysis were undertaken to identify the direction of research in the application and adoption of AI in HRM. Content analysis of the literature through the SLR identified the sub-themes of managerial capabilities required for adopting AI in HRM. The study identified three critical managerial capabilities – cognitive, human capital, and social capital, and associated competencies. Ethical decision-making, problem-solving, and validation were identified as the competencies needed for managerial cognition. Similarly, for human capital, developing technical expertise, leadership skills, institutional configuration, training skills, and agility. For social capital, the ability to source and use AI technologies, maintain social justice, enhance employee experience, mentoring skills, and human-AI collaboration skills were identified as the required competencies. Further, the study proposed a conceptual framework for the effective adoption of AI in HRM and performance. This SLR adds to the existing literature on technology acceptance and also expands the applicability of dynamic capability views theory to AI adoption in HRM. The rest of the paper is organized as follows. First, it discusses the study's theoretical background, followed by a systematic literature review, bibliometric analysis, and content analysis. Finally, the paper discusses the implications for theory and practice and directions for future research.

1.1. Conceptualizing AI and its adoption in HRM

AI has been described a broad cluster of technologies wherein a computer can perform tasks in a human like fashion showing evidence of cognition and its ability to show adaptive decision-making (Tambe et al., 2019). Technologies that drive AI are machine learning approaches, such as deep learning, also called neural networks. Arthur Samuel (1959), who pioneered *machine learning* (ML), argued that this approach enables computers to learn without specifically being programmed to do so. Applications such as spam filtering in the mail, natural language processing, translation, audio-to-text transcripts, voice recognition, driverless cars, and visual inspection in quality control are some examples of AI-enabled systems that use machine learning (Ng, 2020). *Deep learning* is an advanced form of ML that uses *artificial neural networks* and processes a barrage of network information from an input source(s) to deliver a decision output, almost like the human brain processing information with a billion network of interconnected neurons (Ng, 2020; Wang, 2003). Deep learning approaches use complex algorithms that can enable improved performance of an AI system for better decision-making (Ng, 2020). ML and deep learning would allow machines to be autonomous without significant human intervention. The system learns from human input data and evolves as it learns from experience (de Visser et al., 2018). Another ML approach, *Natural Language Processing (NLP)* as an application involves computer systems learning from the human understanding of natural languages so that they can manipulate text or speech that involves natural languages. It can be used in machine translation, text processing, user interface, speech recognition, etc. (Chowdhury, 2003).

AI-enabled technologies are revamping HRM-related practices such as recruitment, training, and competency mapping, resulting in improved organizational performance (Malik et al., 2022a, 2022b; Vrontis et al., 2022). AI adoption in HRM helps create new knowledge sharing configurations in decision-support and problem-solving of existing HR processes, such as hiring, performance management, internal mobility, learning, automation of employee self-service, diversity management, employee well-being, and many more (Biswas, 2018; Guenole and Feinzig, 2018; Malik et al., 2022b). AI-enabled tools lead to organizational learning that helps to recalibrate or reorient the business model (Garavan et al., 2016). Studies demonstrate that HRM functions can utilize AI to benefit employees and employers by processing vast data on platforms (including job portals, social media, etc.). Some of its other applications are to suggest learning programs based on the skill gap of employees and to assess employees' performance with reduced bias (Malik et al., 2022a; Pereira et al., 2023).

AI systems can currently augment human decision-making, helping managers to override decision-making, if needed. At the next level, AI systems have autonomous problem-solving and decision-making capabilities, and can surpass human intelligence and decision-making abilities (Kaplan and Haenlein, 2019). Therefore, while AI adoption in HRM indicates promising benefits, its effectiveness depends on the successful adoption of AI in HRM, which is not dependent on technological infrastructure but on adequate managerial capabilities.

1.2. The Dynamic Capabilities View (DCV)

This study uses the DCV as a theoretical frame to support the claim that adopting AI in HRM requires a network of capabilities (Sunder and

Ganesh, 2021). As a result, business processes interact with and make use of multiple levels of managerial capabilities, learning capabilities, absorptive capacity, and knowledge management and can leverage the capabilities provided by AI tools and technologies, such as predictive capabilities, pattern, and voice recognition, natural language processing, to name a few (Ching, 2020).

While the Resource-based View (RBV) (Barney, 1991) focuses on gaining a competitive advantage in a stable environment, its limitation is that it is static and does not respond to environmental changes. Hence, our focus on the dynamic capabilities view (DCV) as a survival response to a rapidly changing external environment is timely (Teece et al., 1997). Dynamic capabilities include three key elements: resources, strategy, and capability (Teece, 2018). "*Resources* are firm-specific assets like employees, equipment, buildings, and intangible assets that are difficult if not impossible to imitate." (Teece et al., 1997; pg.516; Teece, 2018; pg.365). "A *strategy* at the highest level involves *sensing* the external environment for unstructured data that must be organized and interpreted at the level of managerial capabilities. *Seizing* involves a quick response mechanism like investing in modern technologies or new business models for products or processes. *Transforming* involves aligning current technologies and business models with the organization, which often conflicts with the existing business model. The strength of a firm's *capabilities* determines the degree and speed at which the firm's resources can be aligned and realigned by the organizational strategy (Teece, 2018; pg. 364).

As per DCV, the critical role managers play is asset orchestration, which is defined as "Assembling and orchestrating configuration of co-specialized assets in a dynamic setting" (Helfat et al., 2009; pg.26). Thus, dynamic HR managerial capabilities will play a prominent role in asset orchestration of co-specialized assets like adopting AI into the HR system and coordinate co-specialization between HR department, employees, and AI adoption (Jung et al., 2018). By this, managers play the role of entrepreneur and require competencies to assess the external environment to tap the required market and technology capabilities (Ambrosini and Altintas, 2019). They organize and interpret information obtained from customers, new inventions in the market, and competitor information and apply inductive and deductive reasoning (Teece, 2007). Since leaders and managers are directly involved in critical decision-making regarding adopting AI and having control of the AI-enabled process, managerial capabilities are called *meta-dynamic capabilities* (Pedron and Caldeira, 2011). When it comes to managerial capabilities, three core underpinnings have been identified in the dynamic capabilities literature:

1. *Managerial cognition* or *cognitive capability,* broadly defined as the 'capacity to perform a function' (Helfat and Peteraf, 2015; pg.835). It aids in strategic decision-making by sensing market opportunities using heuristics, mental models, and interpretations in decision-making (Helfat and Martin, 2015; Teece, 2016).
2. *Managerial human capital* includes managerial knowledge and skills shaped by professional and personal experience. Their level of education, functional area, and industry heterogeneity and experience play a crucial role in sensing, seizing, and reconfiguring their resource base (Ambrosini and Altintas, 2019; Helfat and Martin, 2015).
3. *Managerial social capital* – the manager's external relationships help obtain the necessary resources for the firm and understand competitive practices. They take care of sensing and seizing opportunities (Helfat and Martin, 2015). The ability to build relationships and obtain resources because of the relationship is also termed relational capability (Lin et al., 2016).

Several managerial decision scenarios need AI-enabled and cloud-based solutions. AI-based systems are black boxes as their decision-making algorithms and deep learning capabilities are not transparent. From the end-user point of view, it creates issues of explainability (Tambe et al., 2019). Thus, it also requires managerial capabilities that can override AI-enabled decision-making to have control and final say over the decision-making process (de Visser et al., 2018; Guenole and Feinzig, 2018). Even fully autonomous systems, if deployed, will require an overriding decision by HR managers (de Visser et al., 2018). Acknowledging the significance of managerial capabilities, the current study critically assesses and identifies the managerial capabilities required for adopting AI in HRM through SLR, content, and text analysis.

2. Methodology

While there are several excellent examples of bibliometric analysis and review in emergent areas of scholarship, such as sustainable tourism, big data analytics and blockchain applications (Khanra et al., 2020, 2021; Tandon et al., 2021), there are limited efforts in the field of HRM, especially examining the above focus incorporating an SLR, content and bibliometric analysis. To this end, this study adopted a three-phase methodology SLR, followed by a three-phase methodology, SLR, bibliometric analysis, and content analysis. The first research question on the direction of research undertaken towards the application and adoption of AI by HR managers required SLR and Bibliometric Analysis. The SLR provided the perspective of research conducted thus far, while the Bibliometric analysis provided a future perspective on the intersectionality of research that needs attention, especially using thematic maps. While SLR provided the past research trends on the application of AI in HRM, Bibliometric analysis helped provide future directions for AI in HRM research. The second research question required a detailed content analysis of the full text to extract the themes different managerial capabilities needed to adopt AI in HRM. Scopus was identified as the database for this current study. Records indexed in Scopus reflected the quality of papers referred to, and the database had institutional access for further bibliometric download and analysis. The methods adopted to address the research questions are presented as a flowchart in Fig. 1.

2.1. Systematic literature review (SLR)

The SLR was based on the PRISMA methodology (Page et al., 2021), which helped identify the relevant literature on AI in HRM. The SLR was conducted as the synthesis of research papers is transparent and must be documented at each stage (da Silva et al., 2022; Pereira et al., 2023). In addition, SLR is also required when the subject area is delimited in understanding the current state of the subject area and when the research needs to be context-specific (Pereira et al., 2023). The PRISMA method in SLR follows three stages: Identification, Screening, and Inclusion (da Silva et al., 2022).

Stage 1: *Identification* – This phase helped to identify specific databases and formulate Boolean operators to identify relevant articles. The Boolean search strategy used the keywords AI and HRM as expansion and acronyms and keywords like HR manager, HR managerial capabilities, and HR managerial competencies using the OR functionality between keywords and AND functionality within keywords. These were: (TITLE-ABS-KEY (artificial AND intelligence) OR TITLE-ABS-KEY (ai) AND TITLE-ABS-KEY (human AND resource AND management) OR TITLE-ABS-KEY (hrm) OR TITLE-ABS-KEY (managerial AND capabilities) OR TITLE-ABS-KEY (managerial AND competencies) OR TITLE-ABS-KEY (hr AND manager)). The publications included journal articles, conference papers, book chapters, and books. The language of the papers was limited to English. The search period needed to be more specific.

Stage 2: *Screening* – The screening stage consisted of going through the title, abstract, and keywords to filter papers that did not satisfy the search context. Screening involved multi-stage filtering using keywords, abstracts, journals, and full-text articles. Out of $n = 2760$ records, this yielded $n = 254$ records that discussed the application of

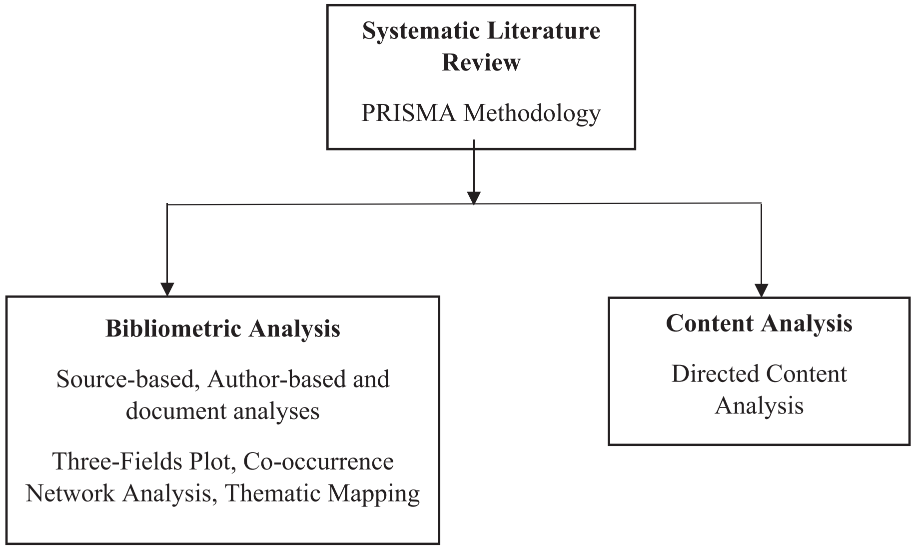

Fig. 1. Methods adopted to address the research questions.

AI in HRM in totality or specifically to HR functions like recruitment/hiring, selection, performance management, learning and development, and rewards, which could be further considered for analysis. After reviewing the literature, $n = 197$ records that did not satisfy the search criteria were removed.

Stage 3: ***Inclusion*** – Finally, $n = 58$ records were considered. Relevant articles from the database and other articles through snowballing references were considered for the study. Fig. 2 provides the systematic flowchart based on the PRISMA methodology in identifying the records considered for the literature review.

The relevant disciplinary categories that yielded the papers for review are represented in Fig. 3 as a pie chart. The studies were mainly listed in business, management, and accounting journals, followed by psychology and social sciences. The year-wise publication garnered several citations is depicted in Fig. 4 as a combination of bar and line chart. While most of the records were between 2015 and 2022, 2019 was the year with only six papers and maximum citations, while 2022 had the most significant number of papers. The number of papers and percentage of citations progressively increased over the years, noting the importance of studies related to the application of AI in HRM. The

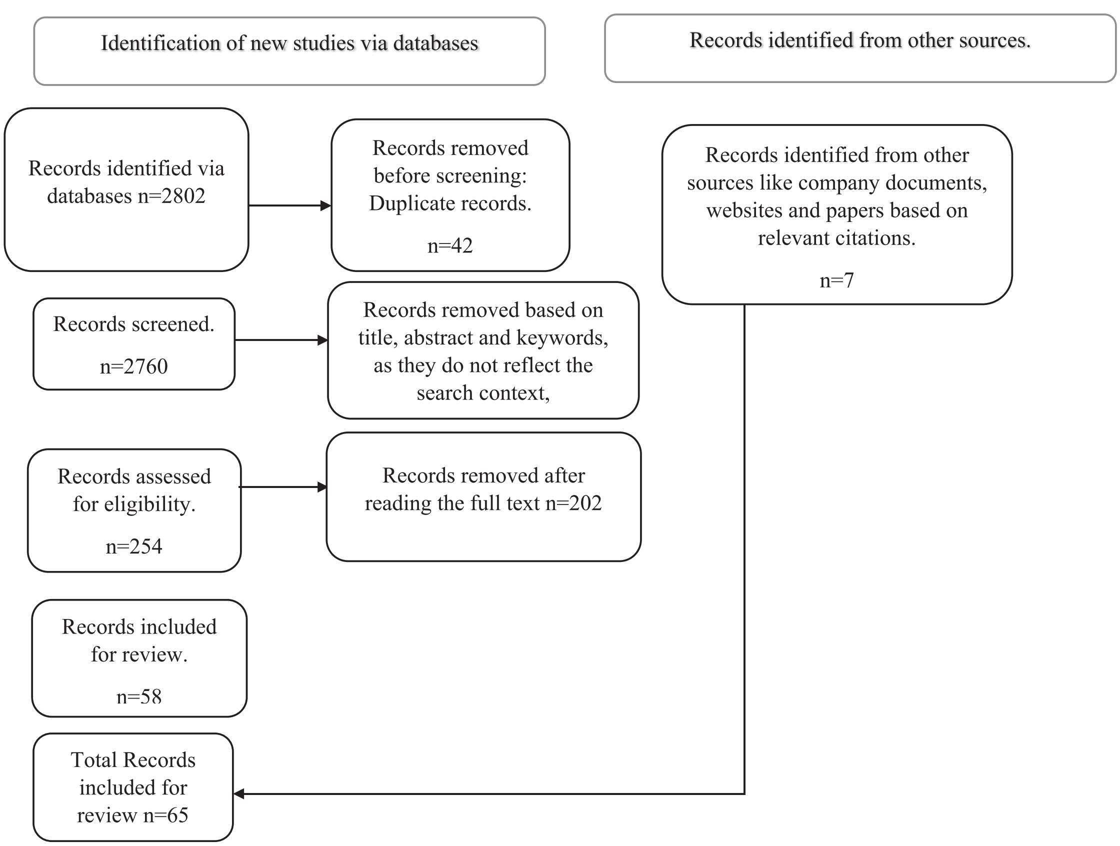

Fig. 2. SLR – PRISMA methodology of reporting.

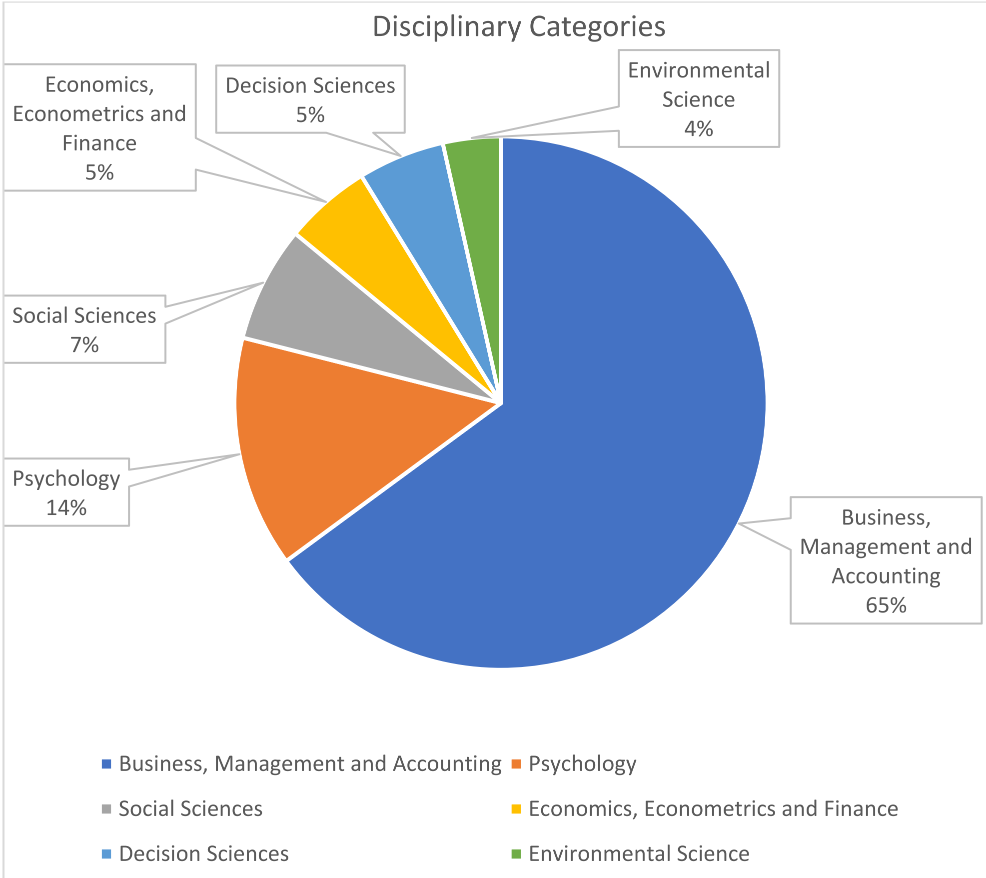

Fig. 3. Percentage (%) of records from various Disciplinary Categories identified in SLR.

literature review revealed that the studies were centered around the application of AI in HRM.

Other sources like company documents, websites, and papers based on relevant citations from the final inclusion records called snowballing yielded $n = 7$ records (Agrawal et al., 2019; Guenole and Feinzig, 2018; Massey, 2019; IBM, 2017; Pillai et al., 2023; Kim and Heo, 2021; Vrontis et al., 2022). So, a total of 65 records were considered for full-text analysis. The inclusion and exclusion criteria are specified in Table 1

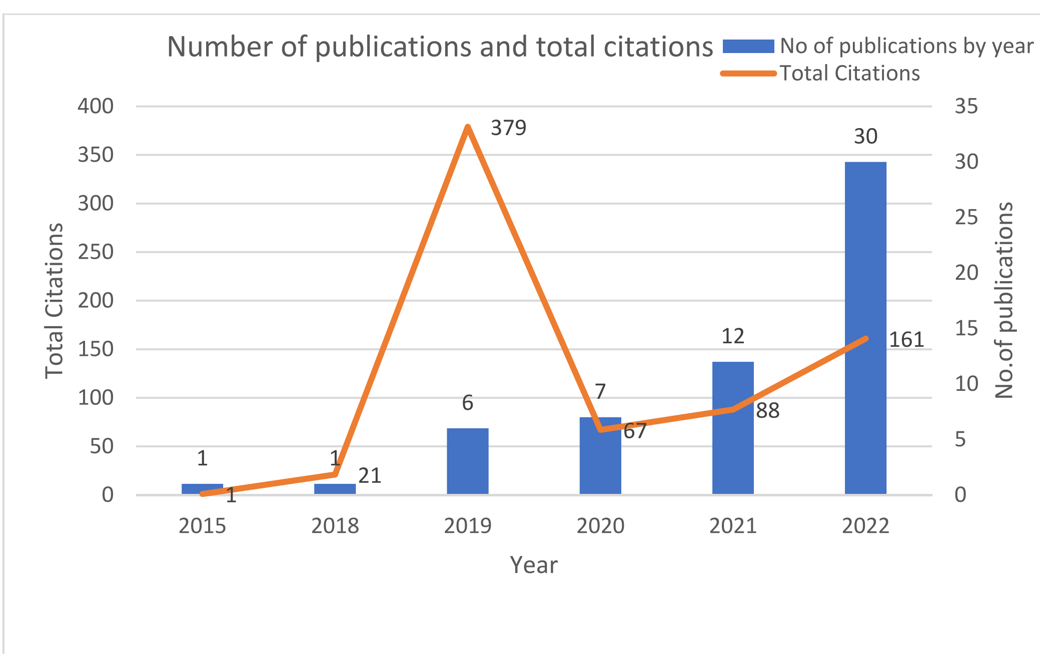

Fig. 4. Combo graph of the number of publications year-wise and total citations for the publications.

given below:

2.2. Bibliometric analysis

The research trends were examined using bibliometric analysis. Bibliometrix, a tool from R-Studio, that is widely used based on the inputs of the SLR database (Wamba, 2022), was considered for this study. The database entered was sourced from Scopus as it is one of the efficient database files that could be used for analysis, and all the review papers were indexed in Scopus. The analysis in Bibliometrix is source-based, author-based, and document-based, consisting of keyword analysis. Bibliometrix also finds application in analyzing the conceptual structure of the data using a co-occurrence network and thematic mapping (Qrunfleh et al., 2023).

Based on the number of papers published, the most relevant journals are ranked in Table 2. They help provide insights into the type of journal that focuses on AI's application in HRM. The top-ranking journals were from HRM, followed by general management. A total of 151 authors have published in the area, and a minimum of two authors have collaborated on a single paper.

The three fields plot, which maps the sources to authors to keywords, reiterated the fact that research of AI in HRM predominantly focussed on a systematic review of literature on the adoption of AI, machine learning, and the fourth industrial revolution in HRM with employee experience as an outcome (See Fig. 5). In addition, the ethics of AI applications in HRM was another important topic for research (Hamilton and Davison, 2022; Prikshat et al., 2023b). Similarly, the most frequently occurring research words, as given in Table 3, and the co-occurrence network that examines the potential relationship of two bibliometric items in the same record (Zhou et al., 2022), as given in Fig. 6, helped identify the underlying themes of AI in HRM literature. They predominantly focussed on recruitment, personnel selection, employee experience, and job design. Specific other word frequencies like automation, augmentation, future of work, robotics, and the Technology-Organization-Environment (TOE) model are also mentioned in the co-occurrence network analysis and thematic maps, as given in Figs. 6 and 7.

Table 1
Inclusion-Exclusion criteria.

S. no.	Criteria	Include	Exclude
1	Topics	Topics related to Artificial Intelligence and Human Resource Management; AI and HRM; AI and Managerial capabilities; AI and Managerial competencies; AI and HR Manager	Topics that are not related to the search context
2	Date	Studies conducted on the topics listed above predominantly consisted of studies conducted from 2015 and later.	Studies not conducted on topics based on the search context.
3	Main Source	The studies are listed in business, management, and accounting journals, followed by psychology and social sciences journals, and indexed in Scopus.	Studies from other journals
4	Secondary Source	Company documents, websites, and papers on the listed topics.	Secondary sources that do not contain the listed topics.
5	Geographic Location of the study	Not specific to any location. National and International studies considered	Non-relevant studies from any geography were not considered.
6	Language	English language studies were considered	Studies in other languages were not considered

Table 2
Ranking of Journals based on the number of articles produced on AI in HRM.

Rank	Journal	Articles
1	Human Resource Management Review	9
2	International Journal of Human Resource Management	7
3	International Journal of Manpower	4
4	Business Horizons	4
5	Technological Forecasting and Social Change	2
6	Asia Pacific Journal of Human Resources	2
7	California Management Review	2
8	Contributions to Economics	2
9	Foresight	2
10	Strategic Management Journal	2
11	Benchmarking	1
12	BPA Applied Psychology Bulletin	1
13	Contributions to Management Science	1
14	East European Journal of Psycholinguistics	1
15	Employee Responsibilities and Rights Journal	1
16	Forum Scientiae Oeconomia	1
17	Frontiers in Psychology	1
18	Human And Technological Resource Management (HTRM): New Insights into Revolution 4.0	1
19	Human Resource Management	1
20	Human Resource Management Journal	1
21	International Journal of Contemporary Hospitality Management	1
22	International Journal of Emerging Markets	1
23	International Journal of Organizational Analysis	1
24	Journal of Decision Systems	1
25	Journal of Information Technology Teaching Cases	1
26	Management Decision	1
27	Management Research Review	1
28	Management Review Quarterly	1
29	Proceedings of the 15th International Conference on Business Information Systems 2020 "Developments, Opportunities and Challenges of Digitization", Wirtschaftsinformatik 2020	1
30	Proceedings of the Human Factors and Ergonomics Society	1
31	Special Human Resource Management Practices and Strategy	1
32	Transfer	1

The themes in the thematic map were either the key technologies and methods used in AI, like data mining, machine learning, robotics, automation, or augmentation, or various HR functions like hiring, talent management, and job design, where AI finds application in HRM. Analyzing the thematic maps from *keywords plus* (Fig. 7) extracted from titles of references cited and *author's keywords* based on algorithms. It helps to identify (Qrunfleh et al., 2023) the motor themes, peripheral or niche themes, emerging or declining themes, and basic themes. The motor themes (Q1, upper right quadrant) are well-developed but still crucial for the field of research. The niche themes (Q2, upper left quadrant) are marginal in developing the research field. Emerging or declining themes (Q3, lower left quadrant) also have a marginal role in developing the research field. Basic themes (Q4, lower right quadrant) are underdeveloped research themes (López-Robles et al., 2019). As per the thematic map in Fig. 7, the keyword plus themes have HRM, resource allocation AI, and decision-making and managers as two clusters that overlap between Q1 and Q4. Though the research fields are individually well developed, the thematic map signifies that as clusters, the research fields are still developing and find more scope for research. This finds consensus with our present study, mainly when managerial capabilities include decision-making and managerial capabilities' role in adopting AI in HR is based on DCV, an extension of the resource-based view.

The thematic map of the author's keywords (See Fig. 8) also identifies important motor themes in algorithmic management and the future of work as a cluster, which have been extensively discussed in the literature. Machine learning, big data, fourth industrial revolution and HRM as a cluster; HRM, systematic review and robotics as a cluster and AI and ethics as a cluster. They are important to be developed as a field of research. The inference drawn based on the themes suggests that studies predominantly focus on applications of AI-based technologies in HRM.

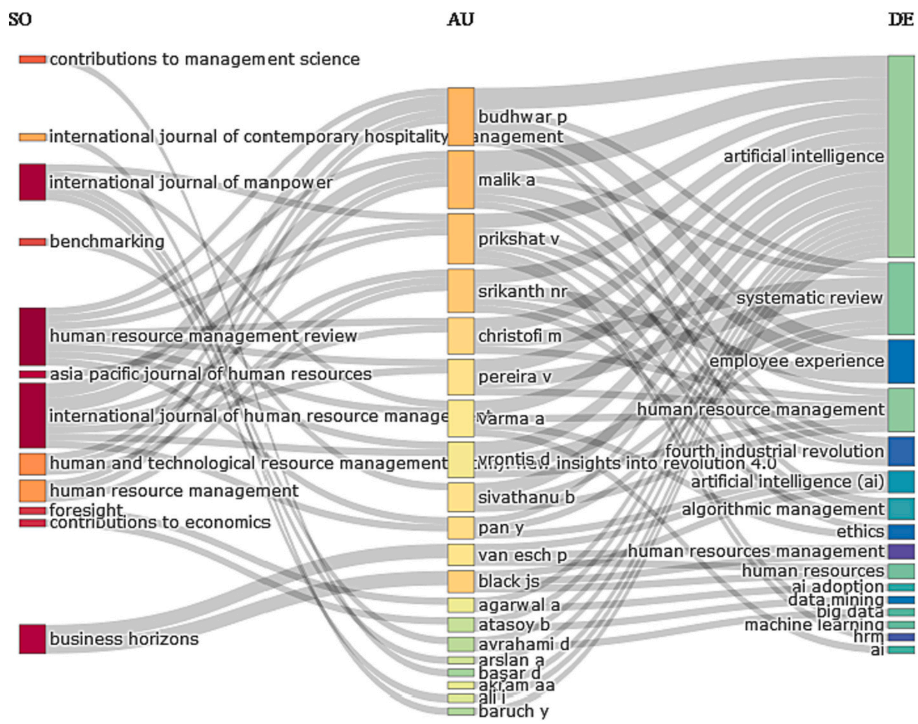

Fig. 5. Three fields plot: source-author-keywords plot.

2.3. Findings based on SLR and bibliometric analysis

The relevant literature discussing the various applications of AI-based tools and technologies used in HRM is listed in Table 4. They were pertinent to the research question in addressing the direction of research undertaken in the applications of AI in HRM. The key advantage of this study in identifying the AI-enabled tools and techniques used in HRM is that several papers ($N = 12$) were based on SLR or bibliometric analyses addressing the application of AI in HRM. Thus, it was advantageous to include these studies, as they encapsulated several works of literature on AI in HRM. The studies also served as a basis to identify the managerial competencies required in adopting AI-based tools and techniques in HRM.

In the HR lifecycle, *workforce planning* was discussed in several studies ($N = 5$), where prediction of future demand and supply of labor can be made using predictive analytics, machine learning, deep learning, soft computing, and evolutionary programming (Avrahami et al., 2022; Budhwar et al., 2022; Margherita, 2022; Massey, 2019; Pereira et al., 2023).

The bibliometric analysis yielded recruitment, personnel selection, employment, hiring, and talent acquisition as part of frequently repeated keywords, co-network analysis, and thematic analysis. This indicates that *recruitment and selection* are a vital part of the HR lifecycle, and AI finds broader application in these two HR functions. The studies ($N = 17$) indicated that AI technology like chatbots are used for pre-hire engagement (Guenole and Feinzig, 2018), while deep learning and predictive analytics are used for text matching and predicting the time taken to fill a position (Allal-Chérif et al., 2021; Guenole and Feinzig, 2018; Margherita, 2022; Massey, 2019; Ore and Sposato, 2022; Pan et al., 2021; Pereira et al., 2021; Rantanen et al., 2020; Rodgers et al., 2023; Tambe et al., 2019; Votto et al., 2021).

Another central area of application has been *performance management* ($N = 10$), where predictive analytics is used to predict employee performance over time and the propensity of an employee to quit (Budhwar et al., 2022; Massey, 2019; Malik et al., 2021a, 2021b; Margherita, 2022; Pereira et al., 2023; Vrontis et al., 2022; Votto et al., 2021; Tong et al., 2021). Further analysis suggested applications of AI in *personalized employee services* ($N = 12$), finding wider applicability in organizations other than recruitment and selection (Malik et al., 2022a). AI-enabled tools like a chatbot, text classification, skill matching and wearable technology are used in employee personalization (Agrawal et al., 2019; Black and van Esch, 2021; Malik et al., 2022a; Guenole and Feinzig, 2018; Kaplan and Haenlein, 2019; IBM, 2017; Pereira et al., 2023; Rodgers et al., 2023; Rantanen et al., 2020; Vrontis et al., 2022; Tambe et al., 2019).

AI applications in *learning and development* ($n = 7$) is another niche area that is finding traction, enabling virtual and self-paced learning for organizational members (Budhwar et al., 2022; Guenole and Feinzig, 2018; Pereira et al., 2023; Votto et al., 2021; Vrontis et al., 2022; Zhang et al., 2018). AI applications also cut across other functions of HRM, but as per the literature, the implementation is in its nascent stages (Pereira et al., 2023). They include *compensation planning and administration, internal mobility and career advancement, job design and virtual digital assistance* ($N = 14$). to the HR department. AI-enabled decision support systems, machine learning, deep learning, pattern recognition, voice, facial recognition and social media scraping are some of the tools that find application in these HR functions (Budhwar et al., 2022; Guenole and Feinzig, 2018; Huang et al., 2019; Kaplan and Haenlein, 2019; Pereira et al., 2023; Rodgers et al., 2023; Tursunbayeva and Renkema, 2022; Todolí-Signes, 2019; Votto et al., 2021; Vrontis et al., 2022; Zhang et al., 2018).

The results of SLR and bibliometric analyses gave an overview of the implications of AI in HRM. However, a detailed content analysis was required to understand the managerial capabilities needed to adopt and implement AI in HRM. The studies based on SLR discussed the role of HR managers in implementing AI. The managerial implications section also provided insights into the managerial capabilities required to adopt AI in HRM.

2.4. Content analysis

The theoretical phenomenon of the DCV drove the content analysis and, more specifically, the dynamic managerial capabilities that HR managers would need to sense the environment, seize the opportunity of

Table 3
Frequently occurring words.

Terms	Frequency
Artificial Intelligence	37
Human Resource Management	6
Systematic Review	6
Human Resources	4
Machine Learning	4
Big Data	3
AI	2
AI Adoption	2
Algorithmic Management	2
Artificial Intelligence (AI)	2
Augmentation	2
Automation	2
Data Mining	2
Employee Experience	2
Ethics	2
Fourth Industrial Revolution	2
Future of Work	2
HRM	2
Human Capital	2
Human Resources Management	2
India	2
Job Design	2
Personnel Selection	2
Recruitment	2
Robotics	2
Talent Acquisition	2
Talent Management	2
Technology	2
Toe Model	2
Adoption	1
Advanced Technologies	1
Age	1
AI-Adoption in HRM	1
AI-Augmented HRM	1
AI-Enabled Chatbots	1
AI-Enabled Recruiting	1
AI Anxiety	1
AI Awareness	1
AI Ethics	1
AI Recruitment	1
AI Transparency	1
Algorithm-based Surveillance	1
Algorithms	1
Artificial Intelligence-Human Resource Management Interface	1
Artificial Intelligence and Hiring	1
Artificial Intelligence Applications	1
Artificial Intelligence Evaluation	1
Attitudes	1
Augmented Intelligence	1
Automated Decisions	1

AI adoption, and reconfigure their people and team resource base (Helfat and Martin, 2015).

The directed approach to content analysis is deductive (Potter and Levine-Donnerstein, 1999), and this method is especially appropriate to address the second research question of this study. The directed approach helps to identify the key concepts based on theory and use it as the initial coding category. Thus, the *managerial cognitive capability, human capital, and social capital of DCV* were considered the initial coding categories. Based on the literature, sub-categories were also identified as competencies (Ambrosini and Altintas, 2019; Jong, 2020; de Visser et al., 2018; Helfat and Martin, 2015; Lin et al., 2016). Finally, the summary of highlighted text from the literature was coded into the relevant categories and sub-categories, thus offering descriptive evidence for the content analysis. Table 5 presents the content analysis of the managerial capabilities and competencies identified from the literature.

Managerial cognition, or cognitive capabilities of HR managers (Teece, 2016) that take care of decision-making, was the initial coding category. *Ethical decision-making* was derived based on codes like perception, judgment, being ethically sensitive to workers' dignity, logical reasoning, eliminating bias from decision-making, upholding ethical principles and decision-augmentation or decision-automation (Giraud et al., 2022; Leyer and Schneider, 2021; Johnson et al., 2022; Prikshat et al., 2023b; Rodgers et al., 2023; Varma et al., 2022). ***Problem-solving*** based on a design-thinking approach, information exchange, delegating routine tasks to AI and retaining crucial decision-making to managers are some of the codes identified from the literature (Ore and Sposato, 2022). Validating AI tools suitable for HR problem-solving and free from ethical and legal concerns were the other codes identified for the competency and its *validation* (Hamilton and Davison, 2022; Pan and Froese, 2022; Varma et al., 2022).

Managerial human capital, based on managerial knowledge and skills shaped by years of experience, was the second coding category considered by the DCV. *Technical expertise* was required for using existing data or capturing new sources of data for data analysis, where managers were required to be digitally savvy for data-based decision-making (de Viron and Gailly, 2022; Malik et al., 2022a, 2022b). ***Leadership skills*** were a significant capability based on the various roles played by HR managers of change leadership, leader of employees and robots, possessing creativity, innovation and imagination, effective communicator, strategic partner, and administrative expert (Budhwar et al., 2022; Hmoud, 2021; Malik et al., 2022b; Varma et al., 2022). ***Institutional configuration capability*** reflected the change management paradigm of managers in planning and implementing digital transformation, being a change agent to bring technological maturity in organizations and develop HRM procedures to adopt AI assets and develop intelligent technologies (Hmoud, 2021; Giraud et al., 2022; Manuti and Monachino, 2020; Nankervis et al., 2021; Pan et al., 2021; Rodgers et al., 2023; Varma et al., 2022; Vrontis et al., 2022). ***Developing the workforce*** was equally imperative along with AI-based tools, including analytics and algorithms for upskilling oneself by *being agile* (Malik et al., 2022b; Margherita, 2022; Nankervis et al., 2021). Managerial capabilities also involve using AI technology like machine learning, deep learning, and AI-based algorithms for training employees. Managers also used AI systems to measure the effectiveness of training (Budhwar et al., 2022; Malik et al., 2022b; Pereira et al., 2023; Varma et al., 2022; Vrontis et al., 2022; Tursunbayeva and Renkema, 2022). Finally, ***jobs designing skills*** for employees to work with AI systems for job design was part of managerial human capital capabilities (Parent-Rocheleau and Parker, 2022; Tursunbayeva and Renkema, 2022).

Managerial social capital, or managers' capability to handle relationships within and outside the organization for obtaining resources or getting things done, was the third primary coding category based on DCV. *Ability to source and use AI-based technologies* in internal and external hiring, improving employee performance, reducing turnover, deciding pay parameters for employees, efforts to improve market share and firm performance, and using data talent and AI tool-designers for the process are part of the relational capabilities of HR managers (Avrahami et al., 2022; Black and van Esch, 2021; Budhwar et al., 2022; da Silva et al., 2022; Demir et al., 2020; de Viron and Gailly, 2022; Leyer and Schneider, 2021; Mirowska and Mesnet, 2022; Pereira et al., 2023). Maintaining *social justice* in terms of procedural and distributive justice in technology includes maintaining transparency in data collection, improving explaining ability, reducing opacity, mitigating trust issues, and monitoring the fairness and equity of AI-based systems (Chowdhury et al., 2023; Langer and Konig, 2023; Todolí-Signes, 2019; Tong et al., 2021; Varma et al., 2022). Co-designing AI-assisted HRM solutions with employees and providing hyper-personalized AI-enabled HR solutions using bots and personal and digital assistants enable managers to *enhance employee experience* (Hmoud, 2021; Malik et al., 2021a, 2021b, 2023a). Managers also play the role of empathetic mentors in coaching and counselling employees to collaborate with AI systems and address employee concerns about replacing jobs with AI (Kong et al., 2021; Malik et al., 2021a, 2021b; Varma et al., 2022; Votto et al., 2021). Managers also *enable human-AI collaboration* and maintain a

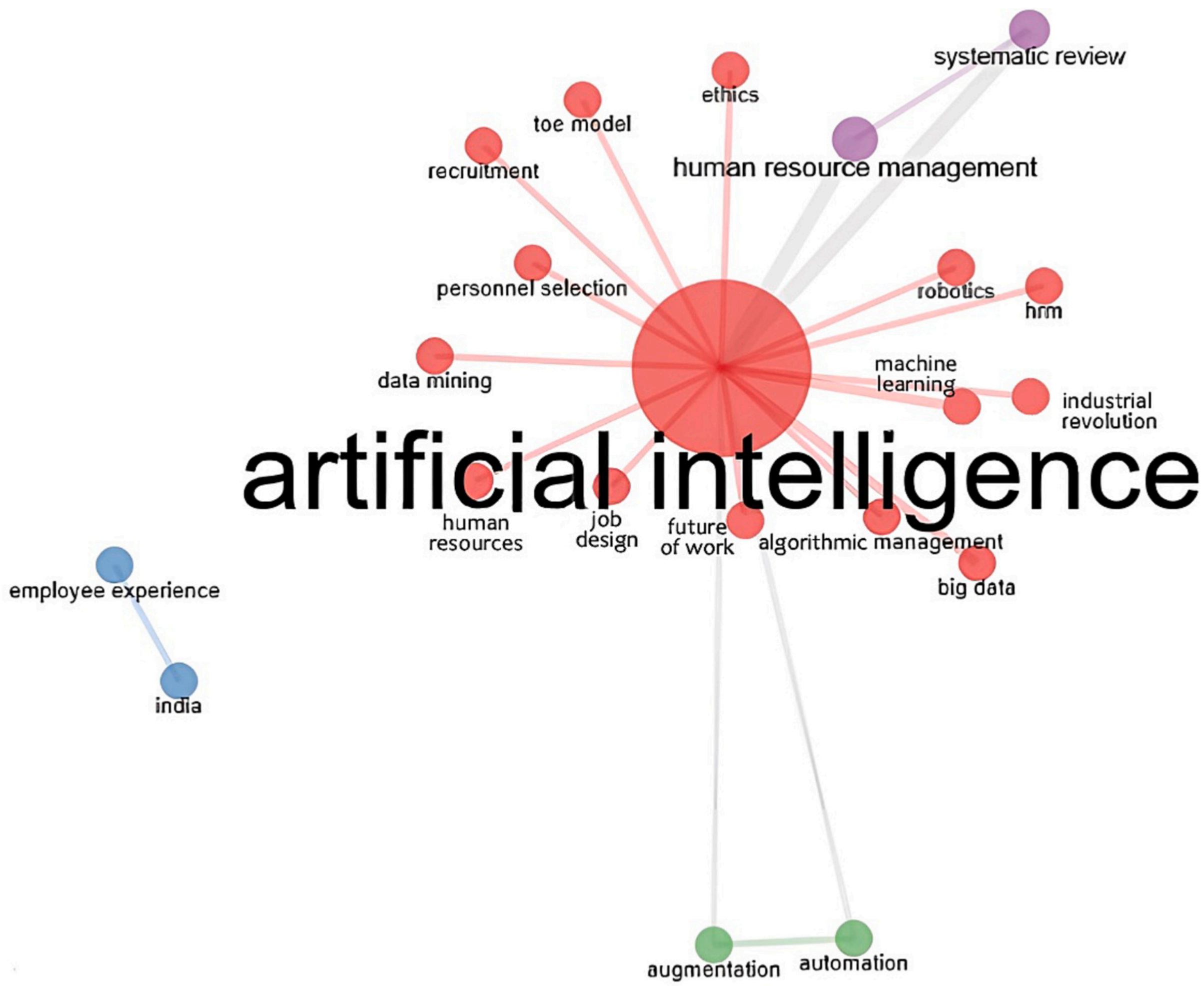

Fig. 6. Co-occurrence network analysis.

collaborative spirit between humans and robots (Arslan et al., 2022; Huang et al., 2019; Leyer and Schneider, 2021). Thus, the directed content analysis was a meaningful mechanism to unearth the managerial capabilities through SLR.

3. Discussion

The current research highlights that advancement in technologies and its penetration in HRM is observed through the application of AI in various functions of HRM – recruitment, performance assessment, onboarding, employee engagement, and self-service. However, bibliometric analysis and SLR indicate that research in AI in HRM is still nascent, and the field of study is dispersed and fragmented (refer to Fig. 4) (Pan and Froese, 2022). The current study attempted to identify the direction of research studies on AI in HRM, and bibliometric analysis indicates that research on AI in HRM had gained traction in 2022, with 30 publications (refer Fig. 4) compared to 6, 7, and 12 in 2019, 2020 and 2021, respectively. It shows the significance of AI in HRM in recent years and its relevance to the field of HRM. Similarly, the thematic maps indicated that research on AI in HRM is still to develop, offering more scope for further investigation in alignment with Malik et al. (2023a, 2023b) and Prikshat et al. (2023b). This serves as a critical supporting reason for exploring the second research question of this current study – identifying the required managerial capabilities for adopting AI in HRM. A study by Pereira et al. (2021) and Vrontis et al. (2022) also indicated that further inquiry is necessary to unravel the managerial capabilities and competencies essential for the adoption and sustained performance of AI in HRM. While the first research question helped to understand the critical AI functionalities, tools, and techniques that will augment managerial capabilities in various HRM applications, the second research question enabled the mapping of the managerial capabilities and associated competencies required to adopt AI in HRM.

Content analysis was carried out on the identified research work through SLR with specific reference to the DCV theory. A directed approach to content analysis identified initial coding referring to managerial cognition or cognitive capability, human capital, and social capital. Research has identified the corresponding sub-themes as competencies that are critical for the adoption of AI in HRM. For example, under managerial cognitive capability - ethical decision-making, problem-solving, and validation are critical competencies to hone this managerial capability. These competencies pose critical challenges for handling bias, upholding ethical principles, design thinking approaches, and validating AI tools for delivering HR functions.

In managerial human capital, technical expertise, leadership skills, institutional configuration, training skills, agility, and job designing skills emerged as key managerial competencies crucial for adopting AI in HRM. These competencies are relevant as AI in HRM demands embracing recent technologies, leading employees, integrating AI systems into the work system, planning, and effective implementation, training the functional teams, and job design capabilities. Under managerial social capital, managers must be able to source and use AI-based technologies, maintain social justice, and enhance employee experience, mentoring skills, and collaboration skills as key competencies to adopt AI in HRM. These competencies are critical owing to the

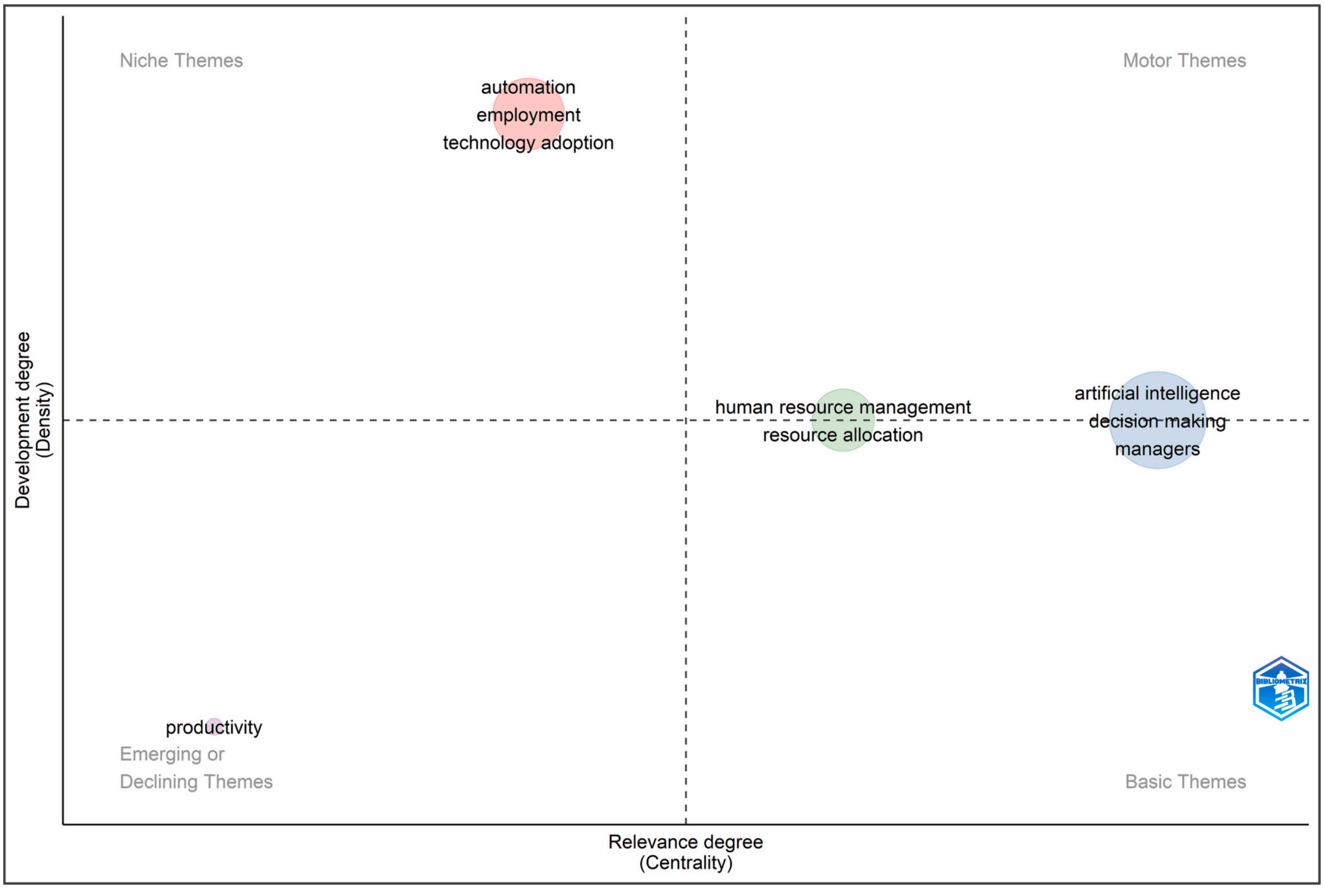

Fig. 7. Thematic map – keywords plus.

availability and relevance of enormous AI-based technologies to HRM functions, data sensitivity and security, the threat of AI in replacing employees, ensuring better interaction of employees, and AI-based technologies. The identification of managerial capabilities finds traction with the earlier study by Guenduez and Mergel (2022), which established that managerial dynamic capabilities are critical for smart city transformation. Therefore, we propose that a set of competencies associated with specific managerial capabilities (i.e., managerial cognitive capability, managerial human capital, and managerial social capital) influence the adoption of AI in HRM and, thus, enhance the effectiveness of HRM function. A summary of the managerial capabilities and competencies is presented in Table 6.

3.1. Theoretical implications

The current study offers significant theoretical implications for adopting AI in HRM. It helps to identify future research gaps based on the identified themes. It proposes a set of research questions and propositions for further inquiry in the domain of technology adoption in HRM. Pan and Froese (2022) indicated that research on AI in HRM is nascent and necessitates more studies in this domain to enhance technology adoption in the HRM field. However, most of the extant studies on the adoption of technology draw from the Technology Acceptance Model (TAM) (Venkatesh and Davis, 2000), the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) and UTAUT2 (Venkatesh et al., 2012) and these models do not discuss on the relevance of specific capabilities required by managers in the adoption of technology in general and AI in particular. Studies by Pereira et al. (2023) and Vrontis et al. (2022) also indicated that further inquiry is necessitated to unravel various competencies required by managers that are essential for the adoption and sustained performance of AI in HRM. Budhwar et al. (2022) and Malik et al. (2022a, 2022b) have called for increased investment in human capital of HR practitioners in the areas of digital literacy, data savviness, and digital transformation and change management. Therefore, based on the DCV framework, the current study lists three key managerial capabilities - managerial cognition, managerial human capital, and managerial social capital- as crucial managerial capabilities necessary for the effective adoption of AI in HRM (Teece, 2018). These findings also expand the work of Guenduez and Mergel (2022), who argue that managers require capabilities that must help them adapt, integrate, and reconfigure internal and external activities, resources, and technologies.

In addition, the current study, based on the content analysis, extends the DCV theory by identifying the key competencies associated with each managerial capability (refer to Table 4) critical for adopting AI in HRM. It also adds to the call of Dwivedi et al. (2023) to include other relevant variables than technology adoption models in studying the adoption of AI. Further, the current study also supports the proposition of Shet and Pereira (2021) that specific competencies that are significant for adopting technologies must be identified. Based on the above theoretical research gaps identified from the literature, the current study identified 13 competencies from the content analysis associated with specific managerial capabilities for the effective adoption of AI in HRM. They are unique competencies associated with the three managerial capabilities that are very specific to the adoption of AI among HR managers.

Towards this, the current study proposes a framework for adopting AI in HRM based on the observations and findings of SLR and content analysis. The synthesis of extant literature resulted in the identification of research gaps. Still, more studies are needed to identify the specific managerial capabilities and associated competencies required for the effective adoption of AI in HRM in diverse contexts. Specifically, more

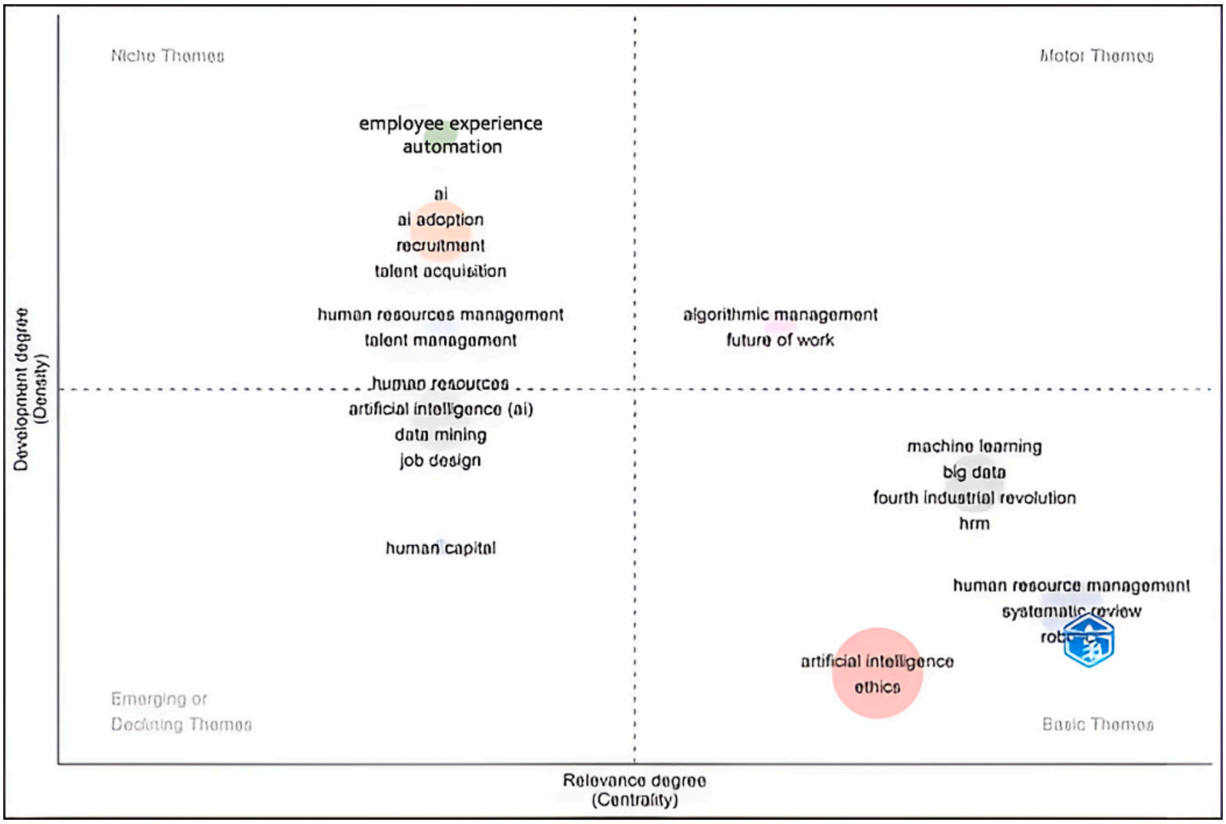

Fig. 8. Thematic map – authors' keywords.

effort is needed to find the required competencies essential to build specific managerial capabilities. Thus, the current study proposes the following research questions for further empirical inquiry:

1. What specific competencies are required to build managers' cognitive capabilities to adopt AI in HRM effectively?
2. What specific competencies are required to build managers' human capital to adopt AI in HRM effectively?
3. What specific competencies are required to build managers' social capital to effectively adopt AI in HRM?

The following propositions are worthy of further refinement and empirical validation from a future research agenda based on the research questions identified above.

P1: *The competencies of ethical decision-making, problem-solving, technical data science expertise, digital savviness, and validation are required to build managerial cognition, which will influence the adoption of AI in HRM and impact the effectiveness of HR functions.*

P2: *The competencies of leadership skills, developing and implementing institutional change agendas, change coping skills, agility, and job redesign/crafting skills required to build managerial human capital will influence the adoption of AI in HRM and, in turn, impact the effectiveness of HR functions.*

P3: *The competencies consisting of the ability to source and use AI-based technologies, maintain social justice, enhance employee experience, mentoring skills, and human-AI collaboration skills required to build managerial social capital will influence the adoption of AI in HRM and, in turn, impact the effectiveness of HR functions.*

Based on the identified research gaps, research questions, and propositions, the proposed conceptual framework emphasizes how competencies relate to the managerial capabilities and capabilities influencing the adoption of AI in HRM and leading to the effectiveness of various functions of HRM, as specified in Fig. 9.

3.2. Practical implications

The current study offers some important practical implications for organizations to enhance the adoption of AI in HRM functions. This study highlights that managerial capabilities are crucial beyond the facilitating conditions, effort expectance, social influence, and performance expectancy for the effective adoption of AI in HRM functions. With the accelerated technological development and its relevance to the field of HRM, firms must hone managerial capabilities – managerial cognition, human capital, and social capital – for the effective adoption of AI. Unless organizations direct their effort towards developing the crucial managers' capabilities, it is unlikely that technology adoption will be effective. Further, the study identified key competencies critical for each managerial capability specific to adopting AI in HRM. For example, ethical decision-making, problem-solving, and validation are relevant to building managerial cognitive capabilities. Thus, organizations should expend resources to provide training programs that enhance the manager's cognitive capability by building competencies in problem-solving, ethical decision-making, and validation.

Similarly, to strengthen managerial human capital, organizations should provide opportunities and targeted training programs that cater to enhance one's technical expertise, leadership, agility, and job design skills. These competencies would improve manager's human capital and act as one of the essential managerial capabilities for the adoption of AI in HRM.

To enhance the managerial social capital capabilities, the ability to source and use AI-based technologies, maintain social justice, mentoring skills, and human-AI collaboration skills are vital competencies. Thus, organizations should facilitate that managers get an opportunity to hone these competencies through training programs, workshops, and

Table 4
Managers' adoption of AI in HRM functions based on the SLR.

S. no.	HR functions	AI-enabled tools and techniques	Source(s)
1	Workforce Planning	Predictive Analytics Machine and Deep learning, soft computing, Evolutionary programming for prediction of future demand and supply of labour	Avrahami et al. (2022); Budhwar et al. (2022); Massey (2019); Periera et al. (2021); and Margherita (2022).
2	Pre-hiring	Chatbots using NLP capabilities for pre-hire communication and engagement	Bhatt (2022); Guenole and Feinzig (2018); Margherita (2022); Rantanen et al. (2020); Rodgers et al. (2023)
		Deep learning neural network for text classification and matching for person-job-organization fit	
		Predictive Analytics for predicting the time taken to fill a position	
3	Hiring	Predictive Analytics for predicting future performance at the time of hiring	Guenole and Feinzig (2018); Massey (2019); Margherita (2022); Ore and Sposato (2022); Tambe et al. (2019);
		Detecting bias patterns in language and word association in job descriptions and resume screening using Deep learning	Guenole and Feinzig (2018); Ore and Sposato (2022); Pan et al. (2021); Pereira et al. (2023); Votto et al. (2021)
		Cognitive Computing (Natural language, speech, and image processing)	IBM (2017); Vrontis et al. (2022); Black and van Esch (2021)
		Data mining and machine learning algorithms for multi-criteria decision-making	Demir et al. (2020); Kim and Heo (2021); Kshetri (2021); Mirowska and Mesnet (2022); Ochmann and Laumer (2020); Yang (2022)
		Voice and facial recognition in video interviewing, social media scraping of digital exhausts, gamification	
4	Performance evaluation	Comparative longitudinal analysis of employee performance over time using data analytics.	Massey (2019); Malik et al. (2021a, 2021b); Vrontis et al. (2022).
		Predictive analytics to predict the propensity of employees to leave	Budhwar et al. (2022); Margherita (2022); Pereira et al. (2023); Tong et al. (2021); Votto et al. (2021); Vrontis et al. (2022).
5	Employee experience	Manager alerts based on the match score provided by neural networks/Due for promotion alerts	Guenole and Feinzig (2018)
		Chatbots using NLP-based machine learning for better employee experience	Dutta et al. (2022); Pillai et al. (2023)
6	Employee engagement	Machine learning and decision-support	Agrawal et al. (2019); Malik et al. (2021a, 2021b); Malik et al. (2022b)
		Cognitive Computing (Natural language, speech, and image processing)	IBM (2017); Vrontis et al. (2022)
		Employee voice-based sentiment analysis using NLP-based machine learning	Guenole and Feinzig (2018); Rodgers et al. (2023)
7	Employee health and well-being –	Online Corporate Reputation, Gauging employee sentiment, concept-mapping, extracting meaning from themes.	Rantanen et al. (2020); Tambe et al. (2019)
		Personalized coaching and counselling and Personalized career advice using	Guenole and Feinzig (2018);
		Chatbots using NLP capabilities	IBM (2017); Periera et al. (2021); Rantanen et al. (2020); Rodgers et al. (2023); Vrontis et al. (2022)
		Cognitive Computing (Natural language, speech, and image processing)	
		Text classification and skill matching of resume using deep learning	
		Machine learning, Physiolytics (Wearable technology)	
8	Compensation administration	AI-enabled algorithmic decision-support systems for compensation planning	Agrawal et al. (2019); Budhwar et al. (2022)
9	Employee skill development	Personalized learning using deep learning based on employee search data, past learning experience and employee skill requirements.	Guenole and Feinzig (2018); Pereira et al. (2023); Votto et al. (2021); Vrontis et al. (2022); Budhwar et al. (2022)
10	Internal mobility/career advancement	Pattern recognition in data and natural language understanding to offer better matching between jobs and skills	Zhang et al. (2018);
11	Job design	Algorithms to create and maintain meaningful jobs	Parent-Rocheleau and Parker (2022); Tursunbayeva and Renkema (2022)
12	Employee self-service	Chatbots and Virtual digital assistants using NLP-based machine learning	Huang et al. (2019); Kaplan and Haenlein (2019); Malik et al. (2022a); Rodgers et al. (2023); Todolí-Signes (2019)

certification courses on AI in HRM through knowledge partners. The study findings listed 13 competencies that are associated with three managerial capabilities as crucial driving factors for the effective adoption of AI in HRM.

The relevance of these competencies is crucial as it is noted that algorithm-based decision-making in HR is a challenge when the criteria used for hiring or performance management are based on past data that may consist of conscious or unconsciously biased managerial information. However, when algorithmic decisions produce an overall bias, it can be overruled by human decision-making. It is also important to build fairness and transparency into the system. Managers can use AI systems to review and reword job descriptions, blind job irrelevant cues like gender or ethnicity, train AI systems to be free of bias using diversity and inclusion experts, and most importantly, give the right data to design the right algorithms (Zhang et al., 2019). They must also be instrumental in data masking, using encryption software and building system firewalls

Table 5
Content analysis to derive the HR managerial capabilities based on SLR.

Dynamic Managerial Capabilities (Initial Coding categories)	Managerial capabilities identified from the literature	Codes based on the literature	Effect on individual/team/organizational levels	Author
	Ethical decision-making	Perception, judgment, use of information, and decision-choice to eliminate bias from decision-making	All three levels	Rodgers et al. (2023)
Managerial Cognitive Capability		AI assistance for objective as opposed to subjective decision-making in HR functions	Individual level	Yang (2022)
		Ethically sensitive to worker dignity and employee privacy	Individual level	Varma et al. (2022)
		Upholding ethical principles in AI-augmented HRM		Prikshat et al. (2023b); Giraud et al. (2022);
		Decide whether AI will be involved in decision-augmentation or decision-automation	Organizational level	Johnson et al. (2022); Leyer and Schneider (2021);
	Problem-solving	Problem-solving through information exchange with AI-based systems		
Managerial Cognitive Capability		Delegate routine tasks to AI while retaining the crucial decision-making to recruiters.		Ore and Sposato (2022)
		Use situational awareness instead of tunnel visioning in resource allocation decisions when using AI-based decision aids.	Organizational level	Jones (2015)
Managerial Cognitive Capability	Validation	Validating AI tools suitable for HR problem-solving by interdisciplinary collaboration between technical and managerial evaluation		Pan and Froese (2022)
		Identify AI systems that appreciate humanity.		Varma et al. (2022)
		Assess the appropriateness of AI tools free from ethical and legal concerns.	All three levels	Hamilton and Davison (2022)
	Technical expertise	Exploit knowledge available in existing data sets		
Managerial human capital		Identify and capture new sources of knowledge.		de Viron and Gailly (2022)
		Digital savviness and data fluency	Organizational level	Malik et al. (2020)
		To use and apply AI-based technology and applications		Kim and Heo (2021); Pillai et al. (2023)
	Leadership skills	Treat AI as a subordinate to managerial discretion		Varma et al. (2022)
Managerial human capital		Change leadership in leading employees and AI systems.		Malik et al. (2022a, 2022b)
		Possessing emotional intelligence, creativity, innovation, and imagination or acquired in the process of competitive interaction with AI systems		Basu et al. (2023); Malik et al. (2022b)
		Effective communication between the organization and employees to offset the unfavorable effect of AI-enabled HRM	Organizational level	Budhwar et al. (2022)
		Administrative expert		
		Strategic partner leading humans and machines	All three levels	Hmoud (2021)
	Institutional configuration capability	Planning and implementing digital transformation effectively		Manuti and Monachino (2020); Nankervis et al. (2021); Rodgers et al. (2023)
Managerial human capital		Pay attention to internal factors like implementation cost, enterprise development needs, top management involvement, external factors like market pressures, policy support, HR support and convenience of AI technology.		Pillai and Sivathanu (2020); Wang et al. (2022)
		Understanding and controlling the process that generates the data		
		Creating a strategy to manage and collect data		Varma et al. (2022); Zehir et al. (2020)
		Bring technological maturity and business performance to organizations.		
		Enable organizational preparedness, technology readiness, change readiness and be a change agent.	Organizational level	Agarwal (2022); Giraud et al. (2022); Hmoud (2021); Suseno et al. (2022);
		Mutual development of HRM strengths and intelligent technologies		Vrontis et al. (2022)
		Develop HRM procedures and routines to increase AI assets and AI adoption with top management support.		Pan et al. (2021)
	Ability to develop the workforce	Start preparing the workforce to collaborate with AI systems	All three levels	Tursunbayeva and Renkema (2022)
Managerial human capital		Ensure other managers are trained in AI and its usage.		Rezzani et al. (2020); Varma et al. (2022)
		Train employees in technology, digital competence, and problem-solving skills.		Lobova and Bogoviz (2019); Malik et al. (2021a, 2021b); Simsir and Mete (2022); Malik et al. (2022b)
		Technology Coaching		
		Use machine learning and deep learning techniques for training employees		Pereira et al. (2023)
		AI assistance to assess training effectiveness and make decisions on employee competency	Individual and team-level	Budhwar et al. (2022)

(*continued on next page*)

Table 5 (*continued*)

Dynamic Managerial Capabilities (Initial Coding categories)	Managerial capabilities identified from the literature	Codes based on the literature	Effect on individual/team/organizational levels	Author
Managerial human capital	Being agile	Introducing analytics and AI capabilities and enabling continuous learning		Nankervis et al. (2021)
		Develop digital and data science skills.		Malik et al. (2022b)
		Possess literacy in algorithms, analytics, and AI tools.	Individual level	Margherita (2022)
Managerial human capital	Job designing skill	Adjust the job design of employees to work with AI systems.		Tursunbayeva and Renkema (2022)
		Using AI-based algorithms in job design	All three levels	Demir et al. (2020); Parent-Rocheleau and Parker (2022)
	Ability to source and use AI-based technologies.	Use data mining techniques, algorithms, and AI evaluation in hiring.	All three levels	Bhatt (2022); Mirowska and Mesnet (2022); Tambe et al. (2019)
Managerial social capital		Use AI assistance to improve job posts, resume screening and minimize selection errors		da Silva et al. (2022); Kshetri (2021); Ochmann and Laumer (2020)
		Use AI-assisted tools for identifying passive job candidates and assessing and interviewing candidates.	Individual level	Black and van Esch (2021); Gupta et al. (2018); Rezzani et al. (2020);
		Ability to identify, attract, recruit, and retain high-performance talent		Allal-Chérif et al., 2021; van Esch and Black (2019);
		Hiring data talent to extract knowledge available from data sources		de Viron and Gailly (2022)
		More interaction with AI tool designers	Individual level	Leyer and Schneider (2021)
		Using AI/ML tools for measuring turnover that could be used for HR planning	All three levels	Avrahami et al. (2022)
		Take AI systems' assistance to manage and improve employee performance.		Pereira et al. (2023)
		Take AI systems' assistance in collecting information about 'employees' compensation and benefits for deciding pay parameters.	Individual level	Budhwar et al. (2022)
		Refocus efforts on improving market share and firm performance because of adopting AI in HRM.	Organizational level	Caputo et al. (2019); Kaushal et al. (2023)
Managerial Social capital	Ability to maintain social justice	Being transparent in data collection		
		Monitor fairness and equity impact of AI-based decisions.		Varma et al. (2022)
		Increase the explainability of AI-based ML models.		
		Mitigate trust issues of AI-based ML models by using techniques and frameworks.	All three levels	Chowdhury et al. (2023)
		Offset the negative disclosure effect of AI-based performance feedback	Individual level	Tong et al. (2021)
		Reduce opacity and increase transparency in algorithm-based HRM	All three levels	Langer and Konig (2023)
		Safeguard employees against discrimination	Individual level	
		Improve workplace data protection by involving 'workers' representatives as part of collective governance	Individual and team-level	Todolí-Signes (2019)
Managerial social capital	Ability to enhance employee experience	Co-design AI-assisted HRM solutions for 'employees' social, psychological, and physical safety needs resulting in a better employee experience.		
		Improve HR cost-effectiveness by providing personalized and hyper-personalized AI-enabled HR solutions using bots, personal and digital assistants	Individual level	Dutta et al. (2022); Malik et al. (2023b)
		Be an employee champion	All three levels	Hmoud (2021)
Managerial social capital	Empathetic mentoring skills	Address employee concerns about replacing them with AI		Kong et al. (2021); Varma et al. (2022)
		Involve employees in AI implementation	Individual level	Varma et al. (2022)
		Be human-centric tactical HR by building trust		Votto et al. (2021)
		Mentoring, counselling, and coaching employees		Malik et al. (2020); Malik et al. (2022b)
Managerial social capital	Human-AI collaboration skills	Help humans and bots to work as a team		Arslan et al. (2022); Huang et al. (2019)
		Integrating machine capabilities with human capabilities based on AI-driven integrated complementation and substitution capabilities		Krakowski et al. (2023)
		Maintain a collaborative spirit between humans and robots		Arslan et al. (2022); Leyer and Schneider (2021)
		Achieve a balance between explorative routines delivered by humans and exploitative routines delivered by robots	Individual and team-level	Del Giudice et al. (2022)

Table 6
Managerial capabilities and competencies required for adoption of AI in HRM.

Capabilities	Managerial cognition or cognitive capability	Managerial human capital	Managerial social capital
Competencies	- -Ethical decision-making - Problem-solving - Validation	- Technical expertise - Leadership skills - Institutional configuration capability - Ability to develop the workforce - Being agile - Job designing skill	- Ability to source and use AI-based technologies - Ability to maintain social justice - Ability to enhance employee experience - Empathetic mentoring skills - Human-AI collaboration skill

to protect employee data against pilferage and theft (Jha, 2022). Similarly, mapping the required managerial competencies for various HR functions where AI finds applications is crucial. For example, AI-based predictive analytics that finds application in hiring will be supported or overruled using managerial cognitive capabilities of ethical decision-making, problem-solving, and validation. Therefore, this competency mapping helps define the competencies required for hiring managers based on various AI applications used in hiring.

To further understand the significance of why organizations should be concerned about enhancing the adoption of AI is evident through the wider penetration of AI systems in HRM operations. For instance, AI has been deployed in hiring and recruiting (in screening & and interviewing the candidates, candidate relationship management, matching the resume against the job description, etc.), training & and development (identifying skill demand, learner engagement, virtual assistance, etc.), workforce planning (optimization of workforce, prediction of future demands, etc.), diversity & inclusion (identification & removal of bias from job descriptions, recruiting diverse candidates, etc.), performance management (track performance, suggest areas for improvement, etc.) and succession planning (identify potential high-potential employees, assigning roles, etc.). Thus, organizations would benefit by honing the critical competencies essential for the adoption of AI in HRM.

3.3. Limitations and future research directions

This study has some limitations that should be noted and addressed by future research. First, it is plausible that additional work on AI in HRM available in other sources would have been ignored, though an effort was taken to include literature that did not reflect in SLR. Future studies should attend to other search engine sources. Themes (managerial capabilities) and sub-themes (competencies) are identified through content analysis of the identified papers through the theoretical lens of DCV. Further studies can apply other theoretical models that help identify other relevant managerial capabilities and competencies required for adopting AI in HRM. In addition to SLR, future studies can conduct meta-analytic studies to understand the relevance of various factors for adopting AI in HRM. Similarly, the propositions based on each of the themes and sub-themes, along with the proposed theoretical model in the 'Theoretical implications' section, can be empirically tested to establish the relevance of identified capabilities and competencies for adopting AI in HRM.

The Bibliometric analysis also sheds light on AI's implications in specific areas of HR, like recruitment, selection, employee experience, and job design, through the frequently occurring research words and the co-occurrence network analysis (Refer to Table 3 and Fig. 6). This can help future researchers to further their research agendas on these specific areas or focus their efforts on other areas of HR that are less focused upon. Other areas of research that can have a future focus include automation, augmentation, future of work, robotics, and the TOE model,

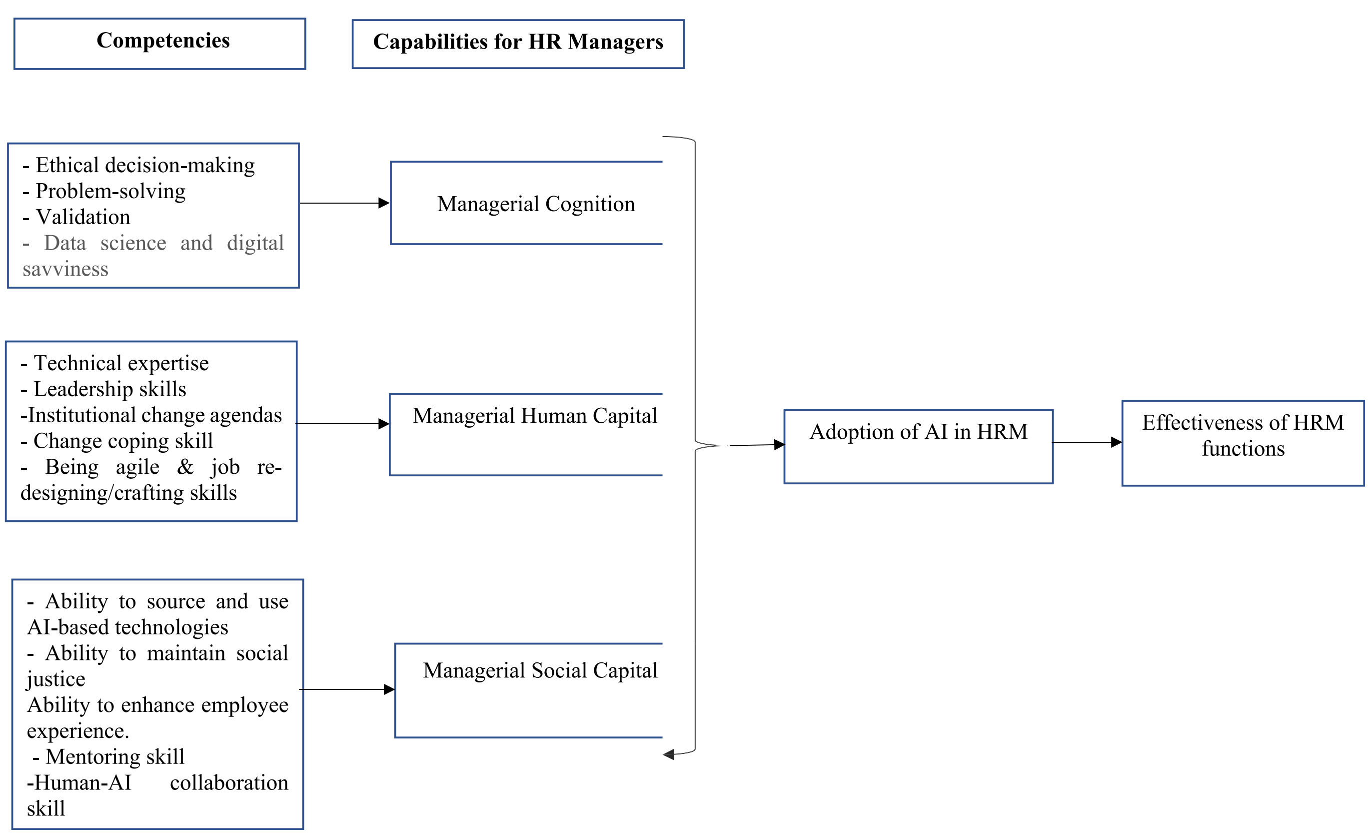

Fig. 9. A conceptual framework of HR capabilities for AI adoption and HR effectiveness.

based on the co-occurrence network analysis and thematic maps (Refer to Figs. 6, 7 and 8). The network analysis also evolves intersectionality of research areas that help create a common ground or provide an overarching synthesis of new research areas based on the relationships between different research domains (Locke and Golden-Biddle, 1997). This synthesized coherence also finds traction with the thematic maps where the congruent relationships between different research domains can be further explored. The thematic maps indicate that researchers working around AI and HRM have significantly advanced the field of research, indicating a 'progressive coherence' in shared theoretical and methodological perspectives (Locke and Golden-Biddle, 1997). However, as basic underdeveloped themes, HRM-Resource allocation-AI; decision-making – managers; machine-learning-big data-fourth industrial revolution-HRM; HRM-systematic reviews-robotics, AI-ethics are the key clusters that call for a synthesized coherence approach to derive corresponding relationships in the intersectionality of these research domains.

Future research can also look at employee outcomes due to effective AI implementation in HR functions, which can be associated with positive or negative effects on employees. Competency mapping and effective AI implementation at the individual, group, and organizational levels and their impact can be a scope for future research. Future research agenda can help in understanding the scope of competency mapping and development for entry-level talent, industry-academia interface required for competency development, organizational initiatives for skill gap analysis and developing managerial capabilities, and the result of an organizational paradigmatic shift in hiring AI-focussed talent and AI-focussed managers. Performance, productivity, and competitive advantage for both HR and the organization because of the practical adoption of AI-focussed managerial competencies can also be a scope for future model development and empirical validation. Developing managerial capabilities that can answer ethical and moral challenges of AI and the role of managerial capabilities and explainable AI in their impact on HR and organizational effectiveness can all scope for future research. Studying the long-term effects of AI on employee morale, job satisfaction, and organizational performance, or how AI might shape the future roles of HR managers, could all be considered as areas of future research. Studying the contrasting role of AI in HRM with other sectors or industries to provide a broader perspective can also be considered a scope for future research.

4. Conclusion

Managerial capabilities and the associated competencies discussed in the study find relevance where AI is used explicitly for decision augmentation. Still, the future of work needs to consider the possibility of automating processes specific to managerial capabilities. Thus, managers must be agile in identifying the requirements of HR functions that require AI applications that will only augment managerial capabilities and not override decision-making. It is vital for managers to also allow automation in tasks that can be let go so that they can focus on organization-specific strategic priorities. This concerns managerial capabilities in deciding whether augmenting or automating AI applications is required for various HR functions. Thus, organizations must provide appropriate development opportunities for managers and employees in adopting AI and create a collaborative environment for managers, employees, and AI technologies to co-exist in a mutually enabling ecosystem.

CRediT authorship contribution statement

R. Deepa: Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Srinivasan Sekar:** Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ashish Malik:** Writing – review & editing, Methodology, Formal analysis, Conceptualization. **Jitender Kumar:** Writing – review & editing, Resources. **Rekha Attri:** Writing – review & editing, Validation, Resources.

Declaration of competing interest

The authors have no conflict of interest in the paper.

Data availability

No data was used for the research described in the article.

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