"I exist because I adapt": Evolving technology HR themes, HR roles with STARA competencies for performance

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ABSTRACT

The paper aims to understand the research themes evolved from 2011-2024 in Human resource (HR) technology field and highlight key HR technology roles with STARA (Smart Technology, AI, Robotics and Algorithms) competencies. To capture the technology shift and research themes in the technology HR field pre- and post-pandemic period, we conducted bibliometric analysis for the two time periods viz., 2011-2019 and 2020-2024. Co-citation and co-occurrence keyword analysis of existing tech-based HRM literature was done for the above two periods for exploring the traditional and emerging HR STARA roles and responsibilities aligned to emerged HR themes. Moreover, a bibliographic coupling on the articles at the intersection of HR skills and HR technology was conducted to map the future technology roles with emerging HR STARA competencies. Research themes such as *e-HRM adoption and consequences, Robotic Process Automation in HR* and *Digital HR transformation* have emerged with HR roles such as *strategic technology integrator* and *institutional digital capability planner*. Similarly, new tech-based HR roles and future-oriented STARA competencies have also been highlighted. The findings are novel in identifying the barriers and enablers to technology HRM systems in organizations. Moreover, identifying HR technology roles with STARA competencies linked to the career capital framework is a unique contribution of this paper. Moreover, the research gaps and future directions of HR technology research with an HR career perspective have both theoretical and practical relevance.

1. Introduction

Over time, the Human Resources (HR) discipline has undergone metamorphosis due to technological disruptions. The organizations have responded to the digital transformation by developing, distributing, and consuming e-HR (electronic HR) services. Currently, e-HR services are developed, distributed, and consumed using digital transformations. By leveraging technology to improve job characteristics, reduce work-to-life conflict, and promote well-being, HR professionals can create a more supportive and productive work environment [1].

Kim et al. [2] elaborate on how technology is conceptualized in organizations and narrate three major research streams that evolved over the last 60 years. According to the research, technology can be understood through three distinct lenses: "as a tool, as a representation for human intent, and as a complex system" shaped by social and organizational contexts. Moreover, research and practice in the field often focus on three main themes- how technology influences employment and organizational structures, how it is applied within various human

resource functions, and how individuals who develop and maintain technological systems are managed. However, Fenech et al. [3] observed the changing nature of HRM (Human Resource Management) in an era of digital transformation, where research on digital disruption in HRM has increased significantly [4]. However, extant research primarily relied on case studies and focus group discussions to evaluate successful digital HR transformations [5]. Moreover, the technical competencies required for HR managers to lead the transformation journey are lacking and, if present amidst the scant research, are highly superficial [6,7]. Also, the impact of technology on the development, implementation and success of HRM operations has not reached a conclusive consensus. This lack of agreement can be attributed to several technological disruptions occurring (e.g., the emergence of e-HR, AI (Artificial Intelligence), Machine learning, and IoT (Internet of Things) within a short span in the highly complex domain of IT-HR. These rapid developments led to a theory-practice gap between practitioners and researchers. Popular technology fads have led many management researchers to produce unnecessary and irrelevant research themes and topics. To date, sparse

research has identified research themes on the tech-enabled HRM topic. A recent biblometric analysis by Ghosh et al. [5] has identified technology HR themes and its relavanec to SDG (Sustainable Development Goals), but includes a time period when STARA (Smart Technology, AI, Robotics and Algorithms) technologies were not in the mainstream research. Therefore, the citation landscape would likely include a broad mix of topics, making it harder to isolate STARA-specific trends. Moreover, to identify HR competencies around STARA (Smart Technology, AI, Robotics and Algorithms), the evolution of technology in HR field has to be systematically understood [8].

A few recent research has tried to list STARA competencies of HR (e. g., Lubberink [9], Tambe et al. [10], McCartney et al. [11] and Abdali [12]). However, researchers must capture the HR manager's skills or competencies depending on the contexts, situations, and configurations prevailing at different organizational periods. Before 2011, research has yet to measure the consequences of e-HRM on the organization or its stakeholders [13]. Through HR managers' strategic thinking skills around technology adoption was fragmently highlighted, core technical skills as a competency should have been considered more in business and HR practices [14]. Moreover, from 2020 onwards, after the COVID-19 pandemic, the rise of virtual HR practices compelled HR researchers/practitioners to examine new STARA compencies [8]. STARA competencies of HR managers to lead the digital transformation journey need to be improved and, if present amidst scant research, are highly superficial [6,7]. STARA competencies should be viewed not just as tools for efficiency, but as platforms for HR to generate long-term value and competitive advantage positioning HR as a driver of innovation, agility, and organizational resilience. It is worthwhile to systematically evaluate the evolved tech-enabled HRM systems in organizations with the founding and new competencies required by the HRs to lead the present and future digital transformation journey. As research on the key competencies required by HR professionals to handle and lead digital transformation is limited, the present paper raises the following research questions (RQs)

RQ1: How STARA roles and responsibilities of HR managers have evolved with technological changes in HR systems?

RQ2: What are the emerging STARA roles and responsibilities of HR managers?

RQ3: What are the emerging STARA competencies of HR managers ?

The paper is structured as follows: Section 2 describes briefly the conceptual background, Section 3 and its subsections clearly explain the methodological approach adopted. Section 4 encompasses the results of the different types of analysis. Section 5 and its subsections are meant for in-depth discussions on the findings and policy implications. Section 6 identifies the research gaps and discusses future research directions with practical and theoretical implications for HR career development. Finally, Section 7 concludes the study with limitations.

2. Conceptual Background

The research article of Lengnick-Hall and Moritz [15] opened up various avenues of research in e-HRM, where internet technology and service-oriented architecture in deploying IT-driven systems played a pivotal role. However, any e-HRM change must consider the strategic role of HR in an IT-enabled environment [15]. Ulrich [16] coined the term "technology proponent" in a suggestive way to make HRs use technology to connect people within an organization. However, most organizations suffer from HRIS implementation failures [17]. According to the authors, the companies must identify their operational, relational, and transformational goals to implement such a model. It was observed that such failures to implement a HRIS successfully were less technology-related but more related to the necessary skills of the change leader [18].

By reviewing a few articles on e-HRM, Strohmeier [19] developed a framework that maps the context and configurations of e-HRM against its actual consequences. In this paper, the technology-driven

interactions with actors via the "front-end" of e-HR applications (e.g., portals, self-service systems, or voice response systems) and subsequent processing of inputs through the "back-end" provided a categorization of different actors, strategies, and technologies relevant to e-HRM implementation. However, in most e-hrm research, there was a lack of theoretical underpinning and the mapping of STARA competencies for implementing such systems. It is to be noted that from a career capital framework, Arthur et al. [20] emphasizes how human competencies may be used for individual career change and organizational change. However, minimal studies exist that explored it from a career mobility and career transition perspective [21].

Although there are limited studies, Votto et al. [22] have tried to synthesize various viewpoints and analyze the existing research environment for implementing AI technologies in HRM [23,24]. Additionally, numerous studies have emphasized the effects of AI on workplace dynamics [25,26], with a significant outcome being the enhancement of managerial tasks and capabilities to foster innovation and develop AI-specific skills [7]. Moreover, adopting AI technologies presents ethical challenges, including data privacy and security, algorithmic biases, discrimination, and concerns over psychological safety [27]. Brenninkmeijer et al., [28] captures the above aspects from a HR job crafting viewpoint using either a promotion focus (aspiring to achieve gains) or a prevention focus (aiming to avoid losses). It underscores the importance of mastering STARA competencies in the era of AI, where the integration of explainable AI (XAI) in business practices can be achieved through fostering competencies related to building human-machine trust, fairness, transparency, understandability, and usability of AI systems [29].

Several researchers emphasize that implementing AI technologies necessitates the development of managerial skills and competencies essential for fostering effective human-machine collaboration and teamwork [6,30,31]. Therefore, it becomes clear that there is an expanding research gap, calling for more studies to explore the managerial skills required to effectively use AI in enhancing the performance of individuals, teams, and organizations [32]. Moreover, our study has implications for *career capital theory* that suggests that if three knowings ("Knowing Why" - purpose, "Knowing-How" – competencies , "Knowing-Whom" - context and boundary) are unearthed, then an "intelligent career" can be developed [20].

3. Research methodology

The present study addresses the RQs following a bibliometric investigation to systematize scientific knowledge. Research reveals that incorporating such techniques improves the objectivity and replicability of reviews [33]. The choice of bibliometric analysis also enables the researcher to look behind the scenes and base their analysis on the aggregated opinions of prominent scholars in the area [34].We used co-citation network analysis, co-occurrences of author keyword analysis and bibliographic coupling to explain knowledge transfer and research themes generated over the 2011-2024 period.

3.1. Research Strategy

We applied Biblioshiny package of R software and VOSviewer for bibliometric analysis [35]. It empirically analyzes the scholarly contribution to HR technology field published between 2011 and 2024. The year 2011 was chosen as the baseline because it marks a period when digital transformation in HR practices began gaining significant momentum, driven by the increasing adoption of cloud computing, data analytics, and AI in organizational processes [36]. This period witnessed the emergence of integrated HR technology platforms and a notable rise in scholarly attention toward the intersection of technology and human resource management. Setting 2011 as the starting point ensures the inclusion of relevant, contemporary literature that captures the evolution and maturity of HR technologies over the past decade. It filters out

irrelevant early-phase digital tech literature and provides a sharper lens to understand how smart technologies are influencing HR functions in the contemporary era.

Moreover, bibliometric analysis helps identify emerging areas through clusters that address RQ 1, RQ 2 and RQ 3. Addressing RQ1 required *co-citation analysis* of relevant papers to extract themes from bibliometric analysis as our goal is to understand how foundational studies are perceived together over time. We have chosen the time period 2011-2019 to capture the foundational studies to understand the evolution of HR technology and STARA roles and responsibilities. To address RQ 2, a *co-occurrence keyword analysis* in bibliometric studies (2020-2024) has been adopted for deciphering current research trends, as it reveals the most frequently appearing and interconnected terms within a given body of literature. By mapping how keywords co-appear across recent publications, researchers can identify trend and knowledge mapping. Additionally, to address RQ3, STARA roles and responsibilities around different technological areas have been mapped to HR digital skills and competencies that a HR manager must possess to remain relevant in emerging technological domains. We adopted *bibliographic coupling technique* to find relevant themes in the intersection of HR competency and HR technology.

3.2 Locating the keywords and inclusion and exclusion criteria of the articles selected in the study

We searched the Scopus database (Elsevier), matching the relevant keywords as article search (Fig. 1). These keywords or search strings were in the articles' titles and abstracts. The initial search resulted in 743 documents. Donthu et al. [37] recommend settling on one database to mitigate errors while consolidation of articles due to different formats across databases. We chose the Scopus database as its developers (Elsevier Co.) claim it to be the largest abstract and citation database of peer-reviewed literature – scientific journals, books and conference proceedings.

< INSERT Fig 1: **Overview of PRISMA framework for selection and screening of research articles** >

3.3. Inclusion and Exclusion Criteria

We applied inclusion and exclusion criteria in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework by Moher et al. [38] for screening and selecting articles. The PRISMA checklist guided the selection of articles, enabling the identification and screening of secondary data by an evidence-based method (Fig. 1) and ensuring that all selected primary studies are pertinent and related to the study.The range of 14 years (2011-2024) includes various
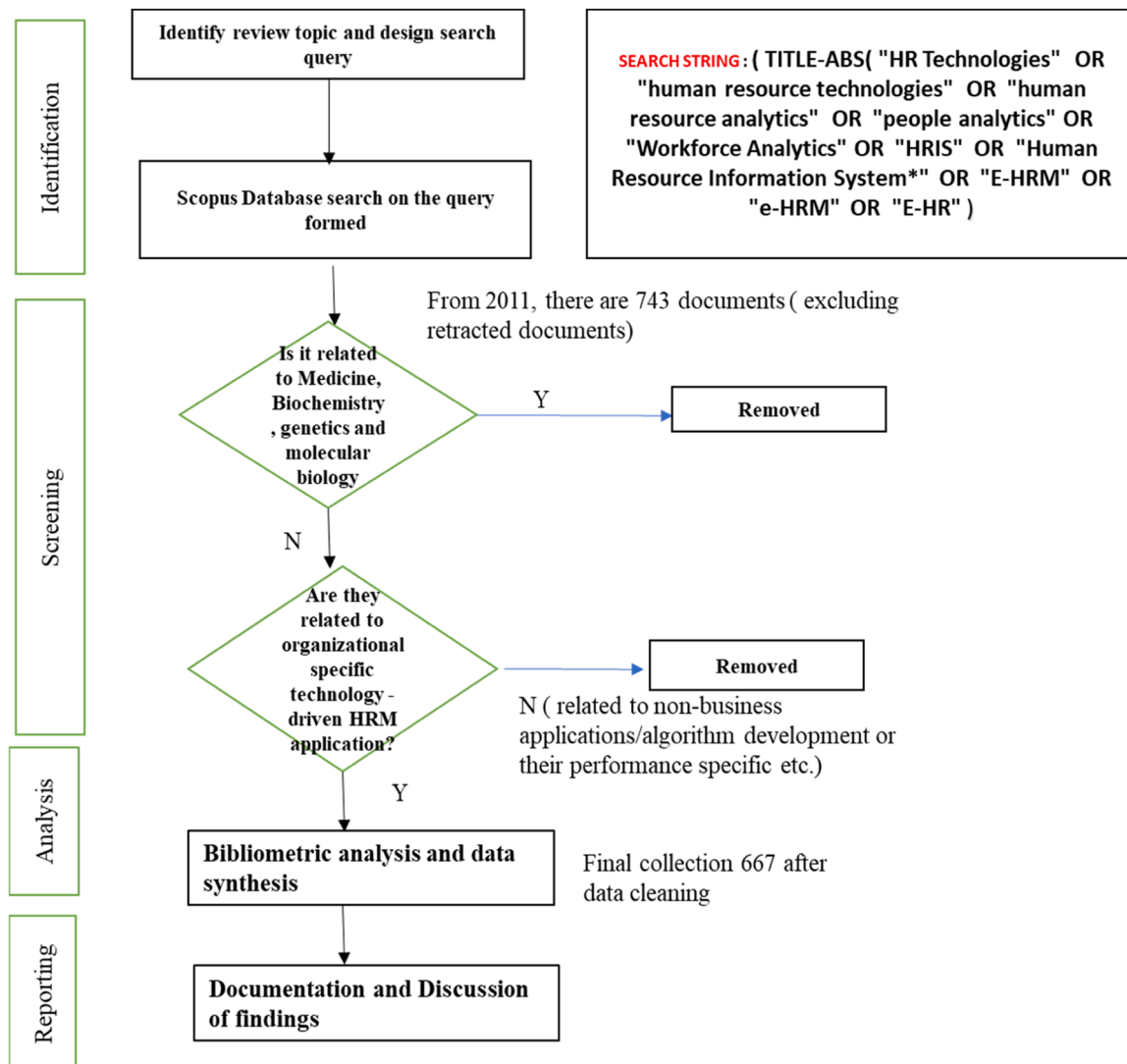

Figure 1. Overview of PRISMA framework for selection and screening of research articles.

articles to capture the evolution of technology in the HRM field. The remaining inclusion criteria are the language, peer-reviewed journals, availability, nature of the study (includes all empirical and non-empirical studies) and database (Scopus). Table 1 lists the criteria for inclusion and exclusion. Grey literature as conference proceedings is included in the analysis as they offer practice-based and multi-dimensional approaches to technology-focused HRM. An omission of grey literature can be considered a disadvantage, especially in areas where no convergence in earlier literature has taken place [39]. A thorough double-blind screening of the documents and data cleaning resulted in a final sample of 667 articles as of May 2024.

< INSERT Table 1: **Inclusion and exclusion criteria in the study** >

3.4. Cluster Analysis Results

The 667 documents for bibliometric analysis are coded in terms of the authors, year of publication, publication title, journal name, and research method. The coding is done by two authours in an iterative fashion to improve consistency and avoid bias in the coding process.

The co-citation analysis of articles from 2011-2019 (n =281) reveals four clusters that highly influence the understanding of technology adoption and use in HRM. A co-citation network analysis mapped the top 60 co-cited articles with a minimum 5 citations in the reference lists of all the articles in the dataset (See Fig. 2). VOSviewer software represents nodes (research articles) in a network of clusters. We review each perspective with the focus on (1) the type of research methodology employed, (2) core focus areas of the perspectives, and (3) the level of analysis or the category of respondents in the study. Moreover, after synthesizing relevant information of the papers with high association links within a cluster (big circles in the network cluster), the content analysis of key papers through the deductive approach helped us to define the HR roles and STARA competencies relevant to the research theme in the cluster (Refer Table 2). The broad research themes generated by Ghosh et al. [5] helped us to validate a few research themes emerged in our analysis, as their paper's broader time period had invariably captured similar clusters.

<INSERT Fig. 2: **Co-citation Network Clusters** >

Table 1
Inclusion and exclusion criteria in the study.

S. N.	Criteria	Reasons for Inclusion and Exclusion	
1	Publication Type	**Exclusion**	Exclude working papers, dissertations with no available abstracts, and erratum.
2	Pre-2011		Articles before 2011are not included in the analysis.
3	Articles in English	**Inclusion**	We select papers written in English due to the dominance of the language in the scientific community.
4	Peer-reviewed Journals		We include research papers from peer-reviewed journals due to higher quality and reliability.
5	Relevant to HR technology		The authors did a double-blind review of the search results to include research articles focused on HR technology in organizations.
6	Quantitative, qualitative and review studies		All empirical and non-empirical studies represent the specific interest of this review.
7	Database		All articles are published in the Scopus (Elsevier) database.
8	Subject Area		Business Management, Computer Science are considered as technology in management domain covers broadly these two subject areas

4. Results

4.1. Clusters generated from co-citation analysis of articles from 2011-2019

Cluster 1: HRIS applications as a strategic advantage in organizations
Lepak and Snell [40] proposed a virtual HR framework emphasizes network-based partnerships—both internal and external—leveraging IT as a strategic enabler. Lengnick-Hall and Moritz [15] pose critical research questions around control vs flexibility in shared services and information dissemination, which are central to technology-driven HR platforms. Their focus on the HRIS hints at the need for systems that balance automation with effectiveness—a key STARA concern. The strategic use of HRIS has significantly helped HR professionals to play a *strategic partner role* in organizations, irrespective of their size [41]. However, the HRIS system's engagement in training and recruitment was low [42].

Cluster 2: Migratiion from HRIS to e-HRM in organizations
Researchers were keen to evaluate the value of e-HRM systems positioned as a strategic tool for cost reduction by automating employee self-services. Parry [43] and Marler and Fisher [44] argue that such a narrow cost-focus undermines strategic potential. STARA-enabled e-HRM systems should not be confined to operational efficiency. Instead, they must be leveraged to empower HR professionals to engage in higher-value strategic work. As automation handles routine tasks, HR's role transforms—from transactional support to strategic partners, leveraging insights from AI and algorithms to shape workforce planning, talent analytics, and organizational development.

Cluster 3 Evidence-based HRM – Analytical perspective
Cluster 3 literature reflects a growing emphasis on measuring the effectiveness of e-HRM systems while forecasting technological advancements [45] and conducting evidence-based assessments [46,47]. Forecasting future tech trends, Stone et al. [45] highlights the urgency for future-ready competencies. HR professionals must proactively reskill and upskill to effectively manage and adapt to AI-integrated, web-based HR environments.

Cluster 4: HR technology adoption and challenges
Bondarouk *et al.* [47] identify technology-related factors—such as data integrity, ease of use, integration efforts, and cost-benefit analysis (in-house vs external systems)—as crucial for e-HRM adoption. HR must collaborate with IT and vendors to ensure seamless system integration, safeguard data quality, and make informed investment decisions in HR technologies. As per Davis [48], perceived usefulness and ease of use are critical factors influencing information system (IS) adoption. However, stakeholder perceptions of e-HRM systems differ, and these differences are often overlooked in HR system design [13]. HR professionals must play a key role in bridging the gap between system design and user expectations, ensuring inclusivity and usability across diverse user groups.

From the themes of above clusters and analysis of core papers within, we address RQ1 by understanding the different research themes evolved from technology-enabled HRM research from 2011-2019. Details of coding and HR technology roles with STARA competencies are depicted in Table 2.

< INSERT Table 2: **Themes and Key papers from co-citation network clusters** >

4.2. Co-occurance key words analysis to identify current and future HR STARA roles and responsibilities evolved from 2020-2024

We conducted a unique co-occurrence keywords analysis using the bibliometrix package in R software on all the publications (n = 387, of which 243 are research articles and 125 are conference papers, 19 are review papers) from 2020 to 2024. Moreover, after synthesizing relevant information of the papers with high association links within a cluster (big circles in the network cluster), we imply the STARA roles
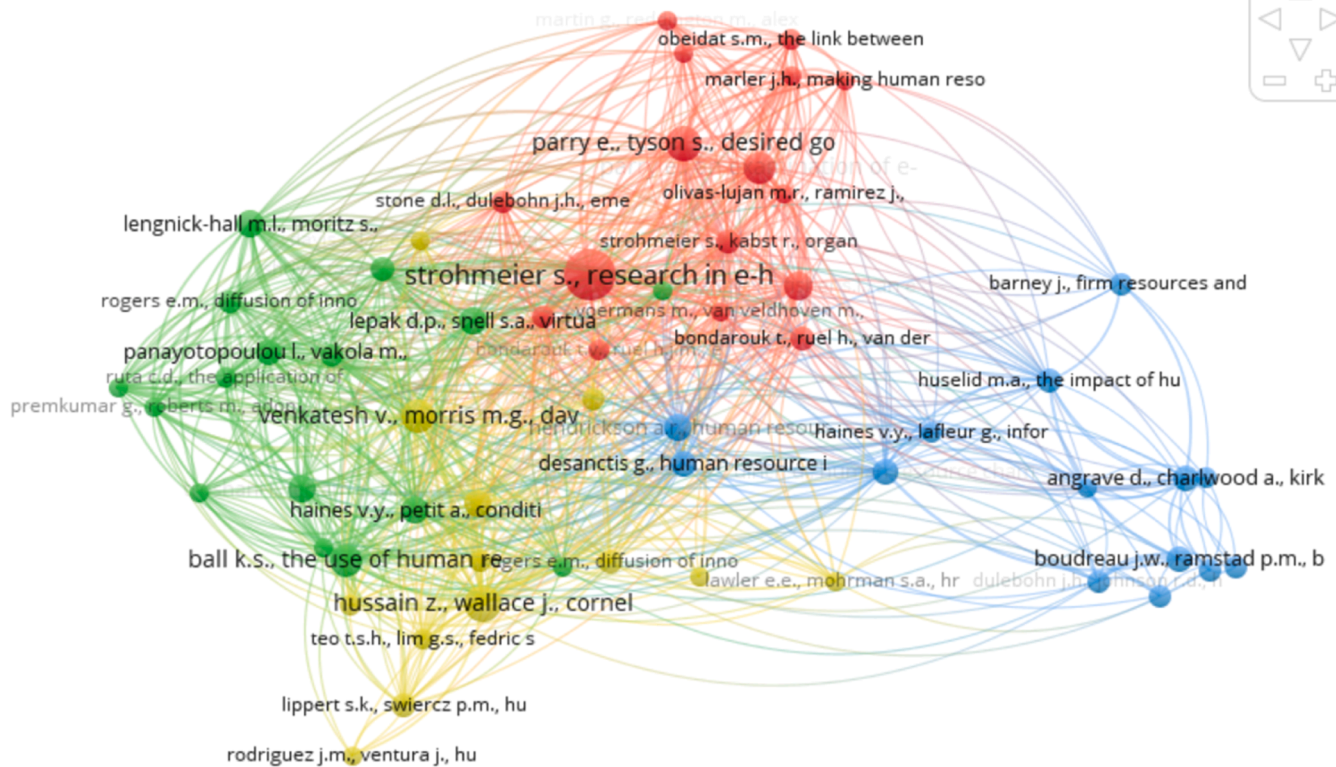
Figure 2. Co-citation Network Clusters.

and responsibilities relevant to the research theme in the cluster (Refer Table 3). We adopted this approach to address RQ2. The keyword analysis has resulted in six contemporary themes (Refer Figure 3) These clusters /themes may help us to determine the trending research areas and guide future research directions addressing RQ 2.

< INSERT Fig. 3: **Keyword co-occurrence network clusters** >

<INSERT Table 3: **The current and future avenues of e-HRM research, future technology HR roles and STARA competencies>**

Contemporary Emphasis 1: Digital HR transformation- A strategic perspective with ethical concerns

STARA roles in HR involve facilitating digital transformation through big data, AI, and blockchain. Responsibilities include enhancing digital literacy, promoting ethical AI adoption, ensuring bias-free and legally compliant tools, and fostering change readiness. HR must act as an *Institutional Digital Capability Planner* and an *Ethical Technology Climate curator*, aligning technology with human values to ensure responsible innovation and improved organizational performance. Details of STARA roles and responsibilities for this cluster are detailed in Table 3.

Contemporary Emphasis 2: Use of Predictive Analytics for competitive advantage

STARA roles in predictive HR analytics involve acting as *Behavioural and Business Data Analysts* who leverage knowledge of analytics to predict employee and organizational outcomes. Responsibilities include extracting insights from structured and unstructured data, understanding psychological drivers behind employee behavior, and identifying new data sources. This empowers organizations to make proactive talent decisions, enhance retention strategies, and gain competitive advantage through data-driven workforce planning and individual-level predictive modeling. Details of coding and STARA roles and responsibilities for this cluster are detailed in Table 3.

Contemporary Emphasis 3: Robotic Process Automation in HR /Human-robot Interaction and use of AI applications

While there is promise in combining human and robotic capabilities,

researchers have raised concerns about the quality of interaction and acceptance of robots in the workplace [49,50]. HR must play a central role in designing environments where symbiotic relationships between humans and robots can thrive—balancing efficiency with empathy and ethics. Findings from anthropomorphology suggest that robots mimicking human appearance but lacking behavioral realism may negatively impact human acceptance [51]. HR leaders need to collaborate with technology designers to ensure that robotic tools are functionally and socially appropriate, enhancing user comfort and trust. Aleksander's [71] non-empirical work highlights the broader organizational and sectorial implications of AI on human control over life and jobs, suggesting the need for HR to strategically manage this transformative shift. Meanwhile, Macchini et al. [52] provide empirical evidence on enhanced human-machine interfaces, emphasizing individual-level integration for teleoperation. Drawing from both perspectives, the *Strategic Human-Robot Integration Specialist* must not only implement strategic policies that harmonize the coexistence of humans and intelligent machines but also focus on fostering inclusive workplace designs that accommodate advanced human-machine interaction.

Contemporary Emphasis 4: Digital adoption and Use of Information

HR professionals must lead efforts to contextualize STARA technologies like e-HRM for local environments. As shown by Gupta et al. [53] in the Indian banking sector, a one-size-fits-all approach can reveal the dark side of technology adoption, such as misalignment with organizational culture or employee expectations. Based on Muhammad et al. [54] and Ratnam et al. [55], the STARA role of *HR Technology Advocate/Influencer* involves promoting digital adoption by identifying enablers and addressing barriers to HR analytics use. This role drives organizational readiness, encourages data-informed decisions, and fosters a culture of innovation. It ensures ethical use of information technologies while supporting strategic alignment between HR functions and digital transformation goals across individual and organizational levels.

Contemporary Emphasis 5: Application of M/C learning, and data mining techniques in HRM

Table 2
Themes and Key papers from co-citation network clusters.

Reference	Research Approach	Scope	Level of Analysis/ Respondent's Category	HR STARA roles and responsibilities
Cluster 1: HRIS applications as a strategic advantage for organizations				
Lepak and Snell (1998)	Non-empirical	The strategic positioning of HR in network-based internal and external partnerships using information technology.	Organizational level	**Strategic Technology Integrator** -Attention to internal factors such as cost of technology, need for technology
Ball (2001)	Empirical	The use of HRIS in smaller firms	Organizational level	-Attention to external factors market pressure, evaluation of COTS applications
Lengnick-Hall and Moritz (2003)	Non-empirical	HR role in enhancing strategic capabilities of organizations	Organizational level	- Figure out web-integration points of different HR functions (training, career development, training, and skills-management functions)
				- As a HR technology change agent, enable organizational preparedness, technology readiness and change readiness
				HR Technology advocate/influencer -Collaborate with IT vendors to facilitate development of HR procedures and routines to increase HR efficiency.
Cluster 2: Migration from HRIS to e-HRM in organizations				
Strohmeier (2007)	Non-empirical	Literature review on empirical works in e-HRM	Individual and organizational level	**Institutional Digital Capability Planner** - Digital technology value assessment capability
Bondarouk and Ruel (2009)	Empirical	Employee perceptions on e-hrm's effectiveness	Organizational level	-Planning and implementing digital transformation
Parry (2011)	Empirical	An empirical investigation of e-HRM as a value-creating system in organizations	Organizational level	- Building digital transformation roadmap and milestones
Marler and Fisher (2013)	Non-empirical	Relationship between e-HRM and strategic HRM	Organizational-level	
Stone *et al.* (2015)	Non-empirical	Current e-HRM issues and how HR systems will evolve in future by adopting the latest technologies.	Organizational-level	
Cluster 3: Evidence-based HRM – Analytical Perspective				
Ulrich (1997)	Non-Empirical	Establishes a relationship between HR practices and business outcomes by summarizing HR measures across its different functions. Provides a framework for HR audit as well.	Organizational-level	**Behavioural and Business Data Analyst** -Exploit knowledge available in existing data sets -Organizational level Identify and capture new sources of knowledge
Marler and Boudreau (2017)	Non-empirical	HR analytics adoption in organizations	Organizational level	-Knowledge of employee psychological variables and their influencers
Hendrickson (2003)	Non-empirical	HRIS capability valorisation across small, mid and large organizations.	Organizational level	**Technology/Digital Process Expert** -Understanding and controlling the digital process that captures, process and measure employee behavioural data
Cluster4: e-HRM adoption and consequences				
Davis (1989)	Empirical	Develops and validates two scales -perceived usefulness and perceived ease of use which determine user acceptance of technology	Individual	**HR Technology advocate/Influencer** - Discussion with top management for adopting state-of the art e-HRM system across different levels in the organization
Venkatesh *et al.* (2003)	Empirical	Users' intentions to use technology	Individual	-Effective communication between the different organizational stakeholders to offset the resistance towards e-HRM adoption
Ngai and Wat (2006)	Empirical	A comprehensive literature review of HRIS implementation in Hong Kong	Organizational level	-Validating e-hrm tools suitable for HR problem-solving by interdisciplinary collaboration between technical and managerial level employees.
Hussain *et al.* (2007)	Mixed Method	Strategic and non-strategic usage of HRIS in big and small firms	Organizational Level	-Advocate adoption of those HR analytics tools that are free from ethical and legal concerns

STARA role of *AI–ML/Big Data Literate* focuses on applying machine learning and data mining to HR functions. Responsibilities include deriving insights from large datasets, aligning AI use with legal standards, and leveraging tools like chatbots and sentiment analysis to enhance employee engagement and morale. This role also anticipates workforce needs by analyzing trends, identifying skill gaps, and improving performance through predictive analytics.

4.3 STARA competencies evolved from 2011-2024 mapped with emerged STARA roles

We intend to map the intellectual landscape around the intersection of HR competencies and emerging technologies (STARA). When HR roles and responsibilities around different technological areas have been mapped, it is essential to understand what skills and competencies HR

managers need to remain relevant in different HR domains. It helps organizations to analyze how HR is preparing (or needs to prepare) for automation, algorithmic decision-making, and AI ethics. From the past literature, it is evident that modern HR managers must bridge the gap between technology-driven disruption and human-centric capability development. We identified research papers specifically dealing with HR competencies around emerging technologies using the following keyword search

"("HR skills" OR "HR capabilities" OR "Human resource skills" OR "Human resource capabilities" OR "HR competencies" OR "Human resource competencies" OR "STARA" OR ("Future of Work" AND "HR") OR ("Future of Work" AND "Human Resource Management")) AND ("HR Technologies" OR "human resource technologies" OR "human resource analytics" OR "people analytics" OR "HRIS" OR "Human Resource Information System*" OR "E-HRM" OR "e-HRM" OR "E-HR" OR

Table 3

The current and future avenues of e-HRM research, future technology HR roles and STARA competencies.

Reference	Type of Methodology (Research Method)	Focus Area	Level of analysis/ Respondents' category	HR STARA roles and responsibilities
Cluster 1: Digital HR transformation- A strategic perspective with ethical concerns				
El-Kassar and Singh (2019)	Empirical	How HR practices can use Big data for firms' competitive advantage	Organizational	**Institutional Digital Capability Planner**
Tursunbayeva *et al.* 2022	Non-empirical	What ethical considerations by people analytics researchers and practitioners have considered or recommend for future.	Organizational level	-facilitating implementation of HR digital transformation using Big data, Blockchain, IOT and
Oswald *et al.* (2020)	Non-empirical	Important areas in industrial psychology and HRM discipline where big data sources and analysis can help	Individual, team and organizational level	Analytics -develop strategic HR plans for
Chillakuri and Attili (2021)	Empirical	Understand blockchain adoption in HRM practices	Organizational level	leading humans, machines and robots
			Organizational level	**Strategic Technology Integrator** -Bring digital maturity and business performance to organizations. -Enable organizational preparedness, digital literacy, change readiness **Ethical Technology Climate curator** -Validating AI tools suitable for HR problem-solving by assessing bias-free algorithms used in HR functions. -Identify AI systems that appreciate humanity and maintain social justice. -Assess the appropriateness of AI tools free from ethical and legal concerns. - Access and use AI tools that are transparent in human-centric data collection - Access and use AI tools that are ethically sensitive to worker dignity and employee privacy -Decide whether AI will be involved in decision-augmentation or decision-automation
Cluster 2: Use of Predictive Analytics for competitive advantage				
Ekawati (2019)	Non-empirical	Discussion on the methods of predictive analytics to predict employee churn	Individual-level	**Behavioural and Business Data Analyst**
Chung et al. (2023)	Empirical	Predictive model of employee churn using M/C learning technique	Individual-level	-Exploit knowledge available in structures or non-structured data sets - Understand employee-related psychological variables in the HR value chain - Identify and capture new sources of knowledge
Cluster 3: Robotic Process Automation in HR /Human-robot Interaction and use of AI applications				
Aleksander (2017)	Non-empirical	Plausible impact that this is likely to have on human control over life and jobs.	Organizational and sectorial level	**Strategic Human-Robot Integration Specialist**
Macchini et al. (2019)	Empirical	A human-body machine interface for enhanced teleoperation	Individual	-Implement strategic HR plans and policies for leading humans, machines and robots.
Kshetri (2021)	Empirical	How AI tools are used across HR functions in Global South	Organizational	-Focus on developing a human-machine co-habitat workplace policy - Collaborate with technology designers - Understanding of metaverse technologies and its applications **AI & Digital Workforce Leadership Officer** - leadership in leading employees using AI systems. -Understanding and controlling the digital process that captures,

Table 3 (*continued*)

Reference	Type of Methodology (Research Method)	Focus Area	Level of analysis/ Respondents' category	HR STARA roles and responsibilities
				process and measure employee behavioural data (Earlier comes under Technology/Digital Process Expert role) -Creating and validating digital twins/avatars in metaverse, employment history using blockchain and AI technologies
Vrontis *et al.* (2022)	Non-empirical	Themes around AI in HRM and how AI influences firm performance and HRM functions	Organizational	
Cluster 4: Digital adoption and Use of Information				
Muhammad et al. (2024)	Empirical	Factors influencing HR analytics adoption	Individual-level	**HR Technology advocate/ Influencer** - *Refer* Table 2 *for key responsibilities*
Ratnam et al. (2024)	Non-empirical	Outline reasons for non-adoption of HR analytics	Organizational-level	
Cluster 5: Application of M/C learning, and data mining techniques in HRM				
Yutian et al (2022)	Non-empirical	Data mining of huge employee data and business data for deriving insights into HR administrative tasks	Organizational-level	**AI-M/c learning-Big data literate** - Ability to apply AI and ML algorithms and derive insights to various HR functions. - Ensure that use of AI/ML aligns with labor laws and data protection regulations (e.g., GDPR, etc.). - Use AI chatbots and sentiment analysis tools to monitor employee morale. - Leverage AI/ML tools to analyze employee performance and engagement. - Use Big Data tools to analyze hiring trends, predict workforce needs, and identify skill gaps.
Mourad et al. (2022)	Empirical	Big data use in deriving insights from employees' performance data	Organizational-level	

("AI" AND "HR*") OR ("Artificial Intelligence" AND "Human resource management") OR ("Robotics" AND "HR*") OR ("Robotics" AND "Human resource management") OR ("RPA" AND "Human resource management") OR ("RPA" AND "HR*") OR ("Robotic Process Automation" AND "HR*") OR ("Robotic Process Automation" AND "Human Resource management")).

We identified 79 documents from 81 extracted from 2011-2024. Bibliographic coupling of these documents would help us a) understand the HR technology domains and validate the HR roles evolved around emerging technologies (Refer to Table 2 and Table 3) b) identifying the specific skills , competencies and capabilities against the HR roles mapped to the HR domains (Refer to Table 4).

To address RQ3, we need to identify domains of researchers working on specific HR skills and competencies in a fast-changing field (such as AI and algorithms), we applied bibliographic coupling technique using VosViewer with minimum 5 citations per document and using fractional counting method to visualize the clusters (Refer to Figure 4). According to Kesslar [56], two documents share one unit of coupling strength if they have one reference in common. Table 4 outlines a comprehensive detail of STARA competencies organized into HR domains and sub-domains, with clearly defined roles aligned to future-oriented HR functions.

< INSERT Fig. 4: **Clusters from bibliographic coupling** >

<INSERT Table 4: **HR STARA roles and competencies required to perform HRM specific tasks >**

5. Discussion

5.1. *Technology HR STARA roles and responsibilites evolved from 2011-2019*

Earlier research exploring the role of STARA in career decision-making (e.g., Gati and Kulcsar [57]; Bartosiak and Modlinski [58]) emphasizes the need for a more comprehensive understanding of STARA's effects on careers. This paper highlighted the critical STARA competencies of HR managers in the last decade (2011-2019) to systematically understand what STARA competencies may have influenced the career competencies of HR. From our analysis of research clusters, *Strategic Technology Integrator* and *Institutional Digital Capability Planner* are the most critical pillars of STARA competencies. The 2011-2019 period is crucial as many technological advancements were happening, and there was a growing need for HR managers to move one step ahead from the strategic business partner role to an integrator role. According to Wang *et al.* [59], technology assessment capabilities are highly sought after because of varied buy vs. built technology pricing. Therefore, digital HR managers must be equipped with skills to evaluate products built on smart technologies.

Hendrickson [60] and Galanaki [61] suggested that future HRs must facilitate the implementation of web-enabled HR functions that integrate multiple cross-domain functionalities of the organization, which require a strategic outlook toward technology integration. Moreover, the competence as an *Institutional Digital capability Planner* encompasses managerial planning and implementation of HR digital transformation [62]. As a change agent HR managers may assist in assessing
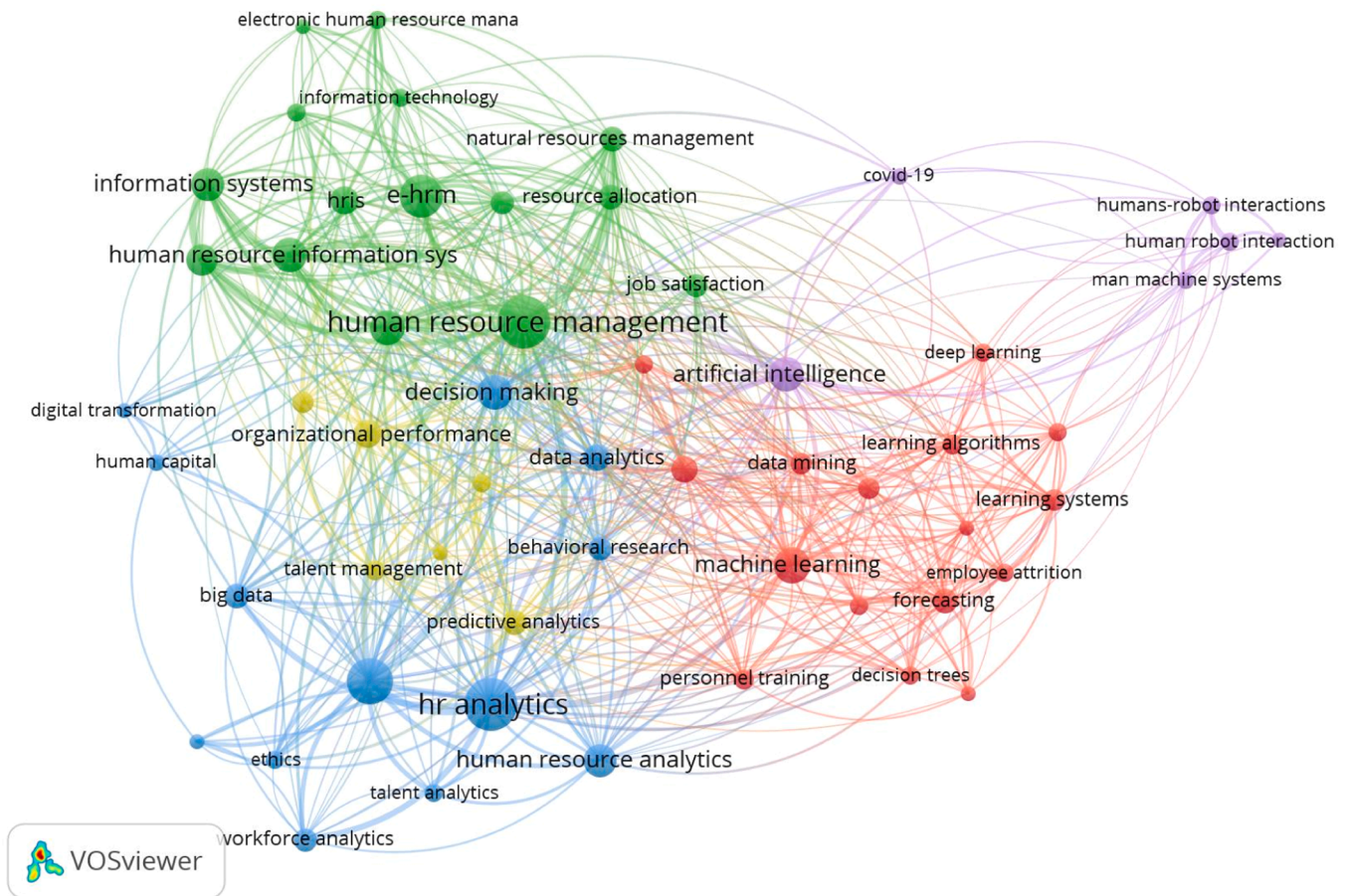
Figure 3. Keyword co-occurrence network clusters.

technological maturity in organizations and develop HRM procedures to leverage the benefits of intelligent technologies. The above-described STARA competencies are beneficial at the organizational level. *HR technology advocate/influencer* role engages top management to implement advanced e-HRM systems, foster stakeholder communication to reduce resistance towards HR analytics adoption, and promote HR analytics solutions (Refer to Table 2). Therefore, through a systematic analysis that involves co-citation analysis RQ 1 is addressed.

5.2. STARA roles and responsibilities evolved from 2020-2025

There is a paradigm shift in the modus operandi of firms after hitting by Covid-19. Almost every organization has promoted remote work as a new way of work execution. Research suggests that HRs underwent many changes in their work style, embracing the current technology trends without increasing cost [63]. More research is needed about the impact of IT-based technology on HRM after the COVID-19 period. Hence, our analysis of the research articles from 2020-2024 helps to find out the new STARA competencies that HR managers have adopted or are suggested to embrace shortly.

Ethical Technology Climate Curator, Behavioural and Business Data Analyst, and *AI-M/c learning data literate* are some of the unique HR technology roles we figured out from the analysis. As an ethical technology climate curator, HR managers must ensure that modern AI tools' algorithms are devoid of inherent biases. Such scrutiny is vital to uphold the principles of equity and fairness in organizations [64,65]. HRs have started relying on data collection using AI tools but must ensure a high degree of transparency, particularly in data collection processes about individuals. This transparency is crucial for building trust among users and stakeholders and a climate of reliability toward AI decision-making

processes [66]. Moreover, depending on the nature of the tasks, the ethical stakes involved, the need for transparency, and the level of trust required from the stakeholders, HR managers must be able to decide the appropriate touchpoints in the decision-making process where AI can act as an augment or an automation tool [7]. Text mining and machine learning techniques are widely used in HR processes such as e-recruitment (e.g., CV screening with AI, predictive analytics for job fit), employee engagement (e.g., sentiment analysis from employee feedback), talent management (e.g., career pathing using AI), and workforce analytics (e.g., turnover predictions). Pereira et al. [30] suggested that future manager capabilities must incorporate machine learning and AI-based algorithms for training employees and evaluating training effectiveness. As an *AI-M/C learning literate*, HR managers need to apply AI-MC learning algorithms in HR functions. HR managers must utilize chatbots, sentiment analysis, and predictive tools to monitor employee morale, assess performance and forecast workforce needs, In the role of *Behavioral and Business data analyst,* we suggest that a deep understanding of the employee-related psychological variables and their outcomes is necessary to extract data and develop varied behavior-employee outcome and organizational outcome frameworks/models. Therefore, through a systematic analysis that involves co-occurrence key words analysis RQ 2 is addressed.

5.3. STARA competencies for digital age

In Table 4, for each subdomain, specialized HR roles are proposed, such as the Strategic Technology Integrator, Ethical Technology Climate Curator, Behavioural and Business Data Analyst, and Strategic Human-Robot Integration Specialist. The table also emphasizes cross-cutting STARA competencies like future work skills, technology coaching, and

Table 4

HR STARA roles and competencies required to perform HRM specific tasks.

Themes in the intersection of HR technology and HR skills, and capabilities	Research	HR Area/function impacted due to advanced technological interventions	HR STARA Role	HR STARA competencies
Information Use via analytics, AI-driven applications	Tursunbayeva et al. (2023)	Job-design being affected by AI applications	Strategic Technology Integrator	Information management, AI-driven decision-making, Big Data management, digital emotional intelligence (Murawski & Bick, 2017) problem-solving (van Laar et al., 2017)
	Tursunbayeva et al. (2022)	Operationalizing bias in AI/Analytics-driven decision-making and data privacy and consent concern	Ethical Technology Climate curator	Ethics and responsibility, critical thinking, evaluating information, data security (Ferrari, 2012; Gonzalez-Vazquez et al., 2019), impart digital resilience, digital rights, effective oral and written communication (Sousa & Wilks, 2018; Oberländer et al., 2020)
	Li et al. (2021)	lack of trust in data accuracy and an inadequate level of control		
	Park et al. (2022)	The lack of transparency in algorithmic decision-making		
Digital HR transformation via implementing AI projects, efficient use of data, models, and computing	França et al. (2023)	Ways of talent assessment	AI-M/c learning data literate + Behavioural and business Data Analyst	Data literacy, information management, communication, digital content creation (OECD, 2018; Gonzalez-Vazquez et al., 2019) Data analysis, evaluation, problem-solving, AI-driven decision-making, digital emotional intelligence (Murawski & Bick, 2017; Ferrari, 2012) Understanding Human behaviour
	Murugesan et al. (2023)	Employee productivity, pay-roll, feedback, health and safety	Strategic Technology Integrator	
Future of work-Technology for competitive advantage	Santana et al. (2023)	Digital competencies required by modern workforce	Institutional Capability Planner + AI & Digital Workforce Leadership Officer + Technology Trainer and coach	Strategic workforce planning, adaptability, digital transformation leadership, AI integration, foresight thinking (OECD, 2018; Gonzalez-Vazquez et al., 2019) Technology coaching, mentoring, digital learning facilitation, change management (van Laar et al., 2017; Sousa & Wilks, 2018)
	Gaur (2020)	Advance tools to leverage people data by HR and leaders	AI-M/c learning data literate	Data literacy, information management, communication, digital content creation (OECD, 2018; Gonzalez-Vazquez et al., 2019)
Future of work - Technology for Employee well-being	Swain et al. (2020)	Social media and ubiquitous technologies to evaluate and enhance remote worker functioning	Strategic Technology Integrator + Ethical Technology Climate curator	
Green HR sustainability	Ogbeibu et al. (2022)	STARA competencies for employees to nurture green initiatives and reduce employee turnover	Technology Trainer and coach	Technology coaching, mentoring, digital learning facilitation, change management (van Laar et al., 2017; Sousa & Wilks, 2018)
	Ogbeibu et al. (2024)	STARA capability to support environmental sustainability through HRM programs	Institutional Capability Planner	Digital competencies to support sustainability, responsible technology use, ethics (Oberländer et al., 2020)
Human-Machine-Workplace Colaboration	Strich et al. (2021)	Employee Identity issues	Strategic Human-Robot Integration Specialist	AI collaboration, digital rights, virtual leadership, adaptability, problem-solving (Murawski & Bick, 2017; Sousa & Wilks, 2018)

Green HR, linking technological proficiency with sustainability and human-machine collaboration. Together, these domains and sub-domains provide a structured approach for HR professionals to develop the competencies needed to thrive in a STARA-influenced future of work.

Drawing from Santana's [67] framework on AI-era competencies, the STARA roles that emerged (e.g., Strategic Technology Integrator, Ethical Technology, and Climate Curator) are aligned with critical skills such as *AI-driven decision-making, digital emotional intelligence, data ethics*, and *communication*. In essence, the influence of AI on employee and organizational performance will be truly realized only when HRs possess the necessary digital competencies aligned with STARA roles. These capabilities ensure a strategic, ethical, and adaptive fit between AI integration and performance outcomes. This study tried to systematize and represent this critical relationship in the framework provided in Figure 5.

Therefore, RQ3 has been addressed.

<INSERT Fig. 5: Digital-HR domain, STARA role and competency framework >

5.4. Policy Implications

Policy implications are crucial for HR STARA roles to ensure ethical, legal, and strategic use of smart technologies. They provide guidelines for responsible AI adoption, protect employee rights, clarify role expectations, and foster trust. Clear policies also help mitigate risks, ensure compliance, and align technology with organizational HR goals.

- Institutionalize training in AI-driven decision-making, data analytics, digital emotional intelligence, and ethical tech use.
- Promote ethical technology climate curators as key HR roles to ensure employee data rights, consent, and digital well-being.
- Encourage the creation of strategic human-robot integration policies, outlining clear boundaries and responsibilities for humans and machines in the workplace.
- Redesign job roles and workflows to accommodate co-working with AI and robotics, ensuring employee identity and morale are preserved.
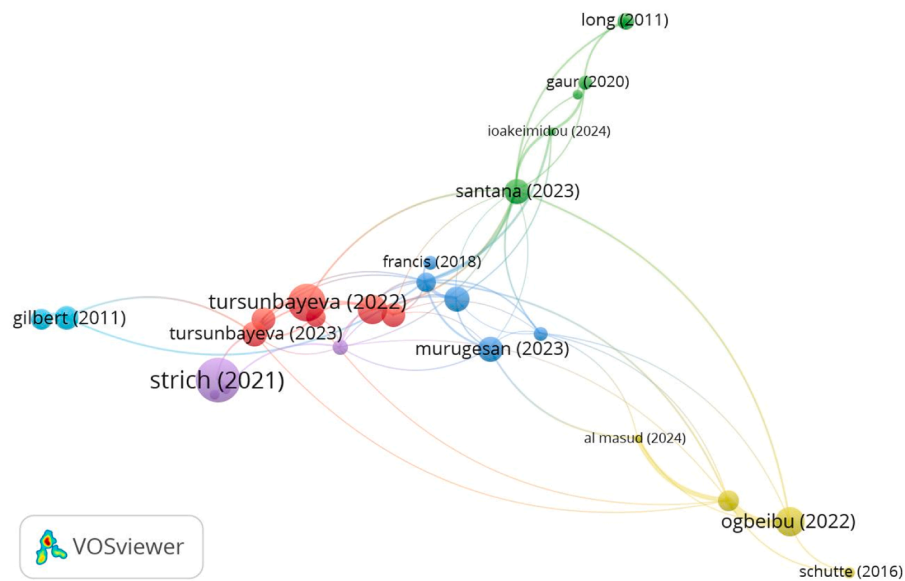
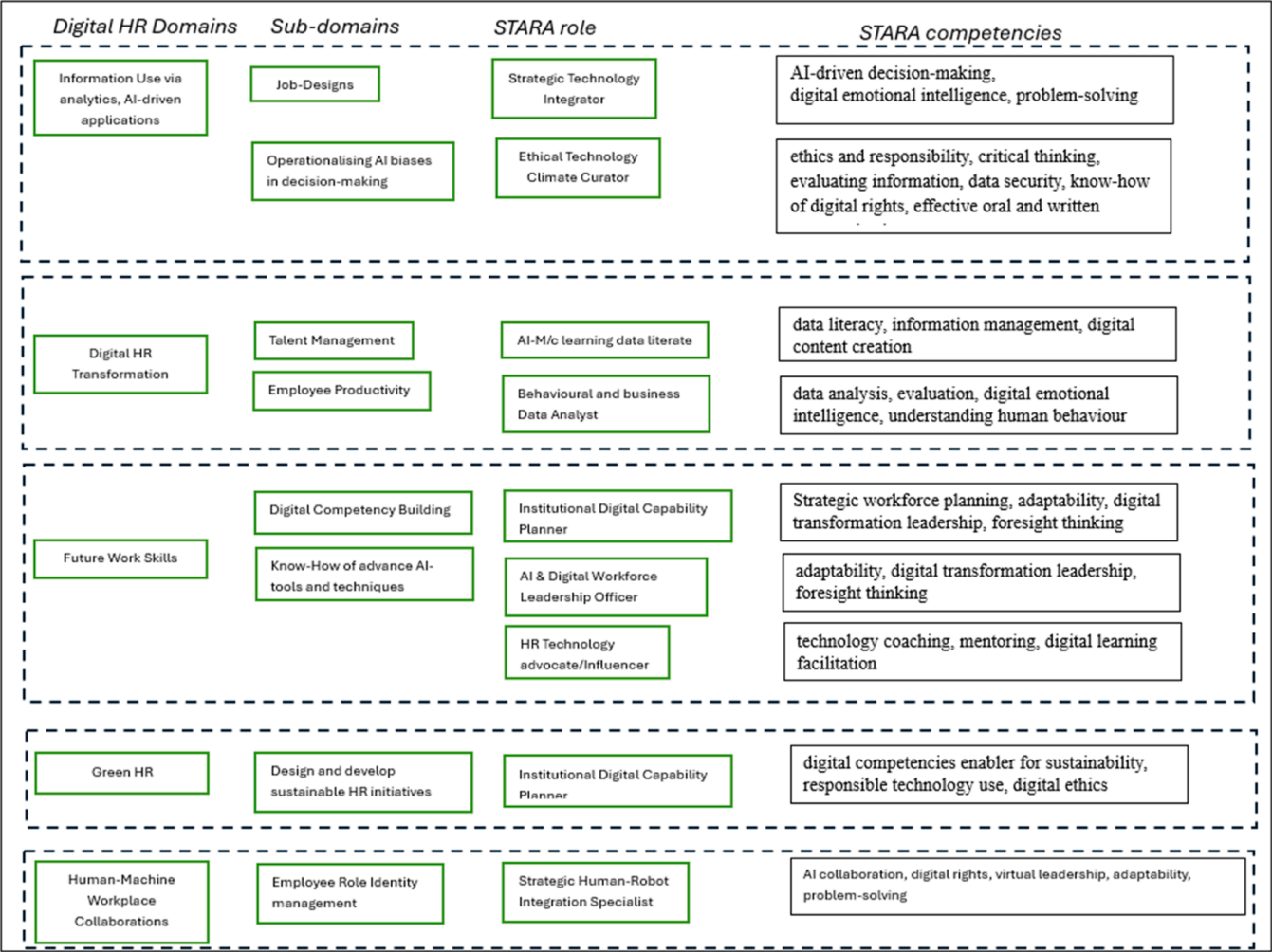**Figure 4.** Clusters from bibliographic coupling.

Figure 5. Digital-HR domain, STARA role and competency framework.

- Promote digital competencies that enable environmentally sustainable HRM practices.
- Include the role of Institutional Capability Planners in designing green policies using digital tools to reduce turnover and promote ethical responsibility.

6. Gaps and future directions of research in HR Technologies and HR STARA competencies

A review of technology-focused HRM research articles over the last 14 years categorizes significant gaps related to HR roles, responsibilities and competencies into the following categories.

HR responsibilities and competencies – from a career development perspective

HRs are not involved in IT-enabled HR system design from the start. HR professionals should be a part of the design process from the stage of digital strategy formulation [68]. A consistent gap in HR skillsets regarding IT capabilities and analytical skills (knowledge of advanced statistics, econometrics, and optimization techniques) exists. As technology integrators, modern HRs must understand emerging digital technologies that may assist digital business transformations. Moreover, a sense of technology that facilitates interactions between humans and machines must be considered a competence for HRs in the future [69]. Though this paper has identified core STARA competencies for HRs and tried to mitigate the role overlap to an extent through thematic analysis and content analysis of research papers, future researchers may examine "*how STARA competencies can be built as part of HR competency development*". Given that some STARA competencies can overlap or be entirely new across different technology HR roles, a looming research question to career researchers can be, " *How do HR career transitions across different HR technology roles affect the psychological well-being of HR managers* ?"

Lack of Empirical Validation of STARA Roles and Competencies

While roles like *Ethical Technology Climate Curator* or *Strategic Human-Robot Integration Specialist* are conceptually rich, there is limited empirical research validating their impact on organizational outcomes. There is a need for case studies or quantitative studies on how organizations are implementing these roles and what performance metrics they influence. Here are two research questions future HR tech researchers could explore based on the noted gap:

"*How do emerging STARA-based HR roles (e.g., Ethical Technology Climate Curator) influence organizational performance metrics such as employee engagement, innovation, and retention?*"

"*To what extent have organizations adopted STARA-defined HR roles, and what empirical evidence exists on their effectiveness in managing human-machine collaboration and ethical technology use?*"

Overlap and Ambiguity in Role Definitions

There's role redundancy (e.g., *Institutional Capability Planner* may appear under multiple domains), which may cause confusion in role allocation and training. Development of a clear taxonomy and framework for STARA role is sought after that distinguishes unique competencies and responsibilities.

Underexplored Soft Skills in AI Contexts

Though soft skills such as *digital emotional intelligence* and *communication* are listed, their adaptation in AI-driven environments isn't clearly addressed. Future research can investigate how traditional soft skills evolve or transform in human-AI collaborative workplaces.

Ethical and Psychological Dimensions of STARA Roles

Though the *Ethical Technology Climate Curator* role hints at moral and psychological considerations, there's an insufficient exploration of employee well-being in algorithm-driven environments. Future studies may integrate psychology, ethics, and technology to develop holistic guidelines for such roles. HR-tech researchers could pursue based on the ethical and psychological dimensions of STARA roles based on the following RQs.

"*How do algorithm-driven HR practices impact employee psychological*

well-being, trust, and perceptions of fairness in the workplace?*"

"*What ethical frameworks and psychological principles can guide the role of HR professionals (e.g., Ethical Technology Climate Curator) in promoting responsible AI use and employee digital well-being*?"

6.1. Practical and theoretical Implications of HR STARA

The career capital theoretical framework provides a valuable framework to understand the career transitions within the different roles of a technology HR, Role transitions can be challenging and stressful for individuals. Our paper has tried to sensitize the HR technology career transitions adhering to the career capital framework. It is implied that to address the "Knowing Why", "Knowing How", and "Knowing Whom" of the career capital framework, different research themes rooted in the literature of HR technology have to be unearthed. The process through which we have identified research themes (2011-2019), and current and future research avenues (2020-2024) is unique, and to an extent, the coding process in deductive content analysis (Table 2 and Table 3) has helped to address the three knowings of the career capital framework.

The "Knowing Why" emphasizing task purpose can be identified from our research themes. For example, *the Strategic Technology Integrator and the Ethical Technology Climate curator role is aligned with the research cluster Digital HR transformation- A strategic perspective with ethical concerns (Refer* Table 3). The "Knowing how" part is addressed from the key responsibilities defined under each role (Refer to Table 2 and Table 3) that may help future career researchers curate HR technology career progression or career transition plans. To an extent, the scope of each highly cited paper (e.g., Levels of Analysis) under research themes and avenues may help future researchers to define the purview, boundary, and context addressing the "Knowing Whom" part of the career capital framework. For example, research suggests that in *AI & Digital Workforce Leadership Officer* role where change leadership for leading employees and AI systems is concerned, its scope cuts across individual, team, and organizational levels [70].

7. Conclusion and Limitations

The present review maps the evolution of HR technology and informs practitioners and managers of several theory-practice gaps in the highly complex domain of IT-HR. The study also attempts to understand the strategic positioning of smart technology-driven HRM systems and future technological avenues in modern organizations. Organizations must transform digitally to survive in today's business landscape. The implications of the RQs are as follows:

- RQ1 implies that the HR managers' STARA roles are meant to integrate advanced technologies across HR functions, champion digital adoption, align stakeholders, and ensure organizational readiness for continuous transformation, innovation, and strategic workforce development.
- RQ2 addresses HR managers' new roles and competencies which are demanded beyond a business partner role focusing on managing and implementing HR digital transformation. However, with the integration of big data, AI, blockchain, and robotic process automation, several new roles (e.g., Strategic Human-Robot Integration Specialist, AI-M/c learning-Big data literate) have emerged that reflect the strategic, ethical, and technical challenges of the STARA age.
- RQ 3 addresses the HR managers' new digital age competencies. With the evolution of HR systems under STARA, HR managers' competencies have expanded beyond traditional skills. New competencies include AI-driven decision-making, data ethics, digital emotional intelligence, virtual leadership, technology coaching, and strategic adaptability, enabling them to lead digital transformation, manage ethical AI use, and foster human-machine collaboration effectively.

The recent studies highlight a significant gap, emphasizing the necessity for deeper investigation into the managerial skills needed to integrate smart technologies for consistent performance across individual, team, and organizational levels. This present paper indicates that HR managers need to adopt multiple roles and diverse STARA competencies throughout the organization to maintain effectiveness. The decade from 2011 to 2019 was pivotal, marked by technological advancements and an increasing demand for HR managers to evolve beyond traditional strategic business partners.

One of the limitations of the paper is that it soley relies on Scopus database for article extraction. The documents recorded in Scopus may not be exhaustive. Ignoring databases like Web of Science or Google Scholar, may lead to a potential skewed impact on clustering and h-index calculations. Moreover, the STARA roles and competencies unearthed from bibliometric analysis need to be validated based on qualitative, case studies or quantitative studies.

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Vinit Ghosh: Software, Writing – original draft, Methodology, Data curation, Formal analysis, Conceptualization. **Gaurav Kabra:** Methodology, Supervision, Writing – review & editing.

Declaration of competing interest

The Author(s) declare(s) that there is no conflict of interest.

Data availability

Data will be made available on request.

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