

Mapping the Intellectual Evolution of AI-Readiness of Employees: A Bibliometric Analysis of Employee Well-Being and Employee Transformation

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Abstract

The rapid rise of artificial intelligence (AI) in organisations has stimulated debate about people's and entities' readiness to embrace and exploit this disruptive technology. However, bibliometric analyses of the literature on AI in relation to employee outcomes have not been produced. The current bibliometric study aimed to map out this field of research using the PRISMA 2020 declaration and analysed 212 eligible Scopus-indexed journal papers and reviews published between 2020 and 2026 using VOSviewer (version 1.6.20). Various analysis were performed, namely, citation, co-authorship, bibliographic coupling, co-citation, and keyword co-occurrence analyses. The results demonstrate that research on AI's effect on employees has proliferated exponentially after 2024, with the majority of papers producing highly skewed citation distributions, a prevalence of single authorship over international and interdisciplinary collaboration, and the emergence of five clusters: AI adoption and organizational digital transformation, organizational behavior and human capital management, employment, sector-specific AI impact, digital readiness, and employee well-being and ethics. Additionally, the co-citation analysis identified four integrative domains that underpin the current body of research on AI and employees: methodological literature on strategic management, AI-enabled human resource management, occupational stress and well-being literature, and technology acceptance and future-of-work economics. Our findings provide a conceptual groundwork for future empirical studies and a conceptual framework for organisational interventions for managerial psychologists, human capital development professionals, and organisational change agents.

Keywords: Artificial Intelligence; AI-Readiness; AI-Adoption; Employee Well-being, Employee Transformation; Bibliometric Analysis; VOSviewer, Scopus

1. Introduction:

The rapid rise of artificial intelligence (AI) in various fields has transformed work

design, performance, and experience, challenging organizations to constantly adapt their personnel to the emerging AI reality. Such adaptation capacity is determined by AI readiness, defined as the level of infrastructure, competencies, and attitudes that enable an organization or individual to embrace AI technologies (Jöhnk et al., 2021; Tehrani et al., 2024). Unlike AI adoption, which has been extensively explored with a focus on predicting acceptance and use behavior through technological acceptance models (Davis, 1989; Venkatesh et al., 2003), studies on AI readiness investigate the individual- and organizational-level antecedents and outcomes of readiness to pursue AI initiatives (Tehrani et al., 2024).

Although there is accumulating evidence on the impact of AI readiness on employee satisfaction, engagement, burnout, well-being, and career prospects, there is no comprehensive understanding of this topic. Bibliometric reviews have not yet been conducted to identify bibliographic trends, thematic clusters, influential authors, and research foci in the area of AI readiness and its impact on employee well-being and transformation. Most prior reviews either included AI adoption readiness as one of the dimensions of technology acceptance or focused on the outcomes of AI adoption at the employee level. Therefore, the goals of this bibliometric analysis include assessing the development of the topic, identifying research foci and influential publications using Scopus indexes and VOSviewer software, and exploring research trends in AI readiness and its relationship with employees' well-being and transformation.

This study employs bibliometric analysis, a method that allows for the collection, storage, analysis, and visualization of data on scientific publications, citations, collaborations, and other bibliographic items (Donthu et al., 2021; van Eck & Waltman, 2023). Bibliometric analysis can help identify thematic areas, research trends, influential authors, and journal impact, providing an opportunity to quantitatively evaluate the development of a chosen topic. Given this background, this study conducts a systematic bibliometric analysis of the existing literature on the nexus of AI readiness and employee well-being/workforce development in organizational contexts.

Given the background provided above, the current bibliometric study aimed to review published literature on AI readiness and employee well-being/development with regard to five research questions. First, the current study sought to identify trends in terms of publication growth over time, which would enable an appraisal of the development of this field of research (RQ1). Second, the study focused on determining the authors, countries, organizations/institutions, and journals that have made the most significant contributions to the field (RQ2). Third, the current bibliometric study intended to unveil the prevailing thematic clusters in the literature and their chronological development (RQ3). Fourth, the study aimed to identify the field's intellectual structure, which would be achieved by revealing its foundational works, as well as the emerging frontier topics currently influencing its development (RQ4). Lastly, the current research aimed to determine the research gaps that could be

considered for future studies based on the findings of the previous analyses (RQ5). In general, the five research questions provide a comprehensive basis for understanding the intellectual, conceptual, and social structure of research on AI readiness and employee well-being/development.

The contributions of this study to the literature include (1) providing the first systematic bibliometric mapping of AI readiness concerning employee well-being and workforce development, which delineates its intellectual boundary from the general body of AI adoption literature; (2) identifying prominent and evolving thematic clusters that can inform scholars about the directionality of research on AI readiness; and (3) presenting a comprehensive evidence base for practitioners and policymakers on studying AI readiness in terms of employee outcomes that can support better-informed workforce transformation strategies.

2. Literature Review

2.1. AI Readiness Versus AI Adoption

AI readiness and adoption are two different concepts that exist at various levels of analysis, measurement, and implementation. AI readiness is traditionally considered and analyzed at the organizational or team level, with an emphasis on data, leadership, and culture, while individual factors such as digital literacy or self-efficacy are incorporated into these variables (Tehrani et al., 2024). In turn, the concept of AI adoption focuses on individual behavioral intention to adopt, which is traditionally measured using items and scales from the Technology Acceptance Model (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003). Readiness is typically measured as multidimensional maturity or composite measure, which is determined by an array of indicators, while adoption is an outcome, which is associated with subsequent benefits (Chowdhury et al., 2023; Höyng & Lau, 2023)

2.2. AI Readiness, Employee Well-being, and Mechanisms of Effect

Empirical studies have shown that AI integration poses both risks and opportunities for employee well-being. The increased use of AI has led to higher levels of stress, anxiety, and burnout, as well as perceived threats to job security (Ali et al., 2024; ALOqaily et al., 2025; Rizkina et al., 2025). However, self-efficacy and psychological safety buffer the negative impact of AI adoption on employees' mental health (Kim & Lee, 2024; Alawiye et al., 2025). Simultaneously, successful AI adoption through proper training, consultation, worker participation, and organizational support can improve employees' well-being and satisfaction with their jobs if they view the technology as an opportunity rather than a threat (Höyng & Lau, 2023; Xu et al., 2023). Consultation and role redesign, together with workers' perceptions of organizational support, significantly impact their attitudes toward AI (Chowdhury et al., 2023; Jailani et al., 2025; Nadeem et al., 2025)

2.3. Employee Transformation and Organisational Readiness

Employee transformation is the adjustment and adaptation process of employees' cognitive, emotional, and behavioral levels to effectively coexist with AI, including digital literacy, resilience, and upskilling/reskilling (Höyng & Lau, 2023; Mutsuddi & Bali, 2024; Ekuma, 2024). The concept of "AI socialisation," which refers to introducing employees to AI tools and expectations, has been demonstrated to foster trust and collective human-AI intelligence (Chowdhury et al., 2023). In terms of readiness, assessment models focus on technology, leadership, culture, and processes at the organizational level (Sheriffdeen, 2026). Transformational leadership, ethical and inclusive management styles, and effective change communication were found to be critical success factors that reduced employee resistance to change (Aprianto et al., 2025; Siswadhi et al., 2025).

2.4 Barriers and Strategic Practice

The main barriers to the adoption of AI in organizations are fear of job loss and skills obsolescence, privacy and algorithmic bias concerns, and insufficient organizational readiness (Chowdhury et al., 2023; Lee et al., 2023). The emotional toll of automation anxiety on employees is significant, with studies reporting dehumanization and technostress as critical costs, particularly in service and hospitality settings (Chen et al., 2025; Song et al., 2025; Zhang et al., 2025). The reviewed articles suggest conducting readiness assessments before implementation, emphasizing human-centric and participatory approaches, ensuring transparency, and maintaining continuous feedback loops to support employees throughout the transition (Chowdhury et al., 2023; Alawiye et al., 2025; Aprianto et al., 2025).

3. Methodology:

3.1. Database Selection:

In this study, Scopus (Elsevier) was selected as the bibliometric database. As an internationally recognised database, Scopus is the biggest abstract and citation database available. The Scopus database has insurance from peer reviews and includes information regarding 25,000 journals in fields such as technology, social sciences, humanities, and medicine (Mongeon & Paul-Hus, 2016). Scopus is often used as a leading bibliometric database for a wide range of studies related to business, management, and human resource management, providing a high degree of methodological reliability in line with existing studies and comparable for future replication studies (Donthu et al., 2021).

3.2. Search Strategy and Screening

A TITLE-ABS-KEY search combining AI readiness-related terms ("AI readiness," "AI maturity," "AI adoption," "digital readiness") with employee-related constructs ("job satisfaction," "burnout," "upskilling," "reskilling," "career development") was conducted in Business, Computer Science, Social Sciences, Decision Sciences, Psychology, journals, reviews only, English language, 2020–2026, excluding education sector documents at title level (search completed on July 30, 2026). Table 1 and Figure 1 indicate the search strategy, while the complete Boolean search string is provided in

the supplementary files.

Component	Description
Database	Scopus
Search Date	30 July 2026
Search Field	TITLE-ABS-KEY
Study Period	2020–2026
Language	English
Document Types	Journal Articles and Review Articles
Source Type	Journals
Subject Areas	Business, Management and Accounting; Computer Science; Social Sciences; Decision Sciences; Psychology
Bibliometric Software	VOSviewer Version 1.6.20
Export Format	CSV
Initial Records Retrieved	264
Final Records Included	212

Table 1. Search Strategy Used for Literature Retrieval

Note: Data were retrieved from the Scopus database on July 30, 2026, and exported in CSV format for bibliometric analysis using VOSviewer Version 1.6.20.

3.3. Inclusion and Exclusion criteria:

Inclusion criteria: We included papers that focused on AI readiness, AI maturity, AI acceptance, digital readiness, or AI adoption in organisational/workplace contexts and examined at least one employee well-being outcome (job satisfaction, engagement, burnout, etc.) or workforce development outcome (upskilling, reskilling, career development). We were also limited to English-language journal articles and reviews.

Exclusion criteria: Studies focusing on AI readiness/adoption from a consumer/patient/student/citizen perspective, which referred to ‘well-being’ or

‘development’ constructs in passing; those taking place in the context of an educational institution; those considered conference papers/editorial/note; and those that were duplicates.

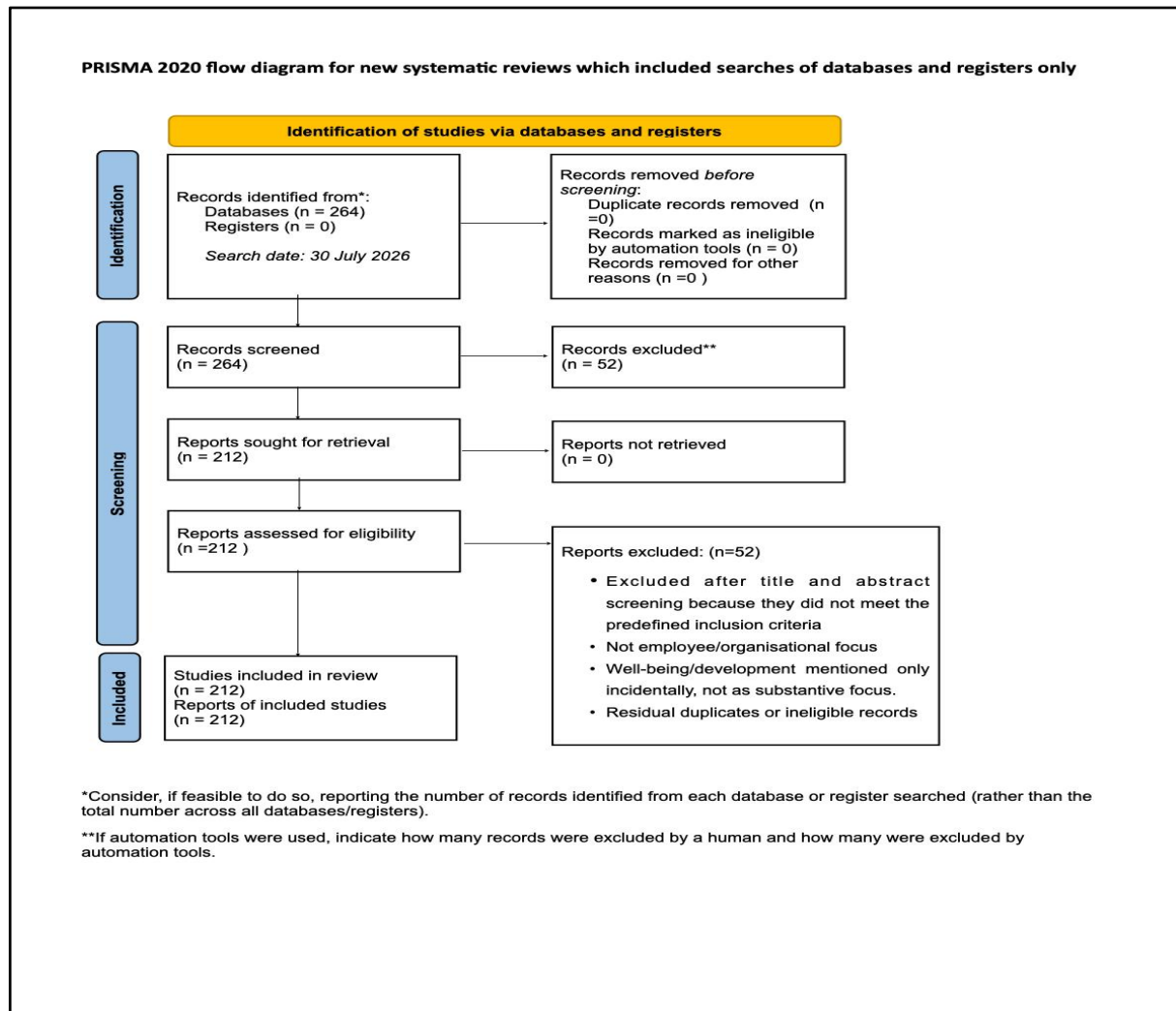


Figure 1. PRISMA 2020 flow diagram documenting article identification, screening, and eligibility. Source: Scopus (July 30, 2026); PRISMA 2020 (Page et al., 2021).

3.4. Data Cleaning and Preparation

The records were exported from the Scopus Discovery system to CSV format and prepared for visualization in VOSviewer 1.6.20 by creating a thesaurus file that integrated the data fields for synonyms, abbreviations, plural forms, and other variants. For instance, the terms AI and artificial intelligence were combined, as were employee well-being, AI adoption, digital readiness, and transformation. Generic indexing terms that did not specify conceptual themes were deleted. The data cleaning process allowed us to obtain a comprehensive list of terms for further network visualization and thematic analysis. After data cleaning, 212 records were obtained and used for the

bibliometric analysis.

3.5. Bibliometric Techniques:

Both approaches to the bibliometric analysis of performance and science-mapping methodologies were applied. Citation analysis was used to determine the influential publications and authors. Co-authorship analysis was used to determine the collaborative trends between authors, organizations, and countries. Bibliographic coupling was used to identify contemporary research topics based on common reference. Co-citation analysis was used to determine the intellectual and foundational structure of the field, and keyword co-occurrence analysis was used to identify dominant and emerging topics.

4. Results:

4.1. Publication and Citation Trends

The final corpus consisted of 212 Scopus-indexed journal and review articles published in English. Most articles were published in 2024, suggesting that the field of AI-readiness is both emerging and growing. Bibliographic coupling in this study was not evenly distributed, as only a small portion of the publications had a strong influence on the rest of the corpus, while the majority had only a few citations. Indeed, Cubric's (2020) article, which appeared to be the most cited one with 373 citations, had only weak bibliographic coupling with the rest of the corpus. Therefore, it can be concluded that the impact of individual publications on bibliographic coupling is limited, with most linked publications not being related to each other beyond a few shared references.

The bibliographic coupling analysis also identified emerging trends in research on AI-readiness. Indeed, there were 75 (35%) publications that had no citations but had bibliographic links with other similar papers. These publications were primarily published in 2025 or 2026; therefore, their impact on the bibliographic coupling appears to be largely underestimated owing to their recent publication date.

4.2. Citation and Productivity Patterns

The majority of citations in the field are power-law distributed: the eight most-cited documents (Table 2) account for over a third of all citations (1,340), while the remaining 212 documents and 300+ authors have substantially fewer citations. Most authors have one document each, so the field has a dispersed authorship profile, lacking a defined set of canonical works or researchers.

Rank	Document	Citations
1	Cubric (2020)	373

2	Braganza et al. (2021)	358
3	Yin (2024)	224
4	El Hajj (2023)	113
5	Fenwick (2024)	111
6	Iaia (2024)	95
7	Rožman (2023)	88
8	Murire (2024)	87
9	Kim (2024)	85
10	Rawashdeh (2025)	66

Table 2. Most highly cited documents in the reviewed corpus

Geographically, the United Kingdom ranked first in terms of total citations, with 996 citations from 20 documents. In terms of quantity, China (24) and India (26) are the leaders, although their impact is relatively low compared with the number of documents. Thus, Turkey and Lebanon have an unusually high number of citations per document. The journals with the highest number of citations were the *Journal of Business Research* (415), *Technology in Society* (389), and *Computers in Human Behavior* (287). This result highlights researchers' tendency to focus on the intersection of technology and organizational managerial fields. Only three organizations met the threshold for further extraction, which may indicate either a lack of data about institutions or non-existent trends.

4.3. Collaboration Patterns

The list of authors and countries with at least one co-author, according to VOSviewer's minimum threshold, has 11 out of 300+ authors and 15 out of 47 countries. Overall, there was little collaborative research reflected in the study. China (13) and the UK (11) have the highest number of links, with others forming a large cluster. These two countries, along with others, form a chain of collaborators. Most articles were written by authors from different countries who did not collaborate.

4.4 Bibliographic Coupling

The number of links between documents per sample ranged between 0 and 366 ($M \approx 62$), and the relation between the number of citations and link strength was almost zero ($r = .09$). This indicates that papers' impact in terms of citations is largely independent of its level of connection to other documents in terms of keywords. Thus, Cubric's (2020) paper, which appears to be the most cited, has a link strength of 6, meaning that it is rather isolated in terms of thematic similarity from other documents. However, a significant number of papers published recently (2025–2026) have not yet

been cited but are linked together and to other papers with the highest frequencies (Braganza, 2021; Kim et al., 2024; Lin et al., 2024; Yin et al., 2024). Therefore, links can help identify a potential research front that has just begun to emerge.

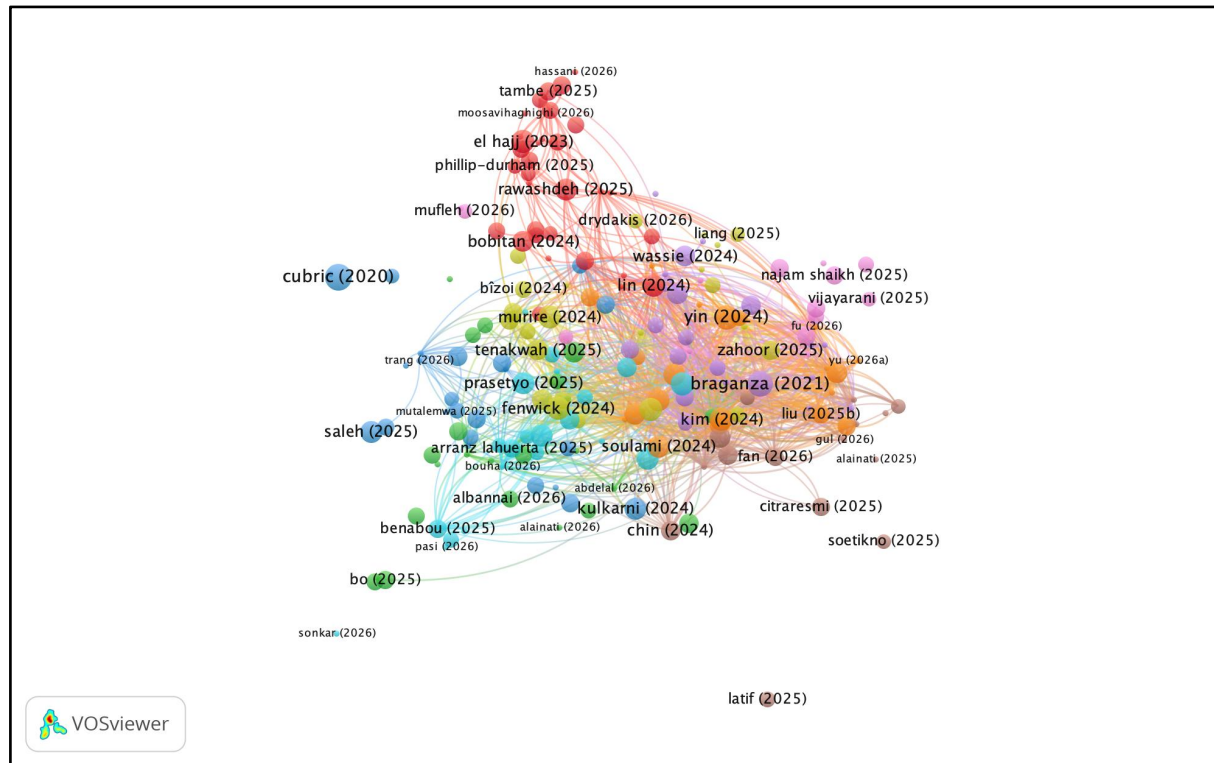


Figure 2. VOSviewer bibliographic coupling map of the reviewed documents, sized by citation count and positioned by coupling strength.

Document	Citations	Total Strength	Link
Jung (2026)	2	366	
Kim (2024)	85	277	
Yu (2026b)	0	272	
Valtonen (2025)	57	265	
Kim (2025)	22	259	
Chuang (2025)	82	243	
Jeong (2026)	2	231	
Zhou (2024)	28	227	
Ahmed Zahrani (2026)	1	219	

Mohamud (2025)	0	200
Arboh (2025)	29	198
Liu (2025b)	14	194
Ghorbanzadeh (2026)	0	183
Hu (2026)	0	174
Lin (2024)	63	171

Table 3. Fifteen documents had the highest total link strength in the bibliographic coupling analysis.

4.5. Keyword Co-occurrence and Thematic Structure

After thesaurus harmonisation, 53 keywords were retained, with “artificial intelligence” dominating the list (“artificial intelligence,” 128), followed by AI adoption (“adoption,” 25), human resource management (“management,” 21), and digital transformation (“digital,” 21). The concept of employee well-being (“well-being,” 14) emerged from combining similar terms (Table 6). The network analysis revealed five clusters, with the first spanning AI adoption, technology adoption, and digital transformation research areas connected to generative AI, governance, and sustainability. Organizational behavior and human capital management constitute the second cluster, with the terms “workplace,” “personnel,” “training,” and “leadership.” Employment and specific sectors (“job,” “satisfaction,” “insecurity,” and “burnout”) comprise the third category. The fourth cluster encompasses digital readiness and systematic review methodology, while the fifth contains the latest findings on employee well-being and ethics. Overall, the study identified employee well-being and human- and workplace-related research areas as the least developed. The temporal overlay analysis demonstrated that research articles used the terms “interpretive structural modelling,” “project management,” and “systematic review” which were published around 2024.8 on average, as older layers. In contrast, the newer layer integrated the concepts of decision-making, sustainability, generative AI, and AI adoption, with an average publication year of 2025.8. Thus, the concepts of well-being, humans, and the workplace were located in the middle layer.

Keyword	Occurrences
Artificial intelligence	128
AI adoption	25
Human resource management	21
Digital transformation	21
Employee well-being	14

Employment	13
Employee engagement	13
Job satisfaction	11
Technology adoption	11
Generative AI	10

Table 4. 10 Most frequent keywords (post-thesaurus harmonisation)

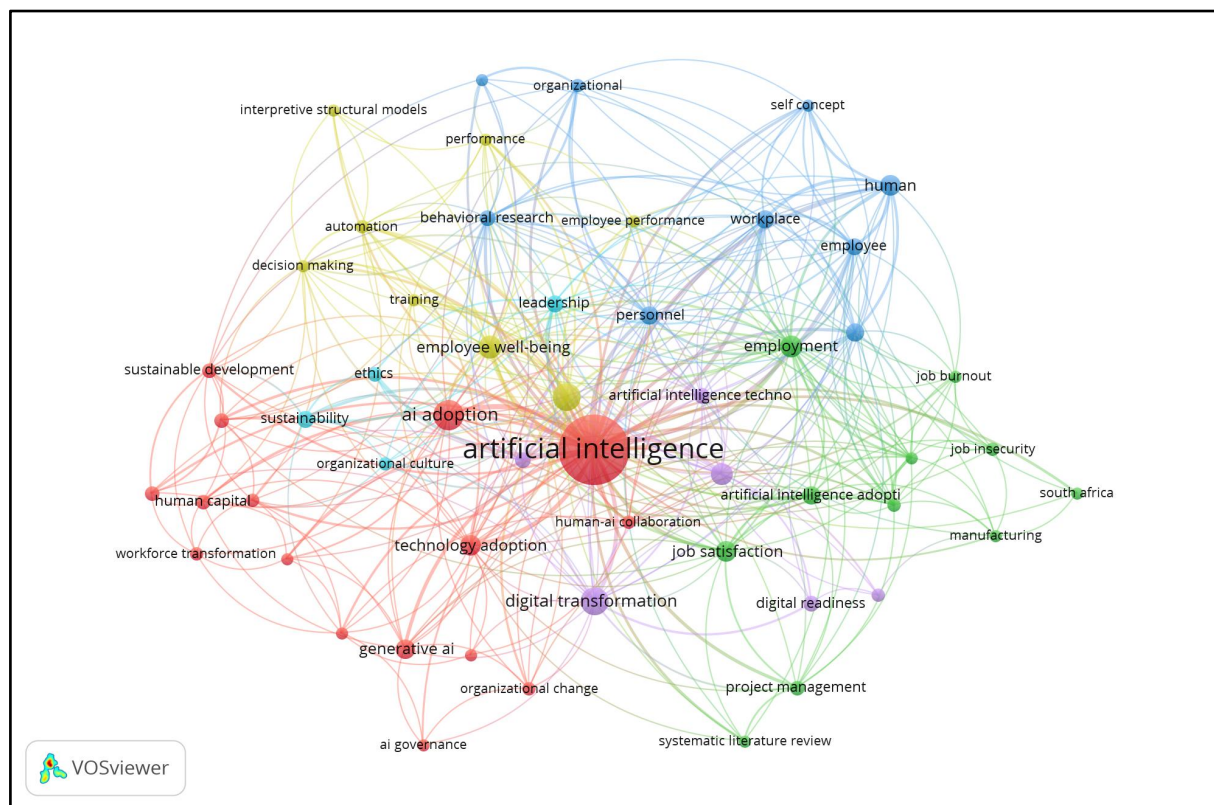


Figure 3. Keyword co-occurrence network (post-thesaurus harmonisation)

4.6. Co-citation Analysis: Intellectual Structure

Co-citation analysis revealed four intellectual fields that formed the basis of this study (Table 7). The first field comprised methodological and strategic management literature (PLS-SEM validity, general strategy theory). The second field is the literature on AI-informed human resource management. The other two fields consisted of studies on employees' well-being and occupational stress, which were related to automation theory and stress process theories (Krakowski et al., 2021; Schaufeli et al., 2001). The latter field appeared to be the largest, merging employee-related literature with strategic management, and was connected to other fields by these two studies. Another field was formed by the literature on technology acceptance theory and future

of work economics (Davis, 1989; Frey & Osborne, 2017). It was noted that no field had a foundational document, as the two most cited documents (Cubric, 2020; Braganza et al., 2021) were found to have only a minor connection with the other documents.

Cited reference	Total strength	link
Vrontis et al. (2022) — A systematic literature review on the impact of AI on workplace outcomes	103	
Fornell & Larcker (1981) — Evaluating structural equation models with unobservable variables and measurement error	91	
Krakowski et al. (2021) — Artificial intelligence and management: the automation–augmentation paradox	86	
Woo et al. (2024) — A multilevel review of AI in organisations	80	
Islam et al. (2023) — Worker and workplace AI coexistence: emerging themes and research agenda	79	
Wang et al. (2021) — Influences of AI awareness on career competency and job burnout	78	
Rust & Huang (2018) — Artificial intelligence in service	77	
Sarstedt et al. (2015) — A new criterion for assessing discriminant validity in PLS-SEM	77	
Truong (2023) — Unlocking the value of AI in HRM through an AI capability framework	76	
Kong et al. (2023) — Challenge or hindrance? How AI adoption influences employee job crafting	73	

Table 5. 10 Most Co-cited References

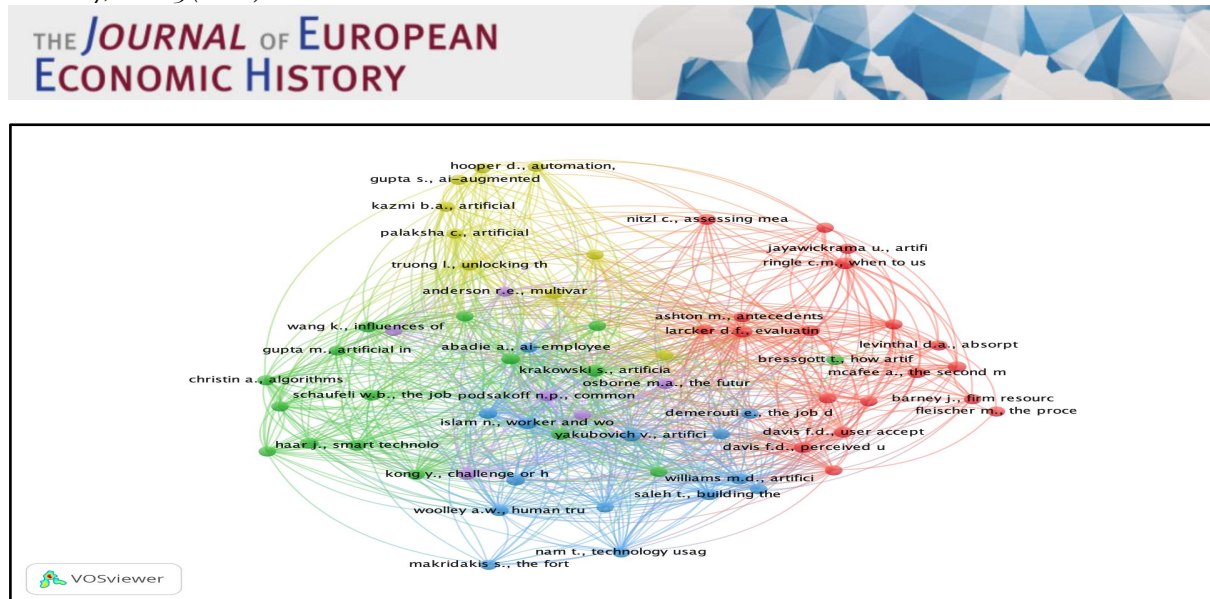


Figure 4. Co-citation network (cited references)

5. Discussion

Concerning the research questions posed at the beginning of the study, the following conclusions can be drawn. First, in terms of research trends (RQ₁), the area appears to be nascent and growing rapidly, with most of the literature produced in the last two years. Second, the distribution of citations and collaborations (RQ₂) indicates that several papers and country pairs dominate the field, while most authors and countries have a low number of collaborations. Third, the thematic areas uncovered by the study (RQ₃) reveal that while adoption/digitalization dominates the discussion, employee well-being/ethics emerges as the key theme, which paradoxically has received limited attention in the previous studies. Fourth, the co-citation analysis (RQ₄) highlights the interdisciplinary nature of research on artificial intelligence readiness with strategic management, human resource management, and organisational behaviour, but without a foundational work or journal. Fifth, the study establishes that although the term AI readiness encompasses both AI adoption/digitalization and AI preparedness, the latter remains poorly articulated and operationalized in extant research (RQ₅).

From this, it follows that subsequent studies should focus on exploring the theoretical foundations and practical implications of employee well-being and ethics as a pre-condition for realising the capabilities of AI. The present study also indicates that international cooperation is needed in this emerging field, as most collaborations tend to be domestic, with few multinational partnerships dominating the literature. Finally, future studies should further differentiate among concepts such as AI readiness, AI adoption, and organisational change, as the former appears to be understudied and imprecisely defined across articles.

6. Conclusion

The present research provides an initial bibliometric mapping of the literature on AI readiness, understood as the relationship between artificial intelligence and employees' well-being and transformation. The study analysed 212 Scopus-indexed articles retrieved from the database using VOSviewer software. The results of the processing

visualized on graphs demonstrate that the area is understudied since most of the articles were published within the last two years, only a few papers have high centrality and impact, and collaboration between authors, organizations, and countries is limited. In total, there are five themes and four areas of knowledge on AI readiness, with several seminal reviews and papers. The results highlight the difference between AI adoption and AI readiness, with the latter concept being a process of human-centered preparation for change, which is far from being well-defined.

The findings of the current study contribute to the literature in two aspects. First, the analysis provides evidence for further academic research into the role of AI readiness, which can lead to the development of a comprehensive theoretical framework. Second, the bibliometric results can be useful for practitioners, policymakers, and researchers to understand the significance of employees' readiness to work with artificial intelligence. Like any bibliometric study, the current research is limited by the availability of sources and the choices made during the database screening, so future studies should consider including articles from other databases and written in different languages.

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