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Artificial intelligence and organizational agility: An analysis of scientific production and future trends

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ABSTRACT

The advancement of Artificial Intelligence (AI) is progressing rapidly, compelling companies to integrate it within their operational frameworks to sustain competitiveness, primarily driven by its impact on organizational agility (OA). Nevertheless, the absence of a robust theoretical framework underscores the limited understanding of the relationship between AI and OA. Within this context, the research aims to establish foundational knowledge, delineate the evolutionary trajectory of the topic, and identify prospective avenues for inquiry. To achieve this objective, bibliometric analysis is employed to gain comprehensive insights into the interplay between these variables and discern trends within this research domain. The utilization of the Web of Science (WoS) and Scopus databases up to January 2024 facilitates data collection, while Bibliometrix and Visme are instrumental in crafting a scientific production map. The analysis corroborates the novelty and growth potential of the subject matter, underscoring heightened author interest, particularly evident in 2023, against a backdrop of sparse and temporally dispersed publications until 2017. Notably, the prevalence of conference papers on this topic stands significantly high at 26.98 % in comparison to the total contributions, indicative of the research community's engagement. Furthermore, the findings underscore a robust association between the keywords AI and OA, delineating a burgeoning research domain that converges with the digital transformation of enterprises and the Theory of Standardization Process. The effective integration of AI into corporate operational frameworks marks the zenith of this transformative process, ushering in the genesis and overhaul of organizational routines. This study represents a pioneering endeavour within the literature, as it constitutes the inaugural bibliometric exploration of this subject matter. Moreover, it serves to underpin the establishment of theoretical underpinnings for future research endeavours as it outlines current trends and emerging future research trajectories, concerning the role of AI in OA.

1. Introduction

In the contemporary landscape, the advent of new digital technologies is driving the digital transformation within traditional businesses, ushering in the emergence of novel business models (Cheng and Wang, 2022). Among these technologies, Artificial Intelligence (AI) has engendered a veritable revolution, profoundly altering the process of value creation in modern enterprises spanning diverse industrial sectors (Klos et al., 2023; Leone et al., 2021), thereby contributing to the culmination of the digital transformation process (Gong and Ribiere, 2021). However, as noted by Davenport et al. (2018), AI diverges from conventional technologies, often operating autonomously (Terzopoulos and Satratzemi, 2019), thereby presenting a new challenge for companies seeking integration and researchers lacking a cohesive theoretical framework to analyse its disruptive role in the business sphere.

The Covid-19 pandemic has not only accelerated the digital transformation of companies (Amankwah-Amoah et al., 2021) but also highlighted the necessity to cultivate organizational agility to enhance

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business competitiveness (Arias-Pérez and Vélez-Jaramillo, 2022). According to authors such as Chen & Siau (2020) or Shafiabady et al. (2023), this agility is nurtured by the utilization of emerging technologies such as AI. In this study, organizational agility is delineated as *"the ability to perceive and swiftly adapt to external and internal changes to achieve pertinent outcomes in a productive and cost-effective manner"* (Shafiabady et al., 2023:2). In essence, agility encompasses not only the anticipation of potential environmental changes or the implementation of relevant internal modifications but also the transformation of these changes into routine practices seamlessly integrated into the organization's daily operations, aligning with the Standardization Process Theory (Carroll et al., 2023). According to May and Finch (2009), this theory encapsulates the hurdles that any innovation must overcome to successfully navigate its implementation process, effective integration, and maintenance, i.e., standardization.

Soto-Acosta (2020) contends that the pandemic has exerted notable influences on both supply and demand dynamics. From a supply standpoint, digital transformation is facilitated through technologies enabling robust data analysis and programming systems that engender efficient interfaces within companies, alongside AI applications expediting customer service and preference identification, thereby facilitating personalized offerings through AI-driven conversational agents, or Chatbots. Conversely, from a demand perspective, digital transformation enhances user and consumer access to commercial information, alongside fostering greater purchasing process flexibility facilitated by applications such as Tesco in South Korea or Mercadona in select Spanish cities (Khin and Ho, 2019). Ultimately, within the business milieu, these technological advancements have culminated in enhanced consumer experiences and process automation.

Moreover, AI holds promise in contributing to the economic development of territories by bolstering the competitiveness and profitability of local businesses (Barba-Sánchez et al., 2019, 2021, 2022). Grounded in the Theory of Innovation Diffusion (Escudero Guirado et al., 2018), early adopters of technological innovations, notably AI, stand to gain competitive advantages, enhancing the efficiency and efficacy of territories and organizations through the utilization of AI-driven chatbots to optimize user experiences and amplify customer engagement (Shah, 2023). Similarly, Fang et al. (2023) suggest that the adoption of new digital technologies by companies can potentially mitigate agency costs or bolster governance structures. However, scholars such as Nucci et al. (2023) and van Ark (2016) caution that these advancements may also coincide with a deceleration in business productivity growth. This phenomenon is attributed to the relatively short duration of AI technology implementation and the delayed realization of its benefits, underscoring the concept of technological normalization within the Theory of Standardization Process. Additionally, potential barriers or inhibitors to AI adoption necessitate consideration, including inherent worker resistance to technological change or the 'Not Invented Here Syndrome' (Arias-Pérez and Vélez-Jaramillo, 2022). Concerns about dehumanization and privacy (Lobschat et al., 2021) or the high cost of implementing this new technology (Li and Yoo, 2022) are also significant barriers to its adoption, which seem difficult to overcome without clear evidence of the benefits it could provide. This underscores the observation made by Han et al. (2021) regarding the discernible gap between corporate interest in AI and its actual adoption, prompting numerous enterprises to delegate AI-related services to specialized firms (Li and Yoo, 2022), albeit with the unwelcome consequence of fostering technological dependency.

The nexus between Artificial Intelligence (AI) and business outcomes remains a topic of burgeoning interest, underpinned by the rapid evolution of AI technology. As companies navigate the integration of AI into their operational frameworks, Klos et al. (2023) underscore the criticality of a preparatory phase, wherein strategic direction is delineated. This necessitates holistic organizational changes to ensure effective integration, as emphasized by Shafiabady et al. (2023), who advocate for strategic foresight and AI modeling as means to forecast organizational agility and anticipate future changes. Defined as "*the capability of a system to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation*" (Haenlein and Kaplan, 2019:5), AI's technological trajectory remains in flux, with a paucity of consensus frameworks elucidating its impact on business realms (Grewal et al., 2021).

Within the scant pre-existing literature, empirical evidence is lacking to definitively ascertain the relationship between AI and business outcomes. The dearth of large-scale studies, compounded by challenges in data collection, as highlighted by Lin et al. (2019); Marchiori et al. (2022); Pantea et al. (2017); Tran & Murphy (2023), and Verhoef et al. (2021), obscures the research landscape on this nascent theme. A comprehensive synthesis of extant studies is imperative to discern potential convergences in thematic dimensions or defining pillars (Haenlein and Kaplan, 2019). This knowledge gap is worrisome, constraining perspectives and practical recommendations for companies, thereby impeding comparative analysis and theoretical advancement.

A significant gap has been identified in the research concerning the intersection between artificial intelligence and organizational agility. This gap is evident due to the lack of consensual frameworks that comprehensively explain how the integration of AI can enhance organizational agility (Wamba, 2022). Current research highlights the need to further explore how AI can be used not only to optimize operations but also to anticipate and adapt to future changes (Arias et al., 2023), ensuring that organizations remain agile and competitive in a constantly changing business environment (Shafiabady et al., 2023).

Against this backdrop, the present research endeavours to provide a comprehensive overview of prevailing trends and emerging research trajectories in the realm of AI and organizational agility, filling a notable gap in the existing bibliometric literature. This study offers three distinctive contributions to scholarship. Firstly, it systematically maps the knowledge base and research fronts pertaining to AI and organizational agility, a pioneering endeavour in the field. Secondly, it conducts a systematic analysis to illuminate evolving pe that could potentially redefine the current knowledge paradigm. Lastly, by delineating prospective research avenues, this study furnishes scholars with a framework to position their inquiries, thereby advancing the scholarly discourse. The study is guided by several overarching research questions:

RQ1: What is the trajectory of publications in the domain of AI vis-à-vis organizational agility?

RQ2: What are the central thematic domains within the sphere of AI and organizational agility?

RQ3: What are the predominant research foci and methodological approaches adopted in previous studies examining AI and organizational agility?

RQ4: What future research avenues warrant exploration within the domain of AI and organizational agility?

By addressing these research questions, this study endeavours to shed light on the evolving landscape of AI and its implications for organizational agility.

The ensuing sections delineate the methodological approach adopted in this study, encompassing the bibliometric analysis employed to delineate the knowledge base and research fronts. A detailed exposition of the coding protocol utilized to discern divergent perspectives is also provided. The findings and analysis segment furnishes the bibliometric findings derived from the analysis, elucidating pivotal authors, countries of origin, and seminal documents contributing to the discourse on AI and organizational agility. It also expounds upon the emergent framework derived from the bibliometric analysis, offering insights into prospective research trajectories. The concluding section encapsulates the study's overarching conclusions, synthesizing the salient insights garnered from the bibliometric analysis. Additionally, the section acknowledges the inherent limitations of the research endeavour, delineating avenues for future inquiry.

2. Methods

Given our primary aim of comprehensively delineating current trends and emerging future research trajectories, we have elected to undertake a bibliometric analysis concerning the role of Artificial Intelligence (AI) in organizational agility. Bibliometric analysis, employing statistical methodologies to scrutinize scientific contributions across various research domains (Callon et al., 1991), holds validity within the realm of management and business organization (Zupic and Čater, 2015), as evidenced by a plethora of bibliometric inquiries conducted in this domain (Galán Hernández et al., 2024; Kumar et al., 2023; Rodríguez-Insuasti et al., 2022). This analytical approach facilitates the discernment of fundamental knowledge, thereby consolidating existing insights on a specific subject, while concurrently elucidating research frontiers through meticulous mapping exercises aimed at delineating research gaps more cogently (Tranfield et al., 2003). Adhering to the PRISMA guidelines (Moher et al., 2009) ensures methodological transparency and replicability, aligning with established best practices in bibliometric research (Calderón-Monge and Ribeiro-Soriano, 2023; Pérez-Romero et al., 2023; Truong et al., 2023; Velastegui-Montoya et al., 2022) (Fig. 1).

2.1. Phase 1. Search criteria and databases

For any bibliometric inquiry, the selection of databases is paramount, necessitating platforms of robust reliability and comprehensive coverage. Accordingly, our investigation centred on two internationally acclaimed databases renowned for their expansive multidisciplinary archives (Kent Baker et al., 2020): Web of Science (WoS) and Scopus. Both databases offer extensive coverage of scholarly literature, characterized by stringent inclusion criteria and temporal scope (Durán-Sánchez et al., 2022). Despite the recommendation by Donthu et al. (2021) to rely on a single database to mitigate issues of data unification, we opted for a dual-database approach to augment inclusivity and mitigate

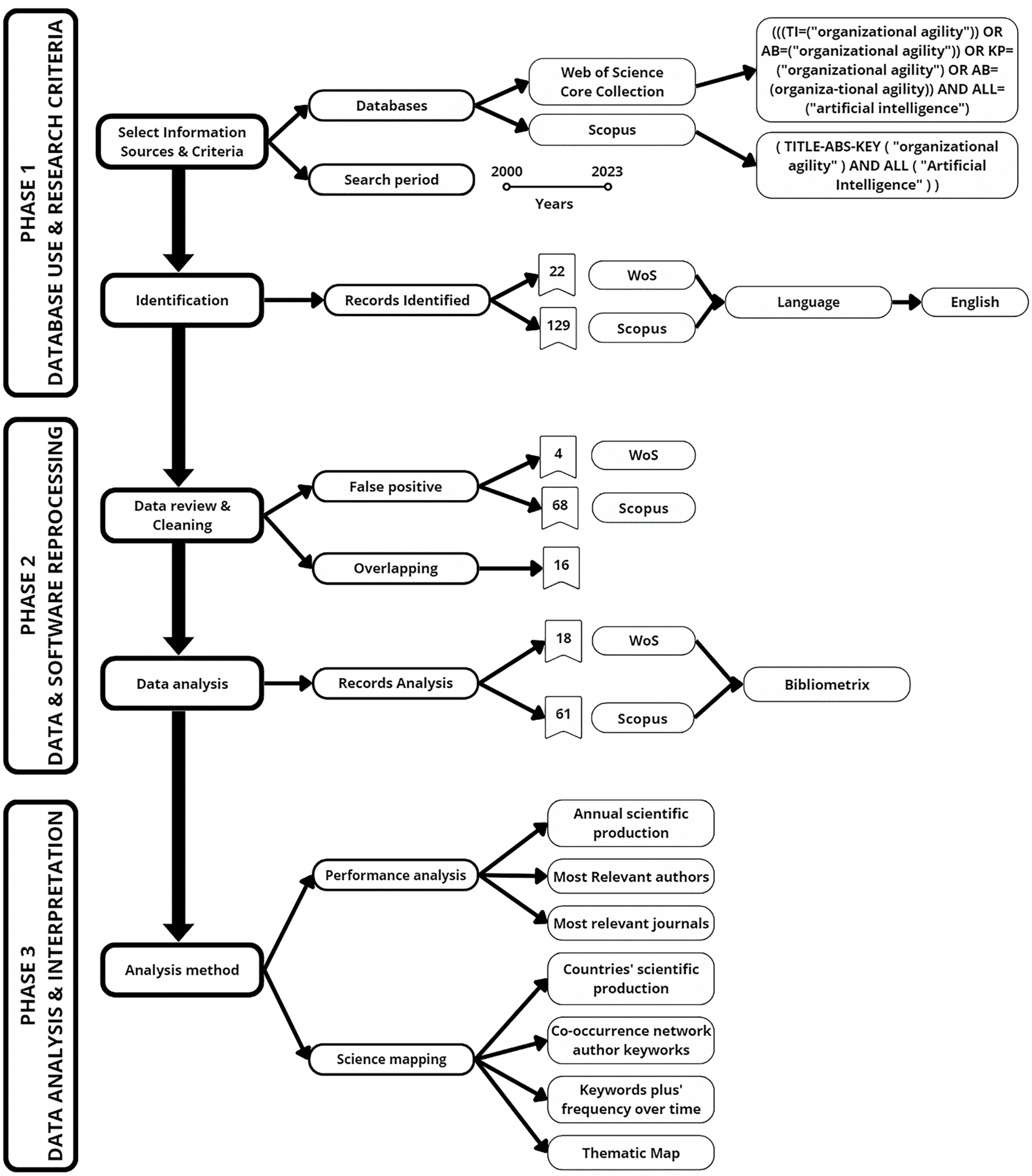

Fig. 1. Methodology of the study based on PRISMA guidelines.

the risk of overlooking pertinent scholarly contributions in this nascent field of study (Álvarez-García et al., 2023).

The search was conducted concurrently in both databases on January 3, 2024, employing the specified search criteria outlined in Fig. 1. Within the Web of Science Core Collection, the advanced search feature was utilized, incorporating the following terms: (((TI=("organizational agility")) OR AB=("organizational agility")) OR KP=("organizational agility") OR AB=("organizational agility")) AND ALL=("artificial intelligence"). Conversely, in Scopus, the advanced analysis function was employed, employing the terms: (TITLE-ABS-KEY ("organizational agility") AND ALL ("Artificial Intelligence")).

The search yielded a total of 151 documents, with 129 retrieved from Scopus and 22 from WoS. Notably, Scopus yielded a higher volume of documents compared to WoS. While WoS archives publications dating back to 1900, Scopus, starting from 1966, boasts broader journal coverage. In selecting the WoS "Core Collection" database, our aim was to prioritize the retrieval of seminal articles. The inclusion criteria encompassed all document types to capture diverse scholarly contributions, with no temporal constraints to maximize relevance acquisition. Publications were restricted to English language to facilitate compatibility with natural language processing and machine learning tools, while encompassing all knowledge domains given the multidisciplinary nature of the study subject. Subsequently, the data underwent refinement and formatting in accordance with bibliometric analysis requirements, adhering to the recommendations of Donthu et al. (2021).

2.2. Phase 2. Information processing using software

Given the magnitude of documents and variables identified (including authors, publication year, journal, among others), a meticulous manual review was imperative prior to exporting the documents in BibTeX format, ensuring heightened accuracy and research quality. This review process was geared towards identifying and rectifying duplicate, erroneous, or incomplete entries, as well as those deviating from the scope of the analysed topic. Following the filtration protocol advocated by Sahid et al. (2023), 63 meticulously curated documents were deemed suitable for inclusion within the unified knowledge base, amalgamated from both databases.

For the execution of the bibliometric investigation, the curated data underwent analysis leveraging Bibliometrix (version R-3.6.1), a software tool developed by the University of Naples Federico II in 2019. This software harnesses the R programming language in conjunction with the Biblioshiny interface (Moral-Munoz et al., 2020). Prior to utilizing Bibliometrix, RStudio was installed, following which the code line "bibliometrix::biblioshiny()" was executed to access Bibliometrix functionalities. Notably, this software enables diverse analyses, encompassing the construction of keyword correlation networks, examination of temporal trends, and visualization of global scientific document production. Additionally, Visme served as a supplementary tool for crafting the scientific production map, while Excel facilitated the tabulation and graphical representation of results derived from Bibliometrix.

2.3. Phase 3. Data analysis and interpretation

Drawing upon the frameworks outlined by Donthu et al. (2021) and He & Liu (2024), this study employs two distinct methodologies to scrutinize the findings. Performance analysis delves into the contributions of individual elements within scientific documents, whereas science mapping elucidates the interrelationships among these elements. The selection of specific bibliometric analyses is contingent upon the objectives delineated. Co-citation analysis is deemed apt for retrospective assessments, elucidating the connections between publications and the works citing them, thus identifying seminal and influential contributions. Bibliographic coupling, conversely, is deployed for contemporaneous evaluations, delineating linkages among disparate publications citing similar sources to ascertain prevailing trends in the field. Looking towards the future, co-word analysis is employed to prognosticate forthcoming thematic interrelations within the discourse.

The initial phase of this investigation entails a performance analysis, directed at assessing scientific production and its impact within the designated topic. Key variables under scrutiny encompass authors, document volume, and journal dissemination. Subsequent to this analysis, a science mapping endeavour is embarked upon, aiming to visually represent thematic evolution, scientific output, and interconnectivity among concurrent keywords networks.

3. Findings and analysis

3.1. Scientific production

A noteworthy observation is the relatively recent emergence of the discourse surrounding Artificial Intelligence (AI) and organizational agility within academic circles. While the term "organizational agility" made its debut in Scopus records in 1994 and "Artificial Intelligence" in 1960, it wasn't until the year 2000 that these terms coalesced within scholarly discourse. Consequently, it can be posited that the seminal work by Huang et al. (2000) serves as the pioneering investigation within the analysed databases. Of significance, the authors contended that the integration of Information Technologies (IT), including AI methodologies, is indispensable for achieving organizational agility, particularly within contemporary, distributed, and networked enterprises. Illustratively, AI-enabled decision-making processes offer expedited rectification of system errors, thereby enhancing responsiveness within businesses.

Fig. 2 inspired by insights from Briones-Bitar et al. (2020), visually illustrates the exponential surge in document publications in recent years. Employing linear (y = 2.8214x-3.8571, R2=0.8517, blue line) and exponential (y = 0.7992^{e} 0.461x, R2=0.9833, green line) trendlines, it becomes evident that the exponential model provides a superior fit, exhibiting higher R2 values.

Despite the inception of the precursor article in 2000, scholarly contributions remained sporadic until 2017. Notably, the study by Lu & Ramamurthy (2011) emerges as a seminal work within the field, accruing 837 citations over time. This empirical investigation delves into the nexus between Information Technologies (IT) and organizational agility, delineating three distinct categories of IT—infrastructure IT, expansion IT, and proactive IT—though the explicit mention of "artificial intelligence" is notably absent.

Commencing from 2017, a consistent and incremental publication trend has been observed, culminating in a peak in 2023 with a total of 20 articles—an unprecedented zenith thus far. This trajectory not only underscores the emergent nature of the topic but also attests to the burgeoning interest within the research community, mirroring broader societal and commercial concerns.

An examination of document citations reveals a progressive uptick over the years. To ascertain a more robust trend, two trend lines were delineated: linear (y = 27.429x+3.8571, R2=0.2661, orange line) and exponential (y = 14.849e0.3723x, R2=0.1411, purple line). Notably, a decline in citations was observed in 2020, likely attributable to the pervasive focus on COVID-19-related research endeavours during that period. Conversely, 2022 witnessed a surge in citations, marking the highest count since 2017, potentially propelled by the pronounced proliferation of documents on the subject matter. However, it is pertinent to note the relatively diminished citation count in 2023, possibly attributed to the temporal lag between article publication and its registration within the analysed databases. Such lag often results in a delayed accumulation of citations, with citations from the preceding year typically witnessing a surge at the onset of the subsequent year.

3.2. Relevant authors and networking

The author ranking presented in Table 1 adheres to the methodology

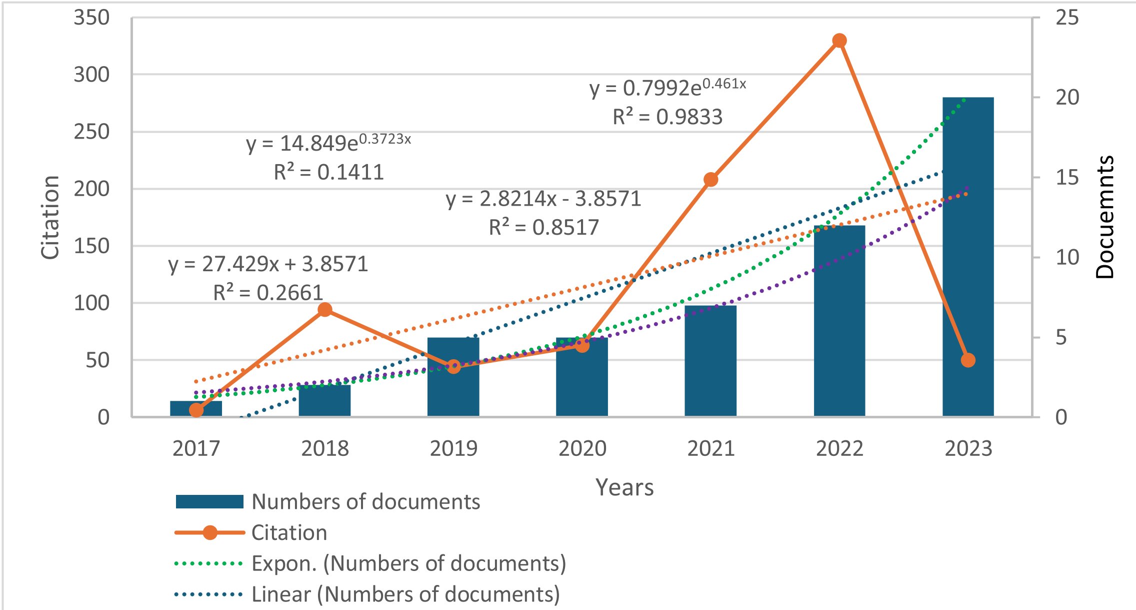

Fig. 2. Document analysis. Annual scientific production.

Table 1
Author analysis: The 10 most frequent authors in the area.

R	Author	Country	Affiliation	IA-AO/ Topic				Global				h-index		TCI		
				A		C		A		C		W	S	DT	AI	OA
				W	S	W	S	W	S	W	S					
1	El Manouar, A	Morocco	Mohammed V University in Rabat	1	3	1	8	11	31	72	147	4	5	1.7	1.2	1.4
2	Marhraoui, MA	Morocco	Mohammed v university in rabat	1	3	1	8	3	9	5	27	1	3	–	1.2	1.4
3	Elidjen, E	Indonesia	Bina Nusantara University	–	3	–	21	11	38	35	246	3	10	1.7	–	1.4
4	Mihardjo, LWW	Indonesia	Bina Nusantara University	–	3	–	21	31	57	720	1136	16	20	1.7	–	1.4
5	Sasmoko, S	Indonesia	Bina Nusantara University	–	3	–	21	5	180	36	988	3	18	1.7	–	1.4
6	Arslan, A	Finland	Oulu University	1	2	47	59	85	99	936	1187	17	19	1.7	–	1.4
7	Vrontis, D	Cyprus	University of Nicosia	2	2	53	75	154	407	4396	9001	39	52	1.7	1.3	1.4
8	Idrissi, MA Janati	Morocco	Mohammed v university in rabat	1	2	1	1	26	18	180	52	6	5	1.7	–	1.4
9	Gong, Y	France	Emlyon Business School	2	2	31	36	117	121	1933	2202	25	27	1.1	4.2	–
10	Choi, J	United States	Pittsburgh State University	1	2	19	28	10	26	151	245	5	6	–	1.1	–

Note: Article (A); Citation (C); Topic Field-Weighted Citation Impact (TCI); Wos (W); Scopus (S); Digital transformation, Strategic alignment; COBIT, Business Model Innovation, Innovation, Enterprise Architecture (DT); Human Resource Information Systems, E-Hrm, Artificial Intelligence, Interpretive research, Hermeneutics (AI); Agile Manufacturing, Organizational Agility, Agility (OA).

outlined by Montalván-Burbano et al. (2021). Notably, the most influential authors in the field hail from Morocco and Indonesia, boasting h-indexes spanning from 1 to 20. However, two standout authors deserve special mention. Firstly, Demetris Vrontis, representing Cyprus, commands an impressive h-index of 39 in WoS and 52 in Scopus. Renowned as a prolific researcher, Vrontis has amassed 4396 publications in WoS since 1999. Secondly, Yeming Gong, affiliated with Emlyon Business School in France, possesses an h-index of 25 in WoS and 27 in Scopus. Gong's affiliation with the Artificial Intelligence in Management Institute underscores their expertise in the domain. Additionally, Gong's collaboration with Hongyu Mao from Shenyang Agricultural University in China is noteworthy.

While the volume of articles authored by these researchers on the subject may not be substantial, their impact, as gauged by citations, is noteworthy. Authors such as A. El Manouar and D. Vrontis exhibit an impactful contribution to digital transformation, artificial intelligence, and organizational agility, as evidenced by a Topic Field-Weighted Citation Impact (TCI) exceeding 1 across all domains. The TCI metric is derived by juxtaposing the citation count of articles authored by each individual with citations accrued by peers exploring similar themes. Furthermore, Y. Gong's substantial TCI of 4.2 within the realm of artificial intelligence attests to their influential standing, likely attributed to their affiliation with a specialized institute in the field.

In terms of collaborations, it's notable that A. El Manouar and M.A. Marhraoui, spearheading the author ranking in Table 1, frequently collaborate on articles, possibly due to their shared affiliation in Morocco. Similarly, E. Elidjen's collaboration with L.W.W. Mihardjo, stemming from the same affiliation, is noteworthy. However, Mihardjo also collaborates with S. Sasmoko, despite their shared affiliation at Bina Nusantara University. No discernible collaboration pattern has been identified among the other authors.

3.3. Relevant journals

Table 2 presents the most pertinent journals concerning this topic. The ranking, as per Carrión-Mero et al. (2022), is determined by the quantity of documents and the journal's quartile in the analysed databases. Leading the list is the journal Technological Forecasting and Social Change, featuring 5 articles relevant to the subject. This journal occupies the first quartile (Q1) and boasts a Journal Impact Factor (JIF) of 12. Moreover, it ranks ninth in the Citation Topic Meso about Artificial Intelligence and Machine Learning (CTMAIML), indicating that its

Tabla 2
Source analysis: The 10 most frequent journals in the area.

R	Journal	CQ	JIF	JCI	NDT	ND	CTMAIML		Topics
							R	ND	
1	Technological forecasting and social change	Q1	12	2.47	8010	5	9	121	Business Regional & Urban Planning
2	Sustainability	Q2	3.9	0,67	75,627	4	19	867	Environmental Sciences Environmental Studies Green & Sustainable Science & Technology
3	International journal of information management	Q1	21	5,72	2951	3	12	29	Information Science & Library Science
4	Journal of enterprise information management	Q1	6.5	1.37	1003	2	2	48	Information Science & Library Science Management
5	Business process management journal	Q2	4.1	0.84	1207	2	10	9	Business Management
6	Technovation	Q1	12.5	2.13	2571	1	10	22	Engineering, Industrial Management Operations Research & Management Science
7	Journal of business research	Q1	11.3	2.32	10,099	1	7	85	Business
8	Journal of management information systems	Q1	7.7	1.65	1106	1	11	14	Computer Science, Information Systems Information Science & Library Science Management
9	Plos one	Q1	3.7	0.91	285,697	1	140	537	Multidisciplinary Sciences
10	Administrative sciences	Q2	3	0.66	998	1	27	3	Management

Note: Ranking (R) Category Quartile (CQ); Journal Impact Factor (JIF); Journal Citation Indicator (JCI); Total number of documents (NDT); Number of documents (ND); Citation topic *meso* Artificial Intelligence and Machine Learning (CTMAIML).

articles receive citations from AI articles in other journals. Given the emergent nature of this topic, the percentage of articles cited by others on this subject in other journals, relative to the total number of articles published, remains low across all analysed journals, as these journals primarily specialize in other areas such as management or business. In this regard, the Journal of Enterprise Information Management stands out as the most significant journal, not only because it secures the second position in CTMAIML but also because 4.79 % of its articles receive citations from others in the field of AI.

Furthermore, it was observed that almost a third (26.98 %) of the sources on this subject are conference papers. This observation is unsurprising, considering that conferences provide the swiftest means to disseminate the findings of cutting-edge research, particularly in burgeoning fields experiencing rapid development and expansion, such as this one. Consequently, it is noteworthy to highlight the prominence of the work by Gonçalves et al. (2022) within this category of scholarly documents.

3.4. Global distribution of scientific production

The distribution of scientific production on a global scale is depicted in Fig. 3, employing the methodology elucidated by Cândido et al. (2023). Notably, the affiliation of the primary author is considered pivotal, while subsequent affiliations establish the network of

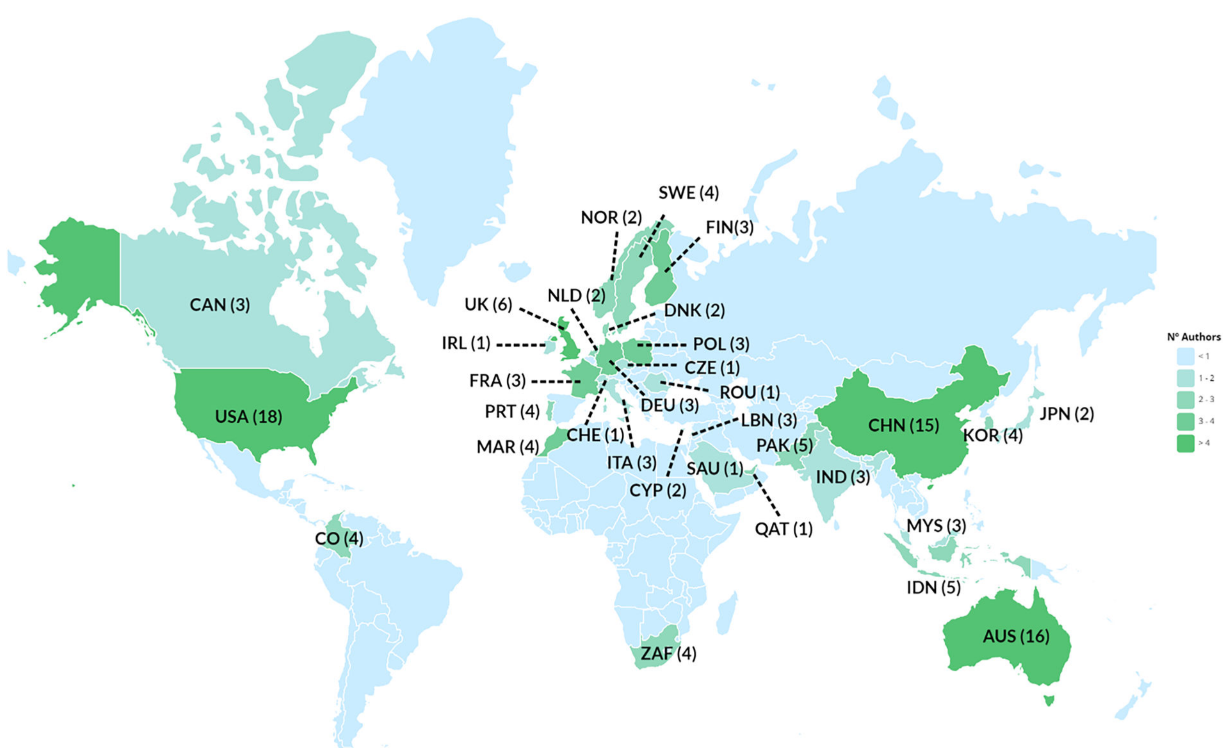

Fig. 3. Country Analysis: Scientific Production by Countries in the Area (Based on the First Affiliation of Authors).

collaborative efforts across countries. Across continents, the following patterns emerge:

In America, the United States takes the lead with 18 authors collaborating with peers from Germany, India, and Saudi Arabia, yielding joint publications with each respective country. Conversely, Canada's collaborative efforts are relatively limited, with only 3 authors co-publishing with counterparts from France.

Across Europe, the United Kingdom emerges prominently with 6 authors engaging in collaborations with researchers from Ireland, the Czech Republic, Denmark, Finland, Switzerland, Italy, and Saudi Arabia, resulting in a joint document for each collaborating nation. Additionally, sporadic collaborations are observed, such as Italy with Switzerland, Finland with Pakistan and Denmark, and Czech Republic with Ireland, among others. Notably, Portugal and Spain have yet to initiate collaborative efforts on this subject.

In Africa, 4 authors, primarily affiliated with Morocco and South Africa, are identified; however, collaborative ventures beyond their respective countries are lacking.

Within Asia, China leads with 15 authors collaborating with peers from Canada, Malaysia, Japan, and France. Collaborative endeavours are also noted among authors from Pakistan, Denmark, Poland, South Korea, India, the United Arab Emirates, and Qatar, each forging partnerships with researchers from various countries.

In Oceania, Australia emerges as the second most prolific contributor, boasting 16 authors who have collaborated with peers from the Czech Republic, Indonesia, Ireland, the United Arab Emirates, the United Kingdom, and the United States, further underscoring the global nature of collaborative research efforts.

3.5. Network of concurrent keywords

The network of concurrent keywords in the bibliometric study is depicted in Fig. 4, revealing a complex interplay of thematic clusters. Six distinct clusters emerge from the analysis, each highlighting specific keyword relationships and thematic foci.

Cluster I underscores the interconnectedness between organizational agility, artificial intelligence, and digital transformation, indicating a strong thematic association among these key concepts. This cluster suggests a pivotal role for artificial intelligence in driving organizational agility within the context of digital transformation initiatives.

Cluster II encompasses keywords related to information technologies, dynamic capabilities, innovation, and management, elucidating the multifaceted nature of technological innovation and its implications for organizational dynamics and strategic management practices.

Cluster III delineates the relationship between information systems and usage information, underscoring the importance of leveraging information systems to enhance organizational effectiveness and decision-making processes. This cluster also encompasses keywords related to agile manufacturing systems, information services, and the broader business environment, highlighting the integral role of information systems in shaping organizational practices and strategies.

Cluster IV elucidates themes surrounding decision-making, organizational structure, and enterprise architecture, shedding light on the fundamental aspects of organizational design and decision-making processes within dynamic and complex business environments.

Cluster V emphasizes the intersection between big data, Industry 4.0, and digital transformation, underscoring the transformative potential of data-driven technologies in reshaping industrial processes and business operations.

Lastly, Cluster VI highlights the relationship between human practice, utilization, and sustainable development, underscoring the importance of human-centric approaches and sustainable practices in the context of organizational development and technological innovation.

Overall, the analysis of keyword clusters provides valuable insights into the thematic landscape of the bibliometric study, offering a nuanced understanding of the key concepts and relationships shaping research in the field.

The analysis of word relationships reveals several noteworthy deductions:

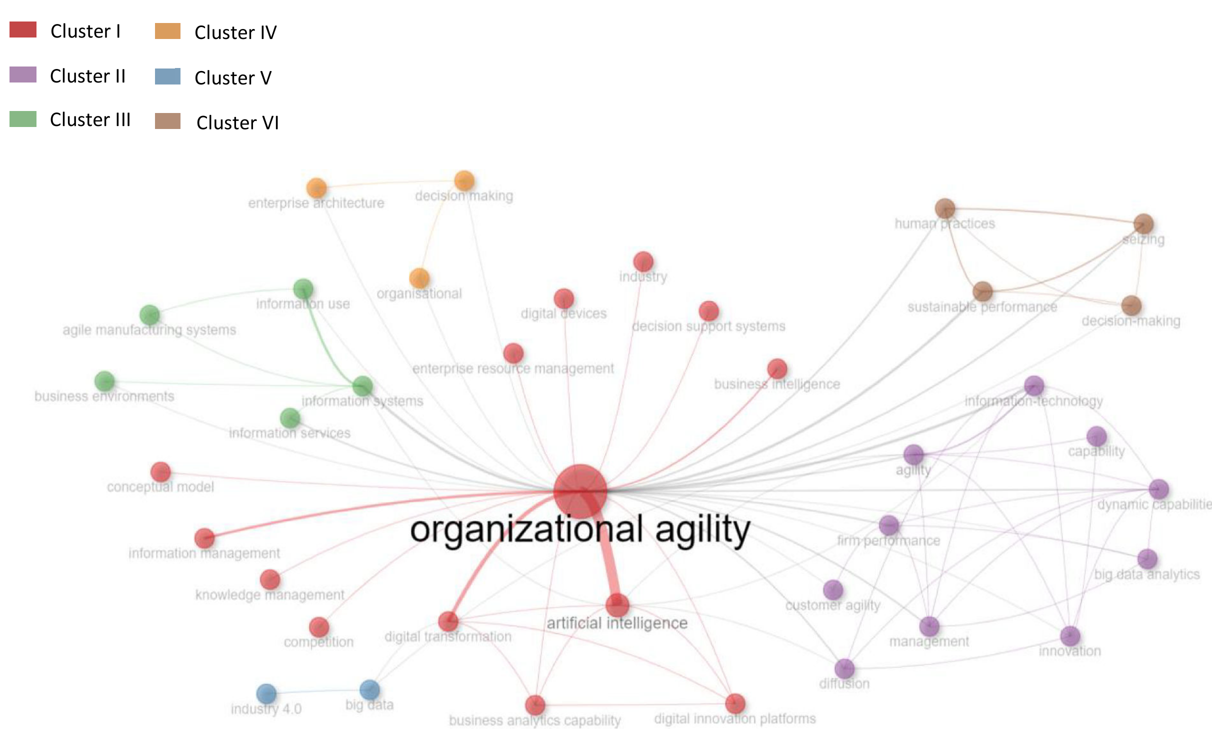

Fig. 4. Keyword analysis: Network of keyword co-occurrences by authors.

· *"Artificial intelligence" and "organizational agility" are closely associated in the same cluster, suggesting a significant relationship between them, possibly indicating AI's role in enhancing organizational agility.*
· *Digital transformation is linked to organizational agility, being in the same cluster. This agility could be achieved in part thanks to digital transformation.*
· *Additionally, the organizational agility node is linked to cluster III related to information systems. Thus, agility is related to the storage, processing, and distribution of information.*

3.6. *Frequency of keywords over time*

In this study, we examined 10 keywords, tracking their cumulative frequency over the years. As depicted in Fig. 5, "organizational agility" first appeared in 2002, although its association with AI emerged in 2000. Conversely, "artificial intelligence" was not listed as a keyword until 2007, possibly due to the terms' gradual consolidation or infrequent use. The prominence of "organizational agility" has steadily increased, reaching 20 occurrences cumulatively in 2023, while "artificial intelligence" had 10 occurrences in the same year, indicating a growing interest in these topics.

The keyword "information systems" debuted in 2007, concurrent with AI's listing, and has since shown a gradual rise in usage. Conversely, keywords such as "decision-making," "information management," "agility," "business structure," "information use," "commerce," and "competition" have been less frequent, each appearing 5 to 3 times as keywords in 2023.

The most recent article, authored by Agrawal (2023), aims to furnish a theoretical framework for standardizing the adoption and maintenance of the GenAI-OI system. The study concludes that generative AI significantly contributes to a company's organizational agility.

3.7. *Thematic map*

The thematic map depicted in Fig. 6, inspired by Nasir et al. (2020), illustrates 11 distinct clusters. Constructed using the top 250 keywords with a minimum frequency of 10, this map adheres to the Strategic Diagram formulated by Callon et al. (1991), serving to position each theme or cluster within the graph. The X-axis represents centrality, and the Y-axis represents density. Centrality, according to Cobo et al. (2012), measures the level of interaction of the theme with others, i.e., the intensity of the external link of cluster nodes to determine the importance of the theme globally. Density measures the internal cohesion of the theme, i.e., the internal links of cluster nodes to determine the development of the theme (Paule-Vianez et al., 2020).

In accordance with the categorization proposed by Paule-Vianez et al. (2020), the themes within the Strategic Diagram fall into four main categories, defining the intellectual structure of AI in the realm of organizational agility:

- Driving Themes (upper-right quadrant): These themes exhibit high centrality and density, indicating their strong relevance and extensive development within the research field.
- Emerging or Declining Themes (lower-left quadrant): These themes display low centrality and density, signifying their underdeveloped and marginal status.
- Niche Themes (upper-left quadrant): Although isolated, these themes are well-developed, boasting high density but low centrality.
- Basic Themes (lower-right quadrant): These themes demonstrate strong connections with other themes, serving as cross-cutting subjects that warrant further exploration.

In this study, the cluster exploring organizational agility and artificial intelligence emerges as a driving theme. While highly relevant, this theme is still undergoing development, with centrality slightly lower than that of the intelligent systems and decision support cluster, which stands as the most mature theme. Another driving theme encompasses information systems and their utilization and management. Positioned closer to the midpoint is the thematic area concerning digital platforms and knowledge management within small and medium-sized enterprises.

Meanwhile, clusters focusing on the holistic approach and sustainable outcomes, incorporating decision-making and human intervention, are identified as niche themes. Notably, the topic of sustainable development garners attention, evidenced by the recent integration of a sustainable development goals (SDGs) filter into Web of Science. Basic themes include operational agility, enterprise absorption capacity, internet research, and behavioural studies.

Conversely, declining themes revolve around information technologies in industrial business processes and innovation capabilities in

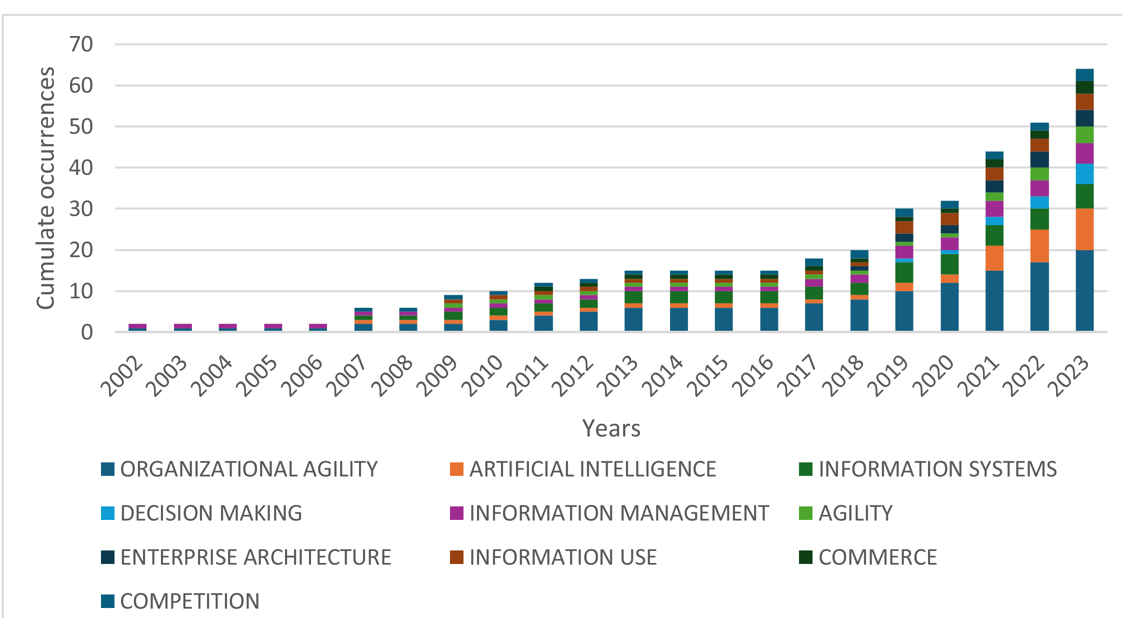

Fig. 5. Keyword analysis: Frequency of keywords over time.

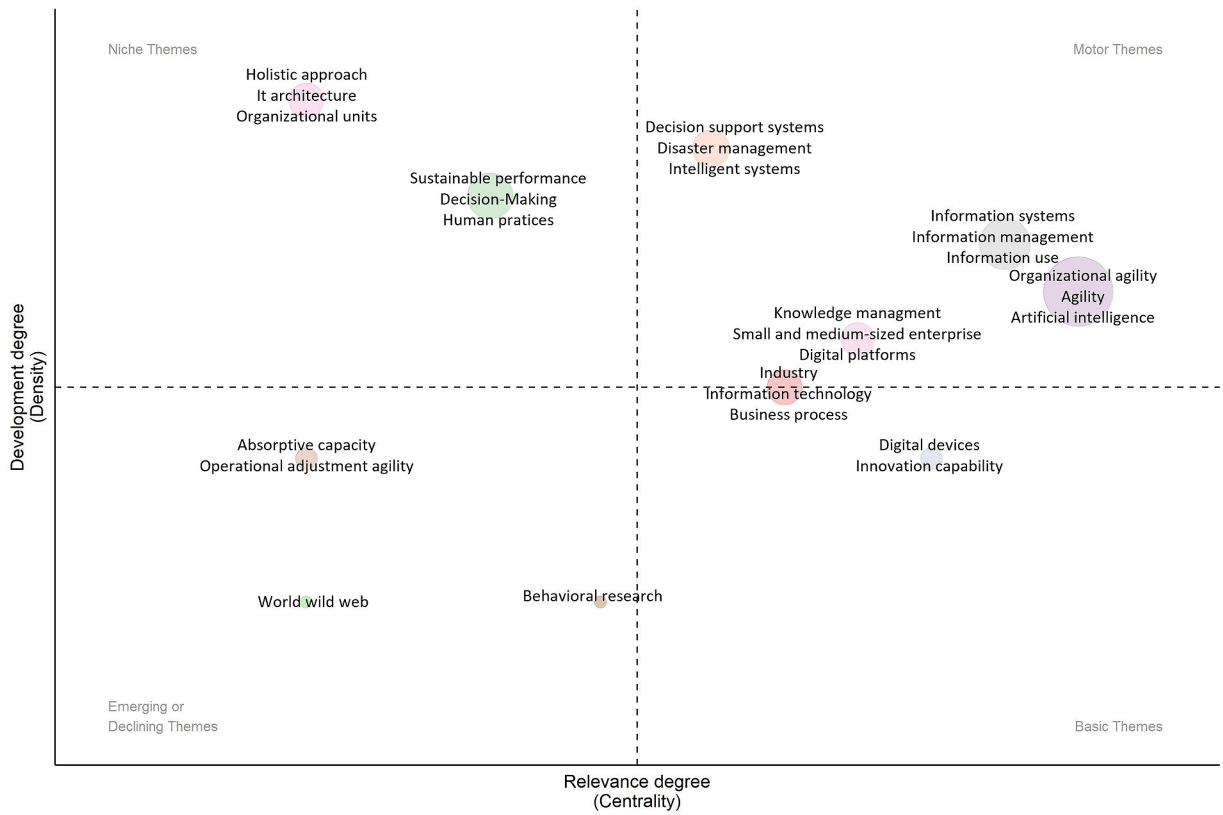

Fig. 6. Keyword analysis: Thematic map.

digital devices. Once prominent, research on hardware aspects of digitization now appears to have waned, yielding precedence to software-centric investigations.

3.8. Latest articles published on the topic (by publication date)

Table 3 presents the ten most recent articles published on the topic, accompanied by their primary contributions. Among these articles, the majority are quantitative studies, complemented by one qualitative and three theoretical investigations. Notably, all articles are from 2023.

However, it's worth highlighting two significant articles from 2022. The first, titled "Impact of artificial intelligence assimilation on firm performance: The mediating effects of organizational agility and customer agility," has garnered 16 citations. This study underscores the potent influence of AI assimilation on future organizational agility (OA), shedding light on a relatively underexplored area (Wamba, 2022). The second noteworthy article, "How does artificial intelligence create business agility? Evidence from chatbots," has amassed 18 citations. This research elucidates the pivotal role of chatbots in fostering organizational agility (OA) within companies (Wang et al., 2022).

4. Conclusions

This study represents the inaugural endeavour to comprehensively analyse data concerning the relationship between AI and OA sourced from the WoS and SCOPUS databases. It aims to offer a detailed analysis of research on both domains through the application of bibliometric and network analysis. The interaction between AI and OA constitutes a rapidly evolving field fraught with theoretical and practical challenges, particularly within the context of small and medium-sized enterprises (SMEs), characterized by lower investment capacities in emerging technologies, as highlighted by Arias-Pérez et al. (2023).

Bibliometric analysis has facilitated the identification and visualization of the intellectual structure within this field of study, allowing for an assessment of scientific productivity and the primary thematic trends through an analysis of keyword co-occurrence.

Drawing upon the findings, efforts have been made to address the academic evolution posed by the first research question (RQ1). The majority of literature retrieved from the analysed databases emanates from peer-reviewed journals. An exponential growth trend is observed in both the quantity of documents and citations, signifying a pronounced surge in the field's popularity. Notably, international collaboration among researchers is on the rise, underscoring the growing significance of AI in conjunction with OA (AI&OA). This collaborative effort reflects a collective endeavour to explore AI integration while mitigating associated challenges, such as costs and privacy concerns. Additionally, the study provides insights into prolific researchers in the AI&OA domain, delineating their publication frequency, impact on the field, and the primary academic journals publishing literature on this subject. Furthermore, it examines the contributions of various countries to the advancement of AI&OA literature.

Moreover, network analysis, together with keyword analysis and the thematic map, furnishes an overview of the central themes (RQ2), highlighting the predominant focus on information technologies and information systems within the literature. However, AI&OA has also garnered significant attention from the field of business organization and strategic management, particularly concerning the digital transformation of organizations, underscoring its multidisciplinary nature. Additionally, the identification of 11 thematic clusters underscores the prominence of the topic of organizational agility, derived from the generation and redesign of organizational routines (Zheng et al., 2011), in terms of productivity and impact.

Answering the third research question (RQ3), most studies have examined the integration of AI into the organization using the Technology Acceptance Model (TAM), both in its original version that focuses exclusively on the individual, and in the extended version (Unified Theory of Acceptance and Use of Technology-UTUT) that attempts to incorporate the organizational factors. However, while these models

Table 3
Systematic analysis of the literature. The 10 most recent articles on the subject.

Author (Year)	Article	Methodology	Main Contributions
Agrawal (2023)	Organizational Sustainability of Generative AI-Driven Optimization Intelligence	Theoretical study	Theoretical framework for the integration and maintenance of GenAI-OI systems, enhancing AO.
Islam & Naseem (2023)	Role of Industry 4.0 tools in organizational performance of the IT sector	Quantitative based on primary data from IT companies (SPSS v22)	AI, as an Industry 4.0 tool, drives organizational performance through remote work and AO.
Zhu & Li (2023)	The use of data-driven insight in ambidextrous digital transformation: How do resource orchestration, organizational strategic decision-making, and organizational agility matter?	Quantitative based on primary data from 312 companies in China	Emphasize the contingent role of organizational agility in the relationship between resources employed and the outcome of ambidextrous digital transformation balancing current business exploitation with exploration of new business models, thanks to emerging technologies.
Arias-Pérez et al. (2023)	Unlocking agility: Trapped in the antagonism between co-innovation in digital platforms, business analytics capability and external pressure for AI adoption?	Quantitative based on primary data from 229 companies (SEM)	Refute that institutional pressures reduce organizational agility, and that AI adoption is negatively influenced by external pressures.
Ramadan et al. (2023)	Toward digital transformation and business model innovation: the nexus between leadership, organizational agility, and knowledge transfer	Quantitative based on primary data from 270 SME employees (PLS-SEM)	Determine that leadership plays a fundamental role in digital transformation, fostering organizational agility.
Zhang et al. (2023)	How organizational agility promotes digital transformation: an empirical study	Quantitative based on primary data from 313 government employees	Digital transformation is influenced by organizational agility, which is predicted by dynamic capabilities.
Akter et al. (2023)	A framework for AI-powered service innovation capability: Review and agenda for future research	Theoretical study	-Market AI capability relates to customer orientation, industry, and multifunctionality. -Infrastructure AI capability relates to data, business, models, and the ecosystem. -Management AI capability relates to AI orientation, organizational learning, and AI ethics.
Shafiabady et al. (2023)	Using Artificial Intelligence (AI) to predict organizational agility	Quantitative based on primary data from 44 surveys of Australian industries	They apply an AI model to predict the future organizational agility of the company and determine the potential barriers or benefits of this agility.
Sreenivasan et al. (2023)	Assessment of Factors Influencing Agility in Start-Ups Industry 4.0	Qualitative based on 15 interviews (TISM and MICMAC)	-AI, cloud computing, networking and connectivity, technology, and digital twin are driving or key factors of AO. -Technological agility within organizations is enhanced through the adoption of Industry 4.0 technologies. -New algorithms and artificial intelligence technologies are being developed to optimize existing systems and handle new production challenges.
Lee (2023)	The era of Omni-learning: Frameworks and practices of the expanded human resource development	Theoretical study	AI is an AO-enabling technology that modifies the definition of organizational capability: how to use AI or assist human resources in using it.

aim to explain technology usage, they often overlook the effects of AI adoption on organizational structures and outcomes. Despite attempts to establish causality between AI adoption and OA, there is a lack of analysis on how this conjunction affects business outcomes. However, there is abundant literature on the effects of OA (Stei et al., 2024) and digital transformation (Wamba et al., 2020), separately, on business outcomes. In this sense, according to Reis and Melão (2023), most bibliometric reviews on digital transformation and business performance highlight the need for research focused on measuring the performance of the integration of specific digital technologies, given the variety of technologies that can be implemented in the company. This further reinforces the potential role of AI in building OA, in line with the work of Sambamurthy et al. (2003).

Regarding future research directions to explore in this area (RQ4), recent research papers offer intriguing avenues. Specifically, understanding how AI application to big data analytics or networks contributes to OA is paramount. The volume, variety, and speed in data acquisition and analysis can significantly impact an organization's ability to adapt to VUCA (Volatility, Uncertainty, Complexity, Ambiguity) environments. Moreover, network analysis presents opportunities for identifying contextual factors influencing OA. In conclusion, the evidence provided yields numerous theoretical and practical implications and recommendations, along with potential future research directions, detailed below.

4.1. Theoretical and practical recommendations

A review of the latest contributions to the field exposes several theoretical challenges, including the absence of conceptual consensus regarding the definition of AI, the restricted diversity of measurement methodologies, and the dearth of applied theories. The absence of a standardized terminology impairs the comparability and quality of research outcomes, underscoring the need for theoretical inquiries aimed at standardizing concepts and advocating for practices and standards to enhance research quality.

With respect to methodologies, regressions and structural equation modelling abound, with little application of mixed methods or alternative performance measurement tools. Future theoretical research is therefore encouraged to explore and propose new methodologies, such as stochastic frontier analysis (SFA) or data envelopment analysis (DEA), to enrich the understanding of performance in the business context, in general, and in Small and Medium-sized Enterprises (SMEs), in particular, given the configuration of the Spanish business fabric.

Finally, regarding the variety of theories, most of the works are based on the Technology Acceptance Theory (TAM), in its original version or in various extensions of the model, but this theory addresses the problem from the point of view of individuals, but not from the point of view of the organisation, so new theoretical perspectives are needed which focus on the organisational variables involved in the integration of AI in the organisation. In this sense, the Theory of Standardisation may be an option to explore, as it addresses the challenges that any innovation must face at the organisational level in order to successfully complete its implementation, effective integration and maintenance process, i.e. standardisation (May and Finch, 2009). A key role in this standardisation process appears to be played by the generation of organisational routines, as argued by Feldman and Pentland (2003), creating a continuous opportunity for variation, selection and retention of new practices, embedding OC, as in the case of AI integration. In Eisenhards and Martin's (2000) terms, capability-building mechanisms are the organisational and strategic routines that firms design by reconfiguring resources as markets evolve and their embeddedness makes them comparatively more valuable and inimitable.

Additionally, one of the basic research themes identified is operational agility. Therefore, although this bibliometric analysis has focused on OA as a unidimensional construct, it would be advisable to separately analyse its three dimensions: operational, market, and partnership (Sambamurthy et al., 2003). While the latter two focus on networking with customers or suppliers to generate opportunities, the operational dimension reflects the ability of business processes to achieve speed, precision, and cost efficiency in exploiting such opportunities. The functionalities that AI can contribute in each case may differ, so it would be beneficial to consider OA as a higher-order capability built around these three specific capacities.

Another niche theme highlights human resource intervention as a barrier to AI integration within companies, including ethical considerations and workers' resistance to technological change. It would be beneficial to extend research into these areas, incorporating variables such as employees' attitudes towards AI. Exploring topics like data privacy, responsible innovation, or the 'Not Invented Here' syndrome could also offer valuable insights into understanding the impacts of AI on business outcomes.

From a practical perspective, this study offers researchers a concise overview of prior research concerning the correlation between AI and OA, facilitating the enhancement of their expertise and comprehension in this domain. Moreover, it identifies forthcoming challenges in research. These challenges encompass the need to generalize findings to industries and geographical areas lacking specific investigations, as well as the imperative to homogenize and standardize data. Consequently, current practical research appears to concentrate on leading AI-utilizing enterprises, possibly due to the technology's limited market penetration. However, the absence of information regarding its effects on more traditional sectors discourages integration. To address this issue, it is advisable to expand practical research to encompass diverse sectors, countries, and geographical regions, thus providing a more comprehensive and nuanced understanding of AI's integration into business and its correlation with OA. Additionally, the heterogeneity in the characteristics of organizations studied in previous literature, coupled with the lack of data standardization, may impede the generalization of conclusions. Therefore, it is essential to consider these diverse characteristics and propose practices to enhance the quality and comparability of outcomes.

4.2. Limitations and future research

Concerning the limitations of the conducted bibliometric analysis, it is important to acknowledge that it relied solely on two databases. While these databases offer extensive coverage of academic literature, they may not encompass all pertinent publications on AI and organizational agility. Therefore, future research should contemplate replicating the study across other databases, such as PubMED or EBSCO, to offer a more comprehensive perspective, which may include additional conference proceedings and publications in languages other than English.

Secondly, despite the meticulous selection of keywords, variations in terminology, coupled with the ever-evolving nature of AI, may have resulted in the exclusion of some pertinent articles. In future research, exploring the utilization of advanced natural language processing techniques (NLP), as suggested by Sahid et al. (2023), could enhance the comprehensiveness of keyword selection. Additionally, considering authors such as Morley et al. (2018) or Autio et al. (2021) who contend that digitalization encompasses digital technologies like IoT or AI, the inclusion of this term appears warranted to capture potentially relevant articles that might have been overlooked.

Thirdly, in calculating the impact of citations weighted by topics (TCI), three thematic groups have been identified: the first comprises terms such as Digital transformation, Strategic alignment, COBIT, Business model innovation, Innovation, and Enterprise architecture; the second encompasses Human resource information systems, Digital human resource management, Artificial intelligence, Interpretive research, and Hermeneutics; and the third involves Agile manufacturing, Organizational agility, and Agility. This circumstance complicates the precise assessment of the impact of the primary themes, AI, and OA. Therefore, it would be advantageous to establish a mechanism to determine the proportion of impact attributed to each theme, distinguishing between primary and secondary ones.

In conclusion, the bibliometric study serves as a theoretical and descriptive exploration of prior research, valuable for pinpointing research gaps and directing future inquiries. However, it is imperative to progress further by employing the findings in case studies and empirical investigations to evaluate the practical implications of the conclusions drawn in the business domain.

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María Atienza-Barba: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Data curation, Conceptualization. **María de la Cruz del Río-Rama:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Data curation, Conceptualization. **Ángel Meseguer-Martínez:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Funding acquisition, Data curation, Conceptualization. **Virginia Barba-Sánchez:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Funding acquisition, Data curation, Conceptualization.

Declaration of competing interest

None.

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