Artificial Intelligence and Economic Development: An Evolutionary Investigation and Systematic Review

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Abstract

In today's environment of the rapid rise of artificial intelligence (AI), debate continues about whether it has beneficial effects on economic development. However, there is only a fragmented perception of what role and place AI technology actually plays in economic development (ED). In this paper, we pioneer the research by focusing our detective work and discussion on the intersection of AI and economic development. Specifically, we adopt a two-step methodology. At the first step, we analyze 2211 documents in the AI&ED field using the bibliometric tool Bibliometrix, presenting the internal structure and external characteristics of the field through different metrics and algorithms. In the second step, a qualitative content analysis of clusters calculated from the bibliographic coupling algorithm is conducted, detailing the content directions of recently distributed topics in the AI&ED field from different perspectives. The results of the bibliometric analysis suggest that the number of publications in the field has grown exponentially in recent years, and the most relevant source is the "Sustainability" journal. In addition, deep learning and data mining-related research are the key directions for the future. On the whole, scholars dedicated to the field have developed close cooperation and communication across the board. On the other hand, the content analysis demonstrates that most of the research is centered on the five facets of intelligent decision-making, social governance, labor and capital, Industry 4.0, and innovation. The results provide a forward-looking guide for scholars to grasp the current state and potential knowledge gaps in the AI&ED field.

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Introduction

In recent years, the sound of artificial intelligence (AI) has always been in everyone's ears, and it seems to be telling us that the arrival of AI is the destiny of the age (Makridakis, 2017). Indeed, AI technology is appearing in various forms at all levels of our contact with society, from small daily chatting intelligent robots to large industry and government-level assisted offices, and is quietly changing the way of life around the world (Li et al., 2017). By convention, AI is described as a sub-discipline of computer science dedicated to the development of data processing systems and the execution of functions that match human intelligence, such as learning, reasoning, and self-improvement (Peres et al., 2020). According to Trifan and Buzatu (2020), AI is machine learning, that is, a neural network trained on a data set. Drive resources, data resources and computational theory are the three core elements that influence the development of AI. In contrast to any of the technologies that have emerged in the past, AI can get more brilliant at a particular practical task with the accumulation of time owing to its unique learning ability. AI is designed to serve humans in making the best decisions. To this end, AI has been incorporated into operating systems in the hope of creating systems that can assist humans or even be utterly AI-driven in their decision-making (Gomes et al., 2020). Progressively, AI is becoming indispensable technological support for daily social life and economic activities (Naimi-Sadigh et al., 2021). Its tremendous contribution to sustainable economic development in all industries is rapidly becoming evident, leading it to become an instant focus of attention at the industry, academic and even government levels (Heylighen, 2017). Arguably, AI-related activities will be the driving force for further economic development and result in fundamental shifts in the structure and approach to production, and in the quantity and quality of consumption (Vyshnevskyi et al., 2019).

However, while people are cheering this inspiring fact, some are expressing their skepticism. Although the widespread application of AI will cause a short-lived economic boost at this stage (Goertzel et al., 2017), in the long run, people's over-reliance on AI is likely to pose some potential threats (McClure, 2017). Such as the unemployment fiasco, moral and ethical risks, and personal privacy concerns that are often mentioned by scholars in the literature (Kak, 2018). What is more, the technical bottlenecks in the development of AI technology itself also lead to a large gap between the conception of theoretical research and the blueprint in actual practice. In light of recent events between AI and economic development (AI&ED), it is becoming extremely difficult to ignore the existence of the two colliding with each other. Accordingly, a considerable amount of literature has been published on AI&ED. These studies over the past two decades have provided important information on discussions between AI and economic development. More importantly, the evidence shows the increasing urgency and depth of the intersection between AI and various sectors of economic activity. For instance, to allow the power sector

to provide good services at competitive prices, Hernández-Callejo et al. (2013) designed an architecture model for power load forecasting based on artificial neural networks that conduct short-term load forecasting.

The growing breadth and fragmentation of topics at the intersection of AI and economic activity have made it increasingly difficult for scholars to attempt a comprehensive understanding of the field. To make matters worse, the complexity of the topic has led to a diversity of insights, generating a wealth of ideas and investigations on the link between AI and economic development. While there have been some reviews of the literature on AI and economic development, the multifaceted nature of the field suggests that this is still far from sufficient (Aghion et al., 2018). On the one hand, short-term studies such as these do not necessarily show subtle changes over time. On the other hand, the available reviews are selective in the literature they employ and the range is usually limited to fit the volume and variety of relevant literature. At the same time, it is not easy for scholars themselves to objectively summarize and sort out the literature (Lee & Lim, 2021).

In moving forward to redress this challenge, this paper attempts, through a combination manner of bibliometric analysis and literature review, to gain a one-stop overview on the publications' performance, collaboration patterns and intellectual structure of the AI&ED domain. More pertinently, this study responds to this practical need by answering the following three broad research questions: (1) What is the performance and current status of AI in economic activities and its related fields? (2) Which research themes in the field of AI&ED have received sufficient attention and exploration in recent years in the existing knowledge? (3) Which research agenda should endeavor in this domain in the future? By doing so, we establish an overview of the basic information in the field of AI&ED and its current status and trends, so as to summarize possible knowledge gaps, provide new ideas for investigation and locate areas of expected contribution for subsequent research (Donthu et al., 2021).

The contributions of this study are twofold. Firstly, we position the research perspective at the intersection of AI and economic development. Compared with other investigations, the work in this paper is more contemporary and novel. It helps to establish an understanding of the complexity and interdisciplinary nature of research on the application of AI in economic development. Secondly, the two-phase methodology, i.e., the two-pronged approach of bibliometric analysis and content survey, guarantees the comprehensiveness and reliability of the study (Qin et al., 2022). Using advanced bibliometric techniques, the outline of the evolution and knowledge structure of the AI&ED field is outlined. Also, the emerging research on AI applied to economic activities is clearly perceived, which helps theory and practice to go hand in hand. In particular, for the different knowledge streams, we deploy qualitative content analysis to discuss key publications to determine which topics and issues are front and center in the context of AI and economic development, and how the different topics are bundled in the knowledge streams.

In the remainder of this paper, we present how the two-step methodology works in the "Research Design: A Two-Step Methodology" section. Based on bibliometric techniques, the "Results of Bibliometric Analysis" section is developed from two dimensions: performance analysis and science mapping. In the "AI and Economic Development" section, we conduct a systematic literature review of the five themes

identified. The "Discussions and Implications" section gives discussions and implications. Concluding remarks and limitations end the paper.

Research Design: A Two-Step Methodology

We adopt a two-step methodology to achieve a deeper understanding of the intellectual landscape of the AI&ED research field and the multi-level connections between AI and economic development. The former employs bibliometric techniques to scientifically conduct extensive quantitative analysis of relevant publications for preliminary validation of research ideas. Based on the former, the latter uses a structured literature review approach to describe recent popular mainstream topics in AI&ED to identify potential research gaps. The overall two-step research protocol is depicted in Fig. 1.

Phase 1: Bibliometric Analysis

The implementation of a bibliometric analysis can empower us to identify the dynamic nature of the AI&ED research field (Qin et al., 2021). We chose the most popular and authoritative Web of Science (WoS) Core Collection database as the starting point of the project. In line with the approach of most scholars at this phase,
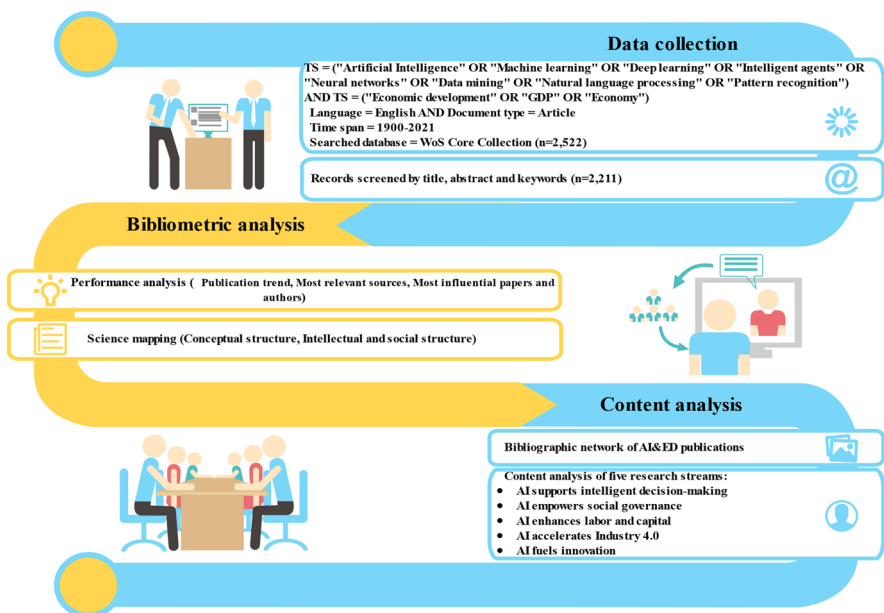

Fig. 1 The two-step research protocol

we defined the field boundary using a set of keywords that are coherent with the purpose of the study. To ensure that the final search results include as much of the desired literature as possible, broader search strings were initially identified, i.e., TS = ("Artificial Intelligence" OR "Machine learning" OR "Deep learning" OR "Intelligent agents" OR "Neural networks" OR "Data mining" OR "Natural language processing" OR "Pattern recognition") AND TS = ("Economic development" OR "GDP" OR "Economy"). In parallel, to ensure state-of-the-art of records, purely peer-reviewed academic journal articles were considered for this study. Only the publications with language in English were taken into consideration. Besides, to guarantee the annual property of the data, we limited the search span during the period from 1900 to 2021. The search was carried out in March 2022, and a total of 2522 items matched these constraints and were initially included in this examination. Prior to the quantitative statistical analysis, we manually checked the titles, abstracts and keywords of the identified documents and those irrelevant publications were removed. In the end, 2211 records were created for this investigation.

To fulfill the objectives of the quantitative analysis and visualization of the retrieved documents, we need to adopt some advanced bibliometric tools. Bibliometrics is based on quantitative methods designed to identify, describe, and evaluate published research (Bretas & Alon, 2021; Garfield, 1979). Its use of scientific mapping and graphical presentation of reproducible statistics reduces the subjective bias of literature reviews on the one hand, and overcomes the limitations of diagnosis and the error-prone nature of manual summarization on the other (Su & Lee, 2010; Tariq et al., 2021; van Eck & Waltman, 2010). Gradually, the ideas and theories of bibliometrics have become an invaluable manner for many scholars to explore and discover new knowledge in academic research (Qin et al., 2020; Wang et al., 2020a, b, c). In response to this trend, many advanced algorithms and sophisticated visual analysis tools have been developed to help scholars quickly perform bibliometric analysis. In this paper, we apply two bibliometric tools Bibliometrix and VOS viewer that are more mature at this stage. Bibliometrix is a powerful open-source tool developed by Aria and Cuccurullo (2017), which supports a recommended workflow to perform bibliometric analysis aimed at performing comprehensive scientific mapping work. By using this tool, we accomplished almost all the bibliometric parts of this paper, that is, the performance analysis and science mapping analysis of the collected records, including publication trend, most relevant sources, most influential papers and authors, conceptual structure, and intellectual and social structure. As an equally excellent structured analysis software, VOS viewer is more focused on the graphical representation of bibliometric maps (van Eck & Waltman, 2010). With the assistance of its bibliographic coupling procedure, this paper achieves an in-depth exploration and examination of the intellectual structure of the core publications of AI&ED.

Phase 2: Literature Review

In the first phase, we utilized bibliometric analysis to provide an objective, but only cursory, understanding of the intrinsic structure and overall extrinsic performance of

the AI&ED domain. This macroscopic model of mathematical statistics appears to be more extensive and clearly demonstrates the connections between different attributes, but it does not allow for profound qualitative conclusions to be drawn. In view of this, clusters formed by core knowledge streams in the bibliographic network based on AI&ED publications are reviewed qualitatively and manually in order to summarize the hot spots and gaps in current knowledge on different topics and thus answer specific research questions. Although the traditional process of qualitative literature analysis can be laced with viewer subjectivity, the benefits of this approach are well recognized (Vallaster et al., 2019). Besides, as Gaur and Kumar (2018) stated, it is the combination of content analysis with other methods that facilitates its tremendous potential. Undoubtedly, bibliometrics perfectly matches the traditional content review (Ante et al., 2021). The complementary content analysis allows us to identify hot spots and blind spots in the various research tributaries in AI&ED, thus prompting subsequent research directions to be discovered.

Results of Bibliometric Analysis

Performance Analysis

In this part, we adopt several performance indicators in bibliometrics to provide valuable insights into the AI&ED field. Concretely, we focus on the publication trend, most relevant sources and most influential papers and authors.

Publication Trend

The 2211 documents included in the final dataset generate the annual scientific production in the field of AI&ED, as depicted in Fig. 2. Studies on AI&ED started
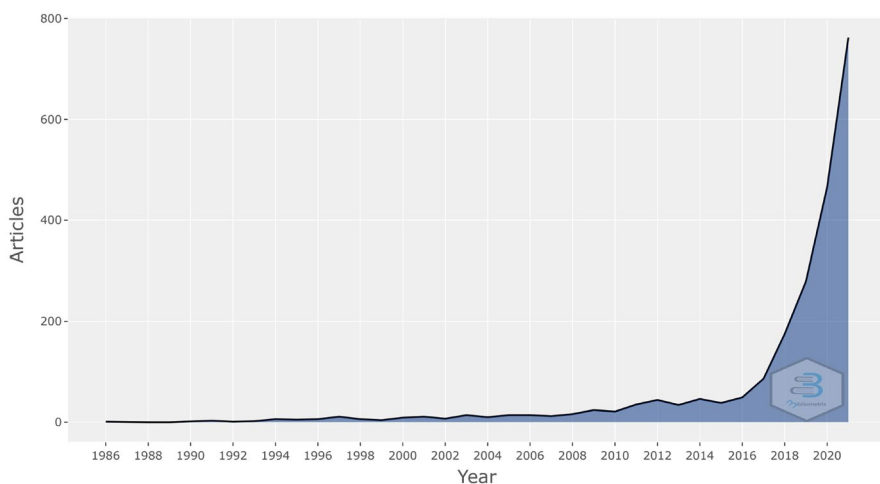

Fig. 2 Annual scientific production

in 1986, when Yamashiro posted their seminal work in which online secure-economy preventive control of power system was presented based on pattern recognition (Yamashiro, 1986). Although research on this issue has received attention from the scientific community since then, the published studies on AI&ED increased dramatically until approximately 2016, especially during the period from 2018 to 2021. The exponential growth pattern of the field in recent years suggests two facts. The extensive application of AI to economic development and relevant areas is a very recent phenomenon. On the flip side, there exists a fierce argument in management research within AI's role in the achievement of economic development. According to the visible observed trend in Fig. 2, research on AI&ED is still immature and in the stage of infancy. With the deepening of AI technology, we can expect a great deal of research in the future dedicated to further enhancing domain knowledge on economic research through AI.

Most Relevant Sources

Overall, the 2211 selected documents cover 1096 different sources. Figure 3 sets out the international panorama of the top 20 most relevant sources in the AI&ED field. In this case, we could easily find that the top source comes from "Sustainability" with a total number of 61 publications updated to 2021. The "IEEE Access" owns the second rank with 60 publications, followed by "Energies" (39 publications). With the same number of 39 publications, "Expert Systems with Applications" is in the fourth position. In this regard, investigators concerned with the AI&ED topic need to be particularly attentive to these sources. Moreover, Fig. 4 provides the year-wise growth of the top 5 sources over the period 1986–2021. The temporal evolution of these sources demonstrates that
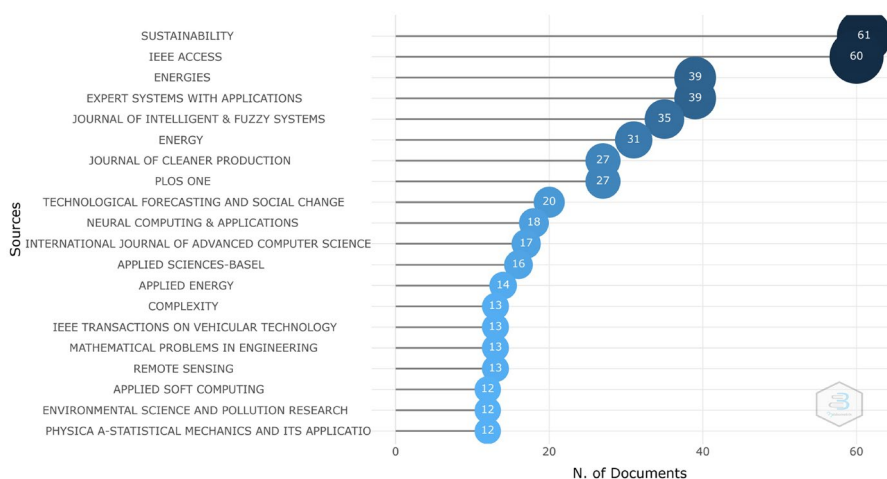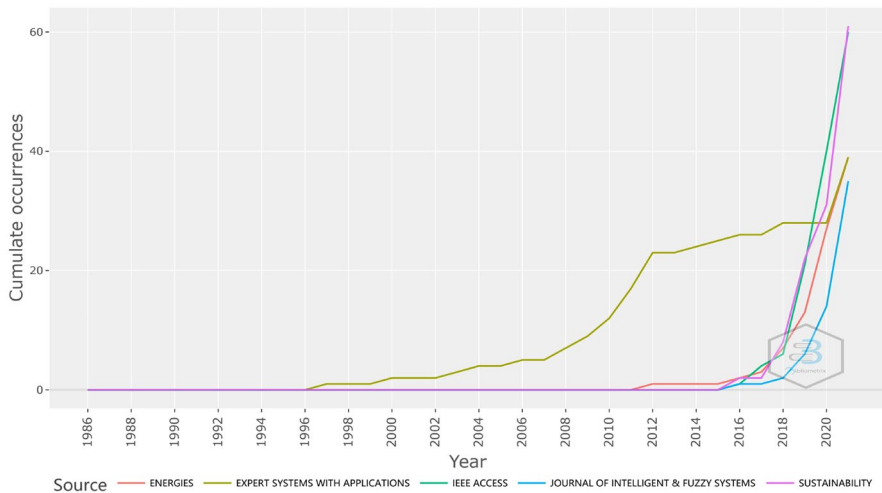

Fig. 3 Most relevant sources

Fig. 4 Source dynamics

the majority of journals are distributed in a growing trend. In particular, "IEEE Access," "Sustainability," "Energies," and "Journal of Intelligent & Fuzzy Systems" become productive during the last lustrum. Instead, "Expert Systems with Applications" exhibits a slower increase trajectory in recent years.

Most Influential Papers and Authors

Citations for an article are regarded as an appropriate manner to measure its influence and authority in the field (Wang et al., 2021a). Given this backdrop, highly cited documents over the period 1986 to 2021 in the AI&ED field are assessed, and the top 10 cited publications are exhibited in Table 1. Nevertheless, the total number of citations (TC) per se does not completely determine the quality of an article, and the time factor usually needs to be considered. Thus, the average number of citations received each year (TC/Y) is also generally deployed as an effective metric for an article's impact.

Table 1 lists the specific TC and TC/Y across the top 10 documents. Also, the other useful information on them is specified. Evidence from Table 1 indicates that more than half of the publications have been cited more than 300 times in total. Besides, two observations could be obtained from this table. In the first place, five of these documents were pressed before the year 2010, and five after 2010. Surprisingly, the article titled "Automated detection of COVID-19 cases using deep neural networks with X-ray images", published in 2020, earned a whopping 622 citations. The sudden appearance of the novel coronavirus in 2019 has brought a great impact on the life and health of people all over the world. To accurately detect and diagnose potential people suffering from this disease, an automated assisted diagnosis tool named DarkCovidNet based on deep neural networks was developed by Ozturk et al. (2020). Furthermore, the article called "Brain

Table 1 Citation analysis of the top 10 documents ordered by the TC

No	Author(s)	Title	Year	Journal	TC	TC/Y
1	Ozturk et al	Automated detection of COVID-19 cases using deep neural networks with X-ray images	2020	Computers in Biology and Medicine	622	207.3
2	Latora & Marchiori	Economic small-world behavior in weighted networks	2003	The European Physical Journal B—Condensed Matter and Complex Systems	503	25.2
3	Leitao	Agent-based distributed manufacturing control: A state-of-the-art survey	2009	Engineering Applications of Artificial Intelligence	464	33.1
4	Lu et al	Brain Intelligence: Go beyond Artificial Intelligence	2018	Mobile Networks and Applications volume	409	81.8
5	Ding et al	A survey on security control and attack detection for industrial cyber-physical systems	2018	Neurocomputing	363	72.6
6	Chen et al	Application of neural networks to an emerging financial market: forecasting and trading the Taiwan Stock Index	2003	Computers & Operations Research	239	12
7	Kaytez et al	Forecasting electricity consumption: A comparison of regression analysis, neural networks and least squares support vector machines	2015	International Journal of Electrical Power & Energy Systems	226	28.3
8	Paya et al	Artificial neural network based fault diagnostics of rotating machinery using wavelet transforms as a preprocessor	1997	Mechanical Systems and Signal Processing	220	8.5
9	Boros et al	An implementation of logical analysis of data	2000	IEEE Transactions on Knowledge and Data Engineering	213	9.3
10	Chen et al	Energy management for a power-split plug-in hybrid electric vehicle based on dynamic programming and neural networks	2014	IEEE Transactions on Vehicular Technology	178	19.8

Intelligence: Go beyond Artificial Intelligence" on the list, despite being published as recently as 2018, has 409 citations (Lu et al., 2018). A novel technology concept named brain intelligence was introduced in their work to break through the many limitations of extant AI. Secondly, in terms of research contents, AI technologies have penetrated various areas of the economy concerned, such as finance, energy and machinery, and are increasingly playing an essential role.

A total of 6871 authors participated in the study on the AI&ED domain, and Fig. 5 depicts the top 10 leading authors in the analyzed dataset. In the specific case of productivity, the top five authors, including Li Y, Hele M, Magazzino C, Wang Y, and Zhang Y, produced 17, 16, 14, 11, and 10 articles respectively. In contrast, the last five authors mostly yielded eight articles. In a nutshell, the distribution of research results in this area is somewhat scattered and lacks core leaders.

Science Mapping

With respect to the analysis at the science mapping level, a series of bibliometric methods are exploited here to identify the conceptual, intellectual and social structures hidden in AI&ED issues.

Conceptual Structure

Keywords are a high level of abstraction and generalization of an article's research content, which empower a good way for scholars to discern the research topic and capture potential trends (Wang et al., 2020a, b, c; Zheng et al., 2016).

Several dominant themes are usually shaped in the development of a particular domain within the research. To this end, Bibliometrix provides the strategic diagram function to identify themes in different phases based on the centrality and density ranking. On the basis of co-occurrence analysis for the author's keywords,
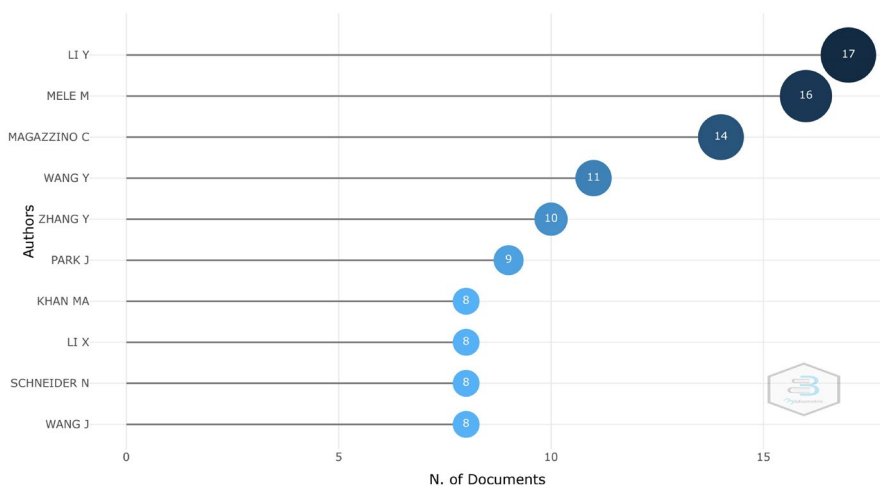

Fig. 5 Most relevant authors

the comprehensive strategic diagram of AI&ED research from 1986 to 2021 is constructed as presented in Fig. 6. As a result, the nutshell overview of the dominant research topics on AI&ED is highlighted. Obviously, the X-axis (centrality) and Y-axis (density) split the two-dimensional space into four different regions (i.e., quadrants). In this setting, four types of themes with different meanings are clearly distinguished (Cobo et al., 2011). Centrality gauges the level of inter-cluster interaction, whereas density measures the level of intra-cluster cohesion (Forliano et al., 2021). More to the point, themes that fall in the first quadrant (upper-right quadrat) are usually well-developed and are significant in shaping the field of study. They have high centrality and density values and are usually referred to as motor themes. A theme is characterized by low centrality and high-density values, which is positioned in the second quadrant (upper-left quadrat) as a highly-developed and isolated theme. Diametrically opposed to the thematic characteristics of the first quadrant, themes in the third quadrant (bottom-left quadrat) are not only low in centrality but also low in density, with disappearing or emerging themes gathering here. Lastly, basic and transversal themes usually lie in the fourth quadrant (bottom-right quadrat) with high centrality and low-density values (Lam-Gordillo et al., 2020). Visible here is that each theme cluster is composed of a number of keywords, and its name is determined by the most frequent keyword. Besides, the higher the frequency of keywords per theme, the larger the area of the circle will be accordingly.

Therefore, five prevalent themes are finally identified in the diagram. Research related to "artificial intelligence," "big data," and "Internet of things" is aligned to the first quadrant, suggesting research on these topics dominates and profoundly influences other topics in the AI&ED field. The developed but isolated theme in the second quadrant, namely "neural network," "optimization," and "energy
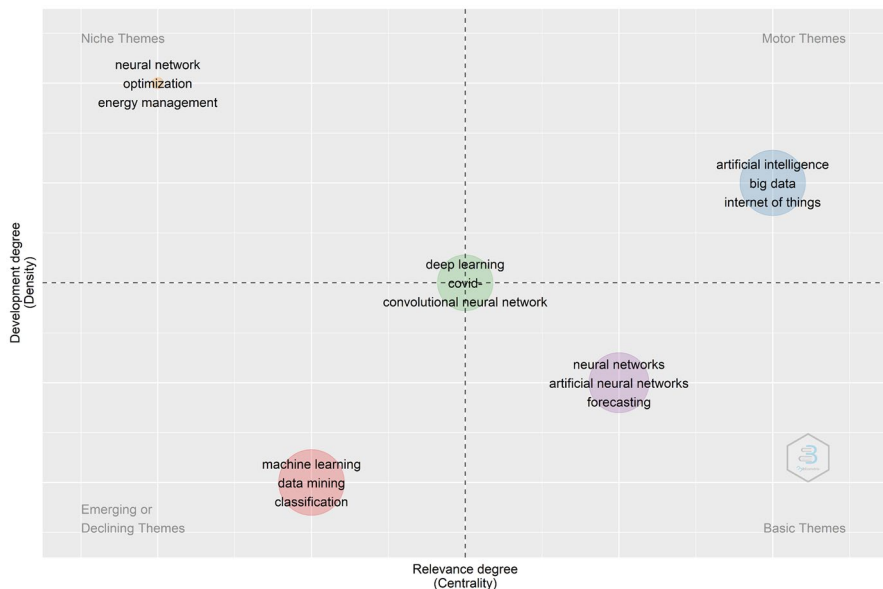

Fig. 6 Strategic diagrams of AI&ED research (1986–2021)

management," should be given sufficient attention to breaking down the silos of research. Interestingly, related studies on "machine learning", "data mining" and "classification" are recognized as disappearing or emerging themes, which to some extent foreshadows future research frontiers. Not surprisingly, the problems about "forecasting" become the general and broadly researched themes. How AI boosts economic development and finding effective paths to it will be a topic of continuous discussion in the future.

Intellectual and Social Structure

After examining the conceptual structure concerning the AI&ED field, the intellectual and social structure would be further revealed in this part. To be specific, we are committed to visualizing co-citation network and country collaboration map in the AI&ED field. Co-citation analysis is used for the analysis of the cited sources, which allows us to quickly capture the mainstream source communities. In the same way, Fig. 7 outlines the three source clusters amongst the

Fig. 7 Co-citation network of cited sources in the AI&ED field

50 most influential sources. In the first cluster (shown in red), 16 sources are detected, and high-quality journals such as "Neurocomputing," "Expert Systems with Applications," and "Decision Support Systems" occupy the main position. 18 sources make up the largest Cluster 2 (shown in blue), in which the representative sources include "Applied Energy," "Renewable and Sustainable Energy Reviews," "Energy," and so forth. In the last cluster (shown in green), 16 sources are more dispersed in the figure, with "Nature" and "Science" journals occupying the center of the diagram.

With consideration to the prevalence of cooperation and linkages between authors from different regions or countries, we conduct a collaboration-based assessment of international cooperation. By performing the Collaboration World-Map function in the Bibliometrix and setting the minimum edges as three, Fig. 8 sheds light on the social structure within the AI&ED domain. Overall, there are 627 pairs of country/region key cooperation on this map. At the same time, the higher the productivity of a country or region, the darker its color is, while the connection of the lines indicates the presence of collaboration, and the more robust the line, the higher the rate of collaboration. The assessment shows that China, the USA, and India are among the world leaders in terms of individual country or regional contributions with 624, 412, and 210 publications, respectively. Another interesting finding shows that scholars from the USA and China are fostering the strongest collaborations, and they are building strong ties with their counterparts around the world. In fact, the highest rate of collaboration between the USA and Chinese scholars has also been maintained, with a total of 66 co-authored articles. As it clearly appears, there are still several authors from
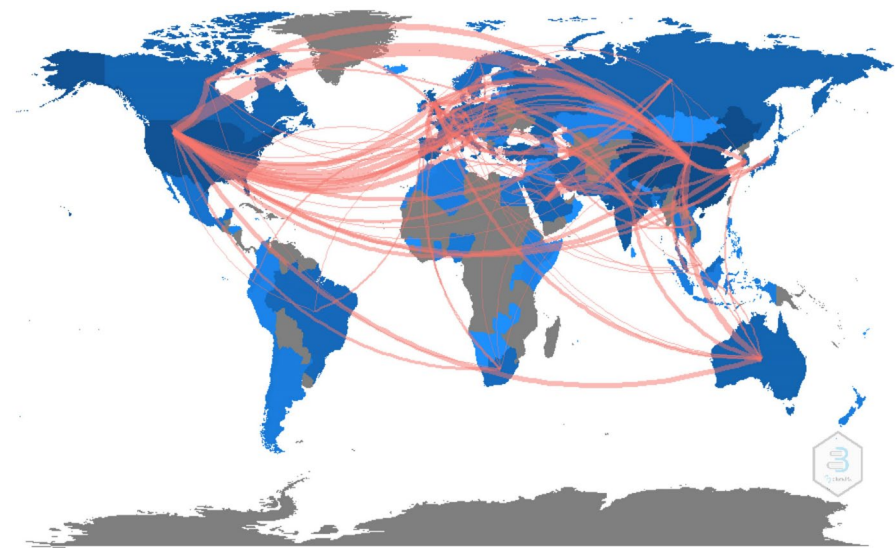

Fig. 8 Country collaboration map

different countries or regions who are not involved in this area of communication and collaboration.

AI and Economic Development

Bibliographic coupling occurs when two publications cite a third common publication in their bibliographies (Wang et al., 2021b). As a similarity measure, it is often used to cluster similar research streams. Obviously, the magnitude of coupling is proportional to the relevance of the research topic and content between publications. The significant difference compared to co-citation analysis is that bibliographic coupling analysis can better identify the distribution of recent research topics and current trends in AI&ED, which can inspire us to ponder about future research (van Oorschot et al., 2018). Thus, with the assistance of the VOS viewer tool, Fig. 9 visualizes the coherent bibliographic network of the AI&ED literature to detect similar subject areas, and determines the mindset of core researchers.

Since the bibliographic network generated by the initial 2211 publications cannot identify the number of controllable and valid clusters, we set some filtering conditions and modulate some parameters to derive the number of clusters that can be analyzed. Expressly, to obtain core insights and capture closely linked research results within each cluster, we eliminate unconnected items to show the largest set of connected items. What is more, in our study, we adjusted the minimum cluster size and set it to 12 instead of the default of 1, which makes the final number of clusters more concentrated. In fact, we have also fine-tuned the final rendering of the graph by changing the repulsion parameter to -1, while leaving the attraction parameter as
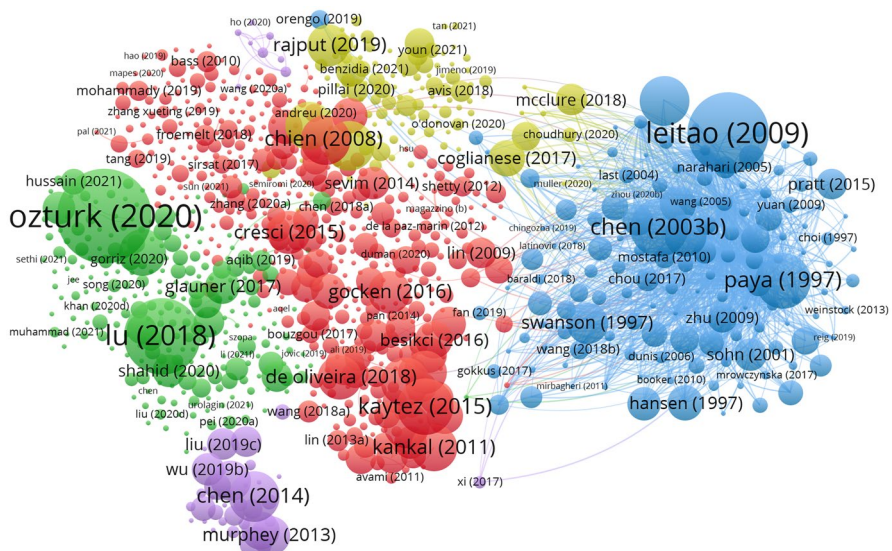

Fig. 9 Bibliographic network of AI&ED publications

default. Finally, Fig. 9 generates five highly distinguishable clusters that are given different colors to highlight. In what follows, this paper will review these five relatively independent research streams in detail. The five presented broad research topics are: *AI supports intelligent decision-making* ("AI supports Intelligent Decision-Making" subsection), *AI empowers social governance* ("AI Empowers Social Governance" Subsection), *AI enhances labor and capital* ("AI Enhances Labor and Capital" subsection), *AI accelerates Industry 4.0* ("AI Accelerates Industry 4.0" subsection) and *AI fuels innovation* ("AI Fuels Innovation" subsection).

AI supports Intelligent Decision-Making

In this cluster, how to use AI techniques to maximize successful decision-making in economic problems becomes the main research focus. Intelligent decision-making could be generally understood as the application of the knowledge representation and thinking process of AI into the decision-making theory, by introducing theories and methods from management, computer science and related disciplines for analysis and comparison, thus providing wise and intelligent aid for managers to make the right decisions (Niu, 2018). However, the prerequisites for efficient prediction largely determine the likelihood that intelligent decisions will eventually be realized. Forecasting is based on the historical data of things, through certain scientific means or logical reasoning, to make estimation, speculation and judgment on the future development of its situation, and seek the future development law of things. In recent years, the fact that correct predictions (or forecasts) will lead to successful decisions and thus provide maximum economic benefits has increased the interest in predictive modeling. Indeed, in contrast to traditional econometric techniques, AI technology, with its mighty computing power, has injected new blood into scientific forecasting, providing more feasible ideas and solutions for forecasting technology. Also, it significantly improves the accuracy and reliability of forecasting and provides decision support capabilities for various industries that beyond traditional statistical-based analysis (Binner et al., 2004). As a consequence, AI-based predictive algorithms are increasingly being considered in various areas of human economic creation.

Energy is of strategic importance to the development and social welfare of any economy (Cen & Wang, 2019). Effective forecasting of energy demand, consumption and prices is directly related to the compatibility between the economy and the environment. For example, Ardakani and Ardehali (2014) developed an optimal regression and ANN (artificial neural network) model for predicting EEC (electric energy consumption) based on several optimization methods, examined the effects of different historical data types on the accuracy of EEC prediction, and then made long-term predictions for two different types of economies, Iran and the United States, respectively. In order to improve the accuracy of oil market price prediction, Cen and Wang (2019) used Long Short Term Memory, a representative model of deep learning, to fit crude oil prices. Moreover, swarm intelligence approaches, including artificial bee colony (ABC) and particle swarm optimization (PSO) techniques were introduced to evaluate the electrical energy demand in Turkey (Kıran et al., 2012). Also for Turkey,

Uzlu et al. (2014) applied the ANN model and TLBO (teaching–learning-based optimization) algorithm to estimate its energy consumption, which also showed good prediction performance. However, a single model cannot always meet the requirements of time series prediction and fuel consumption variation (Liu et al., 2016). In parallel, the fact that energy consumption involves a large number of parameters makes its forecasting a complex and challenging task to carry out. To this end, combining the excellent predictive models available is the most straightforward response, and it has proven to be effective (Li et al., 2018). Predicting the interrelationship between energy activities and real economic fluctuations is also further explored by relying on AI algorithms. In different domestic and international environments, varying oil price shock incentives can cause different oil price shocks and have different macroeconomic impacts. In response to this problem, Ju et al. (2016) proposed an ontology-supported case-based reasoning approach to an incentive-oriented AI early warning system, namely the relationship between oil price shocks and the economy early warning system, for predicting the linkage changes between macroeconomic and oil price shocks in China. Furthermore, the economic dependence between urban development policies and energy efficiency improvement was revealed by building a neural network model (Skiba et al., 2017). In addition to the energy sector, other areas involved in economic development are also actively incorporating AI technologies to achieve the best forecasting results, such as the spatial prediction of land subsidence susceptibility (Arabameri et al., 2020), the prediction of standardized precipitation evapotranspiration index (Soh et al., 2018) and predicting the monthly closing price of major USA indices (Weng et al., 2018).

In fact, forecasting can also be considered as the process of filling in the missing information, i.e., using the information already collected to generate information that we do not yet have or that we expect to have. Based on the vast amount of available data, AI technology can quickly and efficiently make diagnoses or judgments to help people make the best decisions in a short period of time, minimizing economic risk at the organizational, industry and national levels. At the end of 2019, the sudden onslaught of the novel coronavirus 2019 not only posed a huge threat to people's lives and health, but also caused a heavy blow to economic development worldwide. As the epidemic continues to spread around the world, diagnosing infected patients has become one of the urgent tasks to be solved at that time. For this reason, many radiological images have been widely used for the detection of COVID-19. In particular, the integration of AI technology allows the diagnosis of patients with COVID-19 infections at a significant advantage (Tsiknakis et al., 2020). For instance, Ozturk et al. (2020) presented a new model for the automatic detection of COVID-19 using raw chest x-ray images. The model can achieve an accuracy of 98.08% for the classification of binary classes and 87.02% for the classification of multiple classes. It is worth pointing out that despite the widespread use and effectiveness of AI in fraud detection, the emergence of new fraudulent vectors has posed severe challenges to fraud detection in the AI framework (Ryman-Tubb et al., 2018). Besides, the boom in the fitness industry in recent years has led to a critical need for scientific and practical instructional programs. In light of this, real-time monitoring and guidance based on exercisers' daily fitness data, supported by AI technology, has become a trend for future fitness applications (Yong et al., 2018).

The development of computers and information technology gave rise to the creation of a decision support system (DSS) in the mid-1970s to help decision-makers improve the level and quality of their decisions. Suffice it to say that the rapid advancement of AI technology has given people a wonderful aspiration for the intelligence of traditional DSS (Pinter et al., 1995). Later, DSS was combined with AI and expert system technologies, and the prototype of an intelligent decision support system (IDSS) was outlined, enabling the original system to cope with more complex and uncertain decision scenarios. With this opportunity, IDSS has been widely studied by scholars and involved in many human economic activities. For example, to achieve effective management and rapid response to different customer needs in transportation enterprises, He et al. (2014) proposed a general framework that integrates intelligent technologies as components into the architecture of service-oriented group decision support system, and skillfully used AI technology to solve the conflict problem in distributed group decision-making. The multi-agent system theory and techniques in AI likewise provide essential insights for the development of DSS. To address the complex issues in agricultural development, Xue et al. (2013) designed an agent-based regional agricultural economy decision support system (RAEDSS) to simulate and evaluate the impact of policies on rural development under different scenarios. Considering that intelligent decision-making should have the ability to explore and discover uncertain environments, scholars have tried to combine fuzzy logic with IDSS to enhance its knowledge representation and reasoning capabilities. Using fuzzy cognitive maps, Albayrak et al. (2021) developed an IDSS to achieve high yield of honey. In addition, uncertain production goals are extremely common in production plants, and this uncertainty leads to the invalidation of regular management. In view of this, Rodriguez et al. (2020) proposed an IDSS for production planning based on machine learning and fuzzy logic to solve the closed-loop supply chain management problem.

AI Empowers Social Governance

At present, AI technology is developing deeply and AI application scenarios are enriching, which then calls out a new governance concept and governance form for society. Overall, the new pattern of AI-powered social governance is in the preliminary exploration stage (Mania, 2022). What is certain, however, is that AI technology has been used more widely than ever in recent years. These wide ranges of applications are not only reflected in common daily aspects such as image analysis, face recognition and big data analysis, but also gradually rise to the level of major social rulings and human emotional cognition applications (Coglianese & Lehr, 2017; Huang et al., 2019). At the city level, the great strength of AI in processing big data has contributed to a major change in the urban fabric, a prospect greatly facilitated by the emerging smart city concept that promotes the combination of sensors and big data through the Internet of things (Allam & Dhunny, 2019). The core idea of the smart city emphasizes the underlying support of big data, which requires not only tens of thousands of data, but also the integration of multi-dimensional data. This is well evidenced by the full impact of the COVID-19 pandemic. The

recent COVID-19 pandemic has prompted a great deal of thought by many scholars about many vital issues and potential complexities for organizations and societies (Dwivedi et al., 2020; Iandolo et al., 2021), particularly the controversy over data sharing related to the concept of urban health and safe cities (Allam & Jones, 2020). On one side, strengthening standardized protocols to increase data sharing will not only help the efficient development of epidemic prevention and control, but also facilitate the further construction and design of smart cities, as well as lead to better global understanding and management of the same. However, it is undeniable that sharing urban health data has the potential to impact the economy and politics of a country or region. Besides, as AI continues to permeate all aspects of human society, some administrative agencies are attempting to employ intelligent algorithms to improve the intelligence of government governance. On a technical level, this is entirely possible. Hildebrandt (2018) pointed out that data-driven artificial legal intelligence may be much more successful in predicting the content of positive law. Likewise, profound developments in information technology are changing the way banks work, relying more on reliable quantitative information from online and credit bureaus, contributing to AI-based decision-making (Jakšič & Marinc, 2019). Finally, over recent years, AI technology is also quietly changing the face and operation of other social industries such as education (Mehmood et al., 2017; Williams, 2019), marketing (Rust, 2020) and accounting (Moll & Yigitbasioglu, 2019), seeking to improve economic efficiency.

However, we should also see that while AI accelerates economic development and promotes social governance to a new level, it brings additional challenges to human society in terms of legal norms, moral ethics and governance guidelines that should not be underestimated. Firstly, as mentioned earlier, big data gives AI enough valuable data to support it. Generally speaking, the larger and more dimensional the data, the more promising the final effect of intelligent algorithms, which inevitably involves individual-level data analysis, collection and application. Scholars have long debated the protection of personal data and concerns related to privacy (Kak, 2018). On the one hand, some scholars have called for striking as much of a balance as possible between data protection and data-related concerns (Dwivedi et al., 2020). On the other hand, some scholars pointed out that no one owns data and that property rights protection of data is not appropriate to promote better privacy, more innovation or technological progress, but is more likely to stifle freedom of expression, freedom of information and technological progress. Thus, the case for property rights to data is not compelling, and there is no need to create new property rights for data (Determann, 2018). Secondly, Allam and Newman (2018) cautioned against the blind acceptance of technology and encouraged further embedding into the social fabric. Such a reminder stems in large part from the ethical issues of fairness, responsibility or subjectivity that AI can raise. Research in AI could be roughly divided into three stages: mechanical AI, thinking AI and feeling AI. While mechanical AI is already mature and thinking AI is developing rapidly, the highest level of feeling AI is progressing slowly (Huang et al., 2019). Since AI at this phase does not possess self-awareness, AI platforms are not neutral technologies, they are designed with a purpose and exhibit bias and human rights violations (Bourne, 2019). Additionally, government agencies are beginning to widely adopt

AI technology for constitutional democracy and administrative decision-making, and concerns have increased over digital robots replacing the government sector. At the same time, reliance on AI has also led to an increasing challenge to human subjectivity. Therefore, in response to the above challenges, human workers must pay more attention to the extension of the empathy and emotional dimension in their work (Huang et al., 2019). On the flip side, creating a new culture that incorporates the principles of democracy, rule of law and human rights through the design of AI as well as considers diversity in the design and implementation of algorithms is a viable solution for the future (Nemitz, 2018; Turner Lee, 2018).

AI Enhances Labor and Capital

The debate over the conclusion that AI enhances the quality of labor as well as the quality of capital. In the traditional economic development model, the three production factors, i.e., capital, labor and total factor productivity (TFP), determine the development dynamics of the economy. When the two physical factors, capital and labor, rise in quantity or are used more efficiently, they contribute to economic development. Of course, an increase in TFP due to technological or innovative advances would also generate economic development. Collectively, it seems to be an undisputed fact that the widespread use of AI promotes economic development. More importantly, a large body of empirical literature supports this view as well (Chattopadhyay & Rangarajan, 2014).

Firstly, the development of AI has significantly reduced the cost of traditional automation while creating an opportunity for the era of intelligent automation (von Joerg & Carlos, 2022). Although traditional automation technologies have led to dramatic increases in labor productivity, specific and homogeneous settings, allow them to perform only simple and repetitive tasks. In contrast to the former, the era of intelligent automation has created a new kind of virtual labor force, which can be considered as a new factor of production. This phenomenon, on the one hand, diminishes the dependence on manual labor at the current stage of production and triggers the substitution of capital for labor (Autor, 2015). On the other hand, due to its self-learning and self-renewal characteristics, AI will effectively solve the complex labor needs of the many automated jobs in real life (Bahrammirzaee et al., 2011). In particular, this change in the structure of production factors will rapidly produce high-end labor, which in turn will significantly boost economic development (Vivarelli, 2014).

Secondly, with powerful and innovative AI technologies, the efficiency of the existing capital and labor has been enhanced to an unprecedented degree, while enabling the skills and capabilities of labor and physical capital to be also supplemented and improved. In fact, in addition to the above-mentioned substitution relationships, there are also many complementary relationships between AI and human intelligence (Huin et al., 2003). With human–machine collaboration, workers' productivity can not only be effectively utilized and extended, but also be motivated to focus on the areas they are good at and thus do more creative work. The scenario of human–machine integration has led to increasing labor productivity (Wolff, 2014).

For example, accurate estimation of the local scour depth concerning bridge piers is crucial for engineering design and management, which places higher demands on the professionalism of bridge engineers. To this end, a new hybrid smart artificial firefly colony algorithm-based support vector regression model was developed to predict the scour depth near bridge piers by Chou and Pham (2017). The results showed that the model could effectively assist the concerned staff in constructing safe and cost-effective bridge substructures. In terms of improving capital quality, as described in the "AI Supports Intelligent Decision-Making" section, AI is able to model, predict and ultimately optimize decisions in real time from massive amounts of data in the production process. It can almost completely avoid the problems of low accuracy, low integration and low adaptability in production activities, and achieve intelligence in the production process, thus realizing capital efficiency improvements. For the manufacturing industry, this is particularly evident. AI has become an important driver for intelligent manufacturing technology innovation, promoting economic development and improving people's quality of life. Research results showed that the adoption of highly interconnected and deeply integrated intelligent production lines would lead to significant improvements in manufacturing productivity as well as a corresponding reduction in the number of system instructions (Hu et al., 2018).

Finally, AI's ability to increase TFP across the board is well documented, and some existing studies even categorize it as a new factor of production that will further fuel economic development in the future.[1] Nevertheless, in the long run, many scholars are divided on the question of whether the progress of AI will play a sustainable role in promoting economic development. The negative school of thought believes that AI will replace labor and take over human jobs, which will likely lead to unemployed people much faster than productivity can be increased (Vermeulen et al., 2018). In a situation where the labor market is disrupted, income inequality and mass unemployment among workers are probably creating a further future of high unemployment and even economic stagnation (Frey & Osborne, 2017). As a consequence, AI's boost in the economy is seen as unsustainable (Vermeulen et al., 2018). As noted by Gasteiger and Prettner (2017), human dependence on AI would eventually lead to an economic rout, as the utilization of automation inhibited wage development and thus investment growth. In contrast, the positive school of thought argues that while AI can rapidly replace labor, the AI revolution will not necessarily have a fatal impact on employment. Specifically, on the one hand, the development and application of AI technology still require many human resources for research and development and design, as well as the operation and maintenance of AI equipment cannot be separated from the participation of senior technical personnel. This demand for high-end human capital creates a higher economic value, but of course also puts forward higher requirements for the quality of the future workforce (Chen et al., 2009). On the other hand, the skill requirements of jobs are dynamic, and the impact of AI is likely to generate new labor demand and new job opportunities (Frank et al., 2019). The historical experience of the industrial revolution tells us that at this stage, human beings are likely to be in a short transitional period with

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[1] https://www.accenture.com

frictional unemployment, followed by economic prosperity (Vermeulen et al., 2018). On top of everything else, some observers consider that the impact of AI on economic development and employment depends heavily on institutions and policies, and that inappropriate labor market and education policies may reduce the positive impact of AI and automation on employment (Aghion et al., 2019).

AI Accelerates Industry 4.0

According to our consensus, the Industry 1.0 era was marked by the invention of the steam engine by the Englishman Watt, which exponentially increased the efficiency of production technologies that previously relied on human and animal labor. The widespread availability of electricity has inaugurated the era of Industry 2.0. In this context, the productivity of factories has been developed and further improved. The Industry 3.0 era then witnessed the advent of computers and automation (Syam & Sharma, 2018). And in 2013, as the German government introduced the concept of Industry 4.0, it instantly attracted the attention of various countries and industrial giants (Carayannis et al., 2022). Industry 4.0 can be characterized as the emergence of cyber-physical systems involving entirely new capabilities for people and machines (Mhlanga, 2020). Even though these capabilities rely on the previous phase of Industry 3.0, the continued incorporation of extraordinary technologies has allowed for a long optimization of the third computerized industrial revolution (Sharabov & Tsochev, 2020). At the same time, the technology embedded in Industry 4.0 has created a new way of human life at this stage. Underpinned by these disruptive technological advances, Industry 4.0 aims to blur the boundaries among the physical, digital and biological worlds (Huynh et al., 2020). Simply put, it is expected to establish a highly flexible, personalized and digital production pattern of products and services, where the original industry boundaries will be broken down and the industry chain will be redefined (Sharabov & Tsochev, 2020). Journal articles and related reports in the context of Industry 4.0 indicate a huge demand for developing reliable and usable AI for real-world applications (Lee & Lim, 2021). It is foreseeable that AI will play an integral role in the future production paradigm of Industry 4.0 (Skrop, 2018). There seems to be a consensus among social scientists that AI is the key technology of the fourth industrial revolution (Liu et al., 2021).

The principal features of Industry 4.0 are technological transformations, digital revolution and AI (Wang et al., 2020a, b, c). More precisely, Sanz et al. (2021) pointed out that intelligent and automated solutions should be included in industrial processes that employ AI (AI-driven framework) to be competitive in the Industry 4.0 paradigm that essentially affects manufacturing. For this reason, a great deal of research has been conducted on how to combine and embed AI into the existing Industry 4.0 manufacturing value chain (Peres et al., 2020). To meet Industry 4.0 manufacturing standards, Nasr et al. (2020) proposed a hybrid adaptive neuro-fuzzy inference system (ANFIS) based on a multi-objective particle swarm optimization approach to obtain optimal combinations of milling parameters and matching rates to minimize feed force, depth force, and surface roughness. Artificial neural network model for dynamic behavior optimization of robotic arms, an AI technology, was

designed to improve the sustainability of Industry 4.0 (Azizi, 2020). Furthermore, more places for AI in Industry 4.0 have been identified and perceived by researchers, such as predictive analytics, predictive maintenance, industrial robotics, inventory management and computer vision (Sharabov & Tsochev, 2020). Collectively, industrial AI excels in five dimensions: infrastructures, data, algorithms, decision-making, and objectives (Peres et al., 2020). There is no doubt that the role of AI is central to the factory of the future, driven by the Industry 4.0 vision and reflected in the great blueprint for the factory of the future (Bécue et al., 2021). From an industrial perspective, AI can be viewed as enablers for systems to sense their environment, handle the data they acquire and address complicated tasks, as well as study from experience to enhance their ability to tackle particular challenges (Peres et al., 2020). While a high degree of autonomy is one of the core requirements for the future of Industry 4.0, the injection of additional human intelligence may be more beneficial to the operation of future factories and remains true, at least from this phase (Peres et al., 2020). In this regard, different levels of autonomous systems are more in line with the differentiated needs of factories at this stage.

From the above description, we can get that the basic concept of Industry 4.0 lies in the organic combination of hardware and software devices, so as to build a smart factory where people, machines, and resources communicate and collaborate with each other (Dopico et al., 2016). Currently, Industry 4.0 is a common trend in international development, bringing new opportunities to the economic expansion of many countries (Pham-Duc et al., 2021). However, it is not an easy task to truly implement the Industry 4.0 framework in industrial manufacturing processes (Sanz et al., 2021). The realization of this digital revolution is costly, and it is even sometimes impossible to quantify (Trifan & Buzatu, 2020). In fact, people are questioning whether the era of Industry 4.0 will ever exist, because the event space is infinite. And the actual software and hardware will never cover the infinite event spaces (Vogt, 2021). Besides, despite the potential of industrial AI, a large amount of training data and a large amount of computing power are required to make it suffer from a very precarious end as well (Sharabov & Tsochev, 2020). What is worse, real factory environments provide unique and difficult challenges for which organizations are not ready (Peres et al., 2020). And the physical nature of the systems and processes that industrial AI deals with leads to special constraints that other types of AI do not face (Bécue et al., 2021). For instance, the dynamics of anomalous and expected behaviors can cause the original fixed settings to be unable to accurately determine the boundaries between them, making it difficult to detect new threats, which can eventually lead to a series of industrial production security problems (Luo et al., 2021). Still, AI may have a perfect niche for its flourishing and implementation in industrial environments, as its applications can answer different questions and possibilities in each of the main pillars of the Industry 4.0 construct (Dopico et al., 2016).

AI Fuels Innovation

It is now widely accepted that the advent of AI technology has disruptively improved productivity, but its radiating effect of driving innovation through economic diffusion is rarely talked about or even valued. Innovative thinking and creative ideas are becoming mainstream as people slowly get used to the pounding of the fourth industrial revolution era (Chen, 2022). Imagine that if imagination is lost, progress may only be a short-lived blessing (Shakir et al., 2019). Mechanical improvements or instability have a long history of impacting innovation, as has AI, endowed with human intelligence (Shakir et al., 2019). Within a business perspective, innovation is a multi-stage process by which organizations transform ideas into new or improved products, services or processes to successfully move forward, compete and differentiate in the marketplace (Buhmann & Fieseler, 2021). Since AI at this stage is primarily characterized by expanding all aspects of human performance, it is not possible to achieve a high degree of autonomy, or even full autonomy, for the time being. We may question whether AI can take up the burden of influencing or even dominating the innovation management process. At first glance, the vision of AI being used to facilitate innovation purposes seems to be nonsensical. After all, the ability to innovate has traditionally been considered a uniquely human survival capability (Haefner et al., 2021). So far, decisions in the innovation process have been made by humans. Just imagine what it means when they are replaced by machines (Verganti et al., 2020). Nevertheless, along with the gradual blurring of the boundaries between AI and humans, a large number of cases tell us that AI promises to give birth to different explanations and inventions than before. This groundbreaking progress suggests that AI can be defined as the invention of an inventive method. In other words, AI has the ability to increase innovation productivity by helping human innovators with all the supportive tasks that ignite the creative spark and collate innovation propositions based on their merits (Samid, 2021). This is particularly evident in business activities. AI becomes a technology driver for business pattern innovation by steering decisions and automating services to leverage business practices that improve efficiency and profitability (Anton et al., 2021). Arguably, AI plays the role of creative enabler and partner to innovation managers in their innovation process (Kakatkar et al., 2020). More broadly, AI does have the potential to innovate on its own and to disrupt the entire innovation process under conventional perception, thus fundamentally changing the traditional innovation generation patterns (Hutchinson, 2021). The same view is shared by Cockburn et al. (2018). They claimed that AI also has the potential to transform the innovation process itself, with potentially equally far-reaching consequences, and it may dominate the direct impact over time. Moreover, it is not just about improving the efficiency of research activities, but about creating new scripts for innovation itself.

Certainly, the great human emphasis on the adoption of AI technology in the innovation process stems mainly from compromise with the reality of the environment. To begin with, today's increasingly turbulent and competitive innovation environment has inevitably created extremely difficult survival conditions. In addition, with the exponential increase in the amount of information collected by organizations or companies, limited human resources can no longer demonstrate the confidence

to handle the vast amount of information. More importantly, these organizations or companies are no longer willing or even able to bear the high human cost to cope with this challenge and carry out innovation activities (Haefner et al., 2021). On the other hand, AI's revealed strengths on the road to innovation have forged its current brilliance. In particular, in addition to meeting human's high efficiency in product or service design, AI injects unique sensory experiences into product or service with its powerful humanization, intelligence and experience interaction, immensely satisfying people's rich spiritual needs (Wang et al., 2019). Also, a number of outreach studies are filling and enriching this invigorating field. For the intrinsic mechanism of AI influencing technological innovation, Liu et al. (2020) gave a possible answer. They argued that it is because AI ultimately facilitates technological innovation by accelerating knowledge creation and technology spillover, improving learning and absorptive capacity, and increasing investment in R&D and talent. Exciting work on measuring the speed of AI innovation was then developed by Tang et al. (2020). According to their experiment, 5.26 new researchers were entering AI every hour in 2019, more than 175 times faster than in the 1990s. Additionally, the experience of AI to accelerate innovation varies across countries, especially with the dominant discourse currently committed to it in the West (Alami et al., 2020).

The point has to be made that while AI brings great benefits to innovative work, it also creates uncertain risks. Since the time when humans are not satisfied with applying AI to products and services, but rather into the innovation process, resulting in new products and new value chains (Davenport & Ronanki, 2018). People are slowly realizing that too much reliance on AI may generate a major threat in the near future (Cath, 2018). As such, the concept of responsible innovation is presented to address the ethical issue of responsibility at the boundary of innovation in AI, which provides a path for theoretical reflection and realistic response to the innovation and development of AI (de Saille, 2015). According to Buhmann and Fieseler (2021), responsible innovation in AI should be reflected in the following points. Foremost, the responsibility to avoid damage, i.e., risk management methods that should control potential hazards. Secondly, human-centered, the origin of all innovation is to serve human beings. Finally, governance responsibility stands for the responsibility to create and support global governance structures that can facilitate the first two responsibilities.

Discussions and Implications

This work attempts to provide a bibliometric analysis and a methodological study on the scientific knowledge of the performance of publications in the field of AI&ED. For this purpose, a series of activity metrics and precise content analysis are executed. The theoretical contributions and implications for practice are discussed in the following section.

Theoretical Implications and Roadmap for Future Research

As stated previously, AI technology is commonly applied to all levels of national economic development, and its driving role is indisputable and has a broad scope for development. As such, our survey makes several theoretical contributions and insights for further research on AI applications in the economic field.

Firstly, the result of the publication trend shows that the proliferation of AI in the economy domain has been unprecedented in recent years. In particular, the advent of the post-pandemic era has intensified the reliance on and desire for AI for economic development. As a result, future research efforts are foreseeable. However, as far as the publication channel is concerned, the quality of the research is not yet high enough. The percentage of top journals is very low. The intuition behind this embarrassing situation may be on the one hand that the collection, analysis and processing of the underlying economic big data are hindered. On the other hand, the model of AI serving economic development has not yet matured and is still in a lower quality period at this stage. Due to the interdisciplinary nature of this field, it is necessary to strengthen the scenario-based capabilities of the theoretical foundation of AI. In particular, the consolidation of the theoretical foundation will facilitate the construction of a well-functioning paradigm. On this basis, we encourage future scholars to focus on the effectiveness and practicality of interdisciplinary integration to follow the actual needs of economic development.

Secondly, we provide a list of the most cited work as well as a list of the most published authors, as this survey ascertains the most influential works and the most passionately researched scholars. Thus, the hot articles provide a good theoretical cornerstone for exploring substantial breakthroughs in future research. More importantly, practitioners can track their latest work and contributions to gain cutting-edge wisdom and guidance. It is worth noting that the implementation of AI in economic scenarios requires the joint participation of multiple stakeholders and policy makers. Highly productive academics' ambitions often lack practical experience, a gap that can lead to stalemates and dilemmas in AI execution. Thus, future researchers can connect multiple parties and actively collaborate to address this potential threat. More directly, the addition of a community of practitioners will accelerate the exploration and theoretical advancement of the AI&ED field.

Thirdly, a visual topic distribution map is executed to complement the existing content analysis to present the distribution and focus of current mainstream research topics. For example, the results of the conceptual structure reveal that researchers may have greater interest and passion for topics related to deep learning, data mining and classification in the future. Thus, we advocate more future agendas around these valuable and promising research hotspots for further expansion of the AI&ED field. However, the problem of AI-based prediction in economic activities remains the spotlight of research at this phase. For this reason, how to effectively use a large amount of economic information and improve the systemic as well as scientific aspects of forecasting issues in economic development has become an urgent concern. In addition, economic problems are often filled with a large amount of uncertainty and ambiguity, which is exacerbated by the emerging COVID-19 pandemic (Ozturk et al., 2020). Data uncertainty and cognitive uncertainty in forecasting need

to be reconsidered. Based on these facts, uncertainty prediction modeling should be highlighted in future AI&ED problems.

Fourthly, we reveal the collaborative associations and social structure at the country/regional level, and the relative contribution of each country/region to AI&ED research is identified. The results show that China is at the top of the world list in terms of contributions from individual countries or regions. In addition, the USA has established the strongest academic ties with China. This initiative is to be encouraged and supported. The generalizability of AI in solving economic problems needs to be proven in different countries/regions. Cross-border research collaboration can improve the applicability and robustness of AI models. For example, comparing differences in energy forecasting and warning mechanisms across countries/regions is an essential subject to be addressed.

Finally, the bibliographic coupling analysis identifies five mainstream knowledge themes and clusters in the recent AI&ED fields of "intelligent decision-making," "social governance," "labor and capital," "Industry 4.0," and "innovation." The content analysis traces the research boundaries and trends of the five sub-topics to provide directional guidance for future research. More importantly, scholars can use the findings of this survey to focus on new and less-researched issues to promote deeper adoption of AI in economic development. Specifically, (1) most of the existing articles repeatedly emphasize the superiority and intelligence of AI in economic decision-making scenarios, but the existing level of AI technology is only limited to specific scenarios and settings, forming a single point of breakthrough in the AI field. Currently, AI-based intelligent decision-making systems for economic activities are highly prone to fail under slight changes. Therefore, broadening the extension and stability of intelligent decision-making in economic activities is an important breakthrough in the future. Of course, a general-purpose integrated intelligent system is also one of the directions to consider. (2) Admittedly, AI has greatly enriched and improved the means of human social governance as well as the efficiency of governance. However, risky events in the governance process, such as fairness of judging, the bias of algorithms and the privacy of users, often trigger governance failure. Therefore, we propose to include the construction of a rule of law system and ethical framework for AI in the future research agenda (Turner Lee, 2018). (3) AI is a new manifestation of technological development and can be regarded as a complex combination of capital and labor. Therefore, how to prevent the "unemployment panic" caused by the imbalance of labor and capital substitution in the wave of AI reshaping the economic development paradigm is an urgent issue to be solved in the future. Moreover, it is also necessary to establish and improve the appropriate institutions. (4) There is no denying that AI is at the forefront of leading Industry 4.0, enabling the construction of Industry 4.0 to rise to a new level. However, our review shows that the AI-driven Industry 4.0 framework is still in the blueprint planning. How to build out an Industry 4.0 smart factory with practical operations is still the main melody of the future. (5) AI has great potential to enhance human innovation activities, contributing to innovation-driven economic development. However, our survey shows that uncertain risks lie behind the increased efficiency of innovation. To effectively capture and curb the spillover of these risks, the concept of responsible innovation needs to be further refined and implemented in the future (Buhmann & Fieseler, 2021).

Practical Implications

Moreover, the findings of this study also help us summarize a number of practical implications for future development with the aim of removing obstacles to the future development path of AI in terms of its widespread acceptance in economic activities.

Firstly, our bibliometric analysis and content review help practitioners gain a comprehensive understanding of the current state of development of AI as an emerging technology in various areas of human economic development. More importantly, practitioners can increase their confidence that AI will change the future landscape of economic activity and gain possible guidance for their practice from this work.

Secondly, practitioners can derive highly condensed findings and research boundaries from bibliometrics to discuss design choices and trade-offs to remove major barriers and obstacles to the inclusion of AI in economic activities. More pertinently, practitioners in the AI industry may benefit from our survey for more nuanced applications and designs.

Thirdly, our social structure analysis identifies the countries/regions that have achieved more results in the AI&ED field. This finding helps practitioners understand where to seek appropriate collaboration opportunities or advice (Zhang et al., 2021). Fourthly, our review argues that AI is rapidly becoming the new frontier of competitive differentiation for economic development in countries around the world. To this end, the work can help leaders as well as policymakers to capture the potential of AI.

Finally, our findings suggest that AI needs to focus on the legal and ethical dimensions of its involvement in human economic activities. We, therefore, call on policymakers to pay attention to these factors on the path to deepening the role of AI. For example, the safety risks of AI technology should not be underestimated. The security concerns of AI have been mentioned numerous times in the existing literature, including ethical security, technical security, data security and so on. For the technical level deficiencies, the government should increase the financial investment and policy protection in this area to provide a good external environment for the development of the AI industry. When it comes to data and ethical security, on the one hand, people must be aware of the privacy nature of data itself, and respect human privacy by establishing moderate legal provisions to address data security as well as embody data privacy protection without impeding the development of AI technology. On the other hand, a professional code of ethics for AI should be developed. In the process of AI design and development, human ethical guidelines and humanism are incorporated, and efforts are made to find best practices that make AI decisions more ethical.

Conclusions and Limitations

In this investigation, the aim is to provide a synthesized review of the extant studies that specialize in the application of AI technology in the economy and related fields. Answering this critical issue requires detailed knowledge that overcomes the fragmented feature

of scientific debate in this area. As such, we combine advanced bibliometric techniques with a traditional qualitative literature review to balance the quality and quantity of this discussion. Specifically, a total of 2211 articles published in the WoS Core Collection database were collected for bibliometric analysis and literature survey.

Summary

Using the bibliometric tool Bibliometrix, we conducted a performance analysis and science mapping analysis of publications to visualize the landscape and evolution of the AI&ED field and to capture the trajectory of themes over time. The intuitive results show that articles on AI&ED have only emerged in recent years, especially in the last three years, and are now the focus of much scholarly interest. In addition, the most relevant publication sources are concentrated in "Sustainability," "IEEE Access," "Energies," and "Expert Systems with Applications". In particular, "IEEE Access" has seen the most significant increase in the number of publications in this field in the last few years. The most influential paper was published in 2020 by Ozturk et al. (2020) in "Computers in Biology and Medicine", entitled "Automated detection of COVID-19 cases using deep neural networks with X-ray images". As of the time of data collection, this paper has been cited more than 622 times and may be deemed as an extraordinary work in the field. In addition, the scholar Li Y has produced the most articles and is the most active author in the field. The science mapping draws the conceptual, intellectual and social structure across the AI&ED domain. The distribution of topics in the four quadrants and the evolution of topics over time provide a clear picture of the current knowledge structure and orientation of the field. Overall, the extended conversations on the "big data" and "Internet of Things" are still hot topics at this stage. Prediction-related research is an enduring and widely discussed topic in the field. As expected, the agenda for COVID-19 is emerging. More importantly, there is a close international exchange of scholars from different countries/regions working in this field.

On the other hand, with the support of the bibliographic coupling function embedded in the VOS viewer, we identify five key topic areas that are currently the most popular under AI&ED research: AI and intelligent decision-making, AI and social governance, AI and labor and capital, AI and Industry 4.0, and AI and innovation, which is also an outstanding result of this study. In response to these frontier topics, we run a systematic review to gain insight into each economic subfield. For the practitioner sphere, this work provides theoretical basis and guidance to those currently employed in the field, enabling them to quickly seize the unlimited potential of AI in economic development. Nonetheless, for researchers working in this field, we outline the profile of each topic area and the research gaps, which will have an important enlightening force and stimulating effect on future research in this field.

Limitations and Future Scope for Research

Although the study design of this paper ensures the relevance and reliability of the final results, the generalizability of these results is still subject to certain limitations.

First and foremost, for the determination of the data sources, we followed the internationally generally observed rule of access based on the WoS core collection platform. Although the quality of the literature was ensured, a small amount of valuable literature was still hidden in other databases, which to some extent makes the integrity of the sample questionable. Therefore, expanding reliable data collection channels in future research is a feasible way to improve our study. Secondly, out of research needs, we only considered most of the literature in the bibliographic coupling network mapping instead of all the literature, which may cause some bias in the final clustering results. To get a broader picture of the research clusters in this field, we encourage future researchers to consider more literature information to obtain more general and delicate insights. Finally, while the utilization of bibliometric techniques in the paper reveals its advantages of comprehensiveness, it also exhibits its shortcomings of not being able to take into account many details. For the time being, we can only rely on the future improvement of the discipline to remedy this deficiency. Notwithstanding these limitations, this work offers valuable insights for the future boom in the AI&ED field.

Declarations

Conflict of Interest The authors declare no competing interests.

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