

# The evolution of research at the intersection of industrial ecology and artificial intelligence

Yongyue Gong<sup>1</sup>  | Fengmei Ma<sup>2,3</sup> | Heming Wang<sup>1,3</sup>  | Asaf Tzachor<sup>4,5</sup> |  
Wenju Sun<sup>1</sup> | Junming Zhu<sup>6</sup> | Gang Liu<sup>7,8</sup> | Heinz Schandl<sup>3</sup> 

<sup>1</sup>State Environmental Protection Key Laboratory of Eco-Industry, Northeastern University, Shenyang, China

<sup>2</sup>Key Lab of Urban Environment and Health, Institute of Urban Environment, Chinese Academy of Sciences, Xiamen, China

<sup>3</sup>Commonwealth Scientific and Industrial Research Organisation (CSIRO), Canberra, ACT, Australia

<sup>4</sup>School of Sustainability, Reichman University (IDC Herzliya), Herzliya, Israel

<sup>5</sup>Centre for the Study of Existential Risk (CSER), University of Cambridge, Cambridge, UK

<sup>6</sup>School of Public Policy and Management, Tsinghua University, Beijing, China

<sup>7</sup>College of Urban and Environmental Sciences, Peking University, Beijing, China

<sup>8</sup>Institute of Carbon Neutrality, Peking University, Beijing, China

## Correspondence

Fengmei Ma, Key Lab of Urban Environment and Health, Institute of Urban Environment, Chinese Academy of Sciences, Xiamen 361021, China. Email: [fmma@iue.ac.cn](mailto:fmma@iue.ac.cn)

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## Abstract

The intersection of artificial intelligence (AI) and industrial ecology (IE) is gaining significant attention due to AI's potential to enhance the sustainability of production and consumption systems. Understanding the current state of research in this field can highlight covered topics, identify trends, and reveal understudied topics warranting future research. However, few studies have systematically reviewed this intersection. In this study, we analyze 1068 publications within the IE–AI domain using trend factor analysis, word2vec modeling, and top2vec modeling. These methods uncover patterns of topic interconnections and evolutionary trends. Our results identify 71 trending terms within the selected publications, 69 of which, such as “deep learning,” have emerged in the past 8 years. The word2vec analysis shows that the application of various AI techniques is increasingly integrated into life cycle assessment and the circular economy. The top2vec analysis suggests that employing AI to predict and optimize indicators related to products, waste, processes, and their environmental impacts is an emerging trend. Lastly, we propose that fine-tuning large language models to better understand and process data specific to IE, along with deploying real-time data collection technologies such as sensors, computer vision, and robotics, could effectively address the challenges of data-driven decision-making in this domain.

## KEYWORDS

artificial intelligence, circular economy, industrial ecology, top2vec, topic modeling, word2vec

## 1 | INTRODUCTION

Industrial ecology (IE) is a branch of science that studies the flow of material and energy within industrial systems, aiming to enhance sustainability by emulating natural ecosystems to optimize resource use, recover, recycle, and reuse materials, and minimize waste (Fischer-Kowalski et al., 2011;

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Graedel, 1996; Jelinski et al., 1992). It employs methods such as life cycle assessment (LCA), material flow analysis, and the design of industrial symbiosis to achieve these goals. These methods rely heavily on data processing, including data collection, cleaning, integration, and conversion into a suitable structure for analysis to uncover meaningful patterns and relationships. By enhancing these data processing capabilities, artificial intelligence (AI) can improve the effectiveness of IE. AI techniques such as machine learning (ML), predictive analytics, optimization models, natural language processing (NLP), and computer vision can facilitate more accurate and comprehensive data-driven decision-making. These techniques can analyze vast amounts of data to uncover patterns, forecast trends, and optimize processes within industrial systems, ultimately supporting and advancing sustainable practices in production systems and operations (Krenn et al., 2022; Stanton, 1971; Wang et al., 2023b; Wu et al., 2020).

The integration of AI within IE has grown rapidly in recent years to effectively address broader sustainability challenges. For instance, Ebrahimi et al. (2022) proposed enhancing material flow analysis with ML to estimate stocks and flows of road infrastructure innovatively. Rolnick et al. (2023) investigated how ML techniques could be applied across various domains to reduce greenhouse gas emissions and help society adapt to the challenges of climate change. Zhao et al. (2022) developed a deep neural network model to enhance the accuracy of predicting input–output tables, thereby filling data gaps in environmental footprint accounting. Huntington et al. (2023) examined the development of surrogate models using ML, based on traditional process simulation models, to rapidly predict cost, mass, and energy balances in biofuel production, thereby improving the design and testing cycles in bioprocess systems. Within the existing body of literature, there is a notable absence of comprehensive quantitative analysis, often termed “bibliometric analysis,” at the intersection of IE and AI. Such an analysis is crucial for elucidating research trends and hotspots, uncovering hidden connections between topics and sub-topics, and providing evidence-based guidance for future research directions.

Word embedding is a powerful tool for textual data mining, particularly in conducting literature research and advancing scientific discoveries (Charlesworth et al., 2022; Garg et al., 2018). Word2vec, an important word embedding technology in the NLP, generates vector representations of words by analyzing large amounts of textual data. These vectors capture semantic relationships and similarities between words (Ameur et al., 2024; Ning & Chen, 2023; Tshitoyan et al., 2019). For example, Wu et al. (2021) utilized latent Dirichlet allocation, word2vec, and community network analysis to visualize connections in green building research from 1990 to 2020. Similarly, Ding et al. (2021) employed word2vec to extract insights from construction and demolition waste management literature. Zhu and Ren (2023) developed a six-step word embedding approach to enhance word2vec modeling and successfully utilized it to decode research trends and hot topics in *Resources, Conservation, and Recycling* from 1989 to 2022.

In addition to word2vec, top2vec offers a scalable and practical approach to topic modeling, organizing documents into clusters within large-scale text corpora. For example, Smith et al. (2023b) applied the top2vec algorithm to explore topic interconnections between health and Sustainable Development Goals in global scientific research and to measure the semantic closeness between these topics. Additionally, top2vec has been applied in various domains, including the analysis of COVID-19-related news in newspapers (Ghasiya & Okamura, 2021), studies in criminology and criminal justice (Smith et al., 2023a), and social media data (Chen et al., 2023a; Ghasiya & Okamura, 2021).

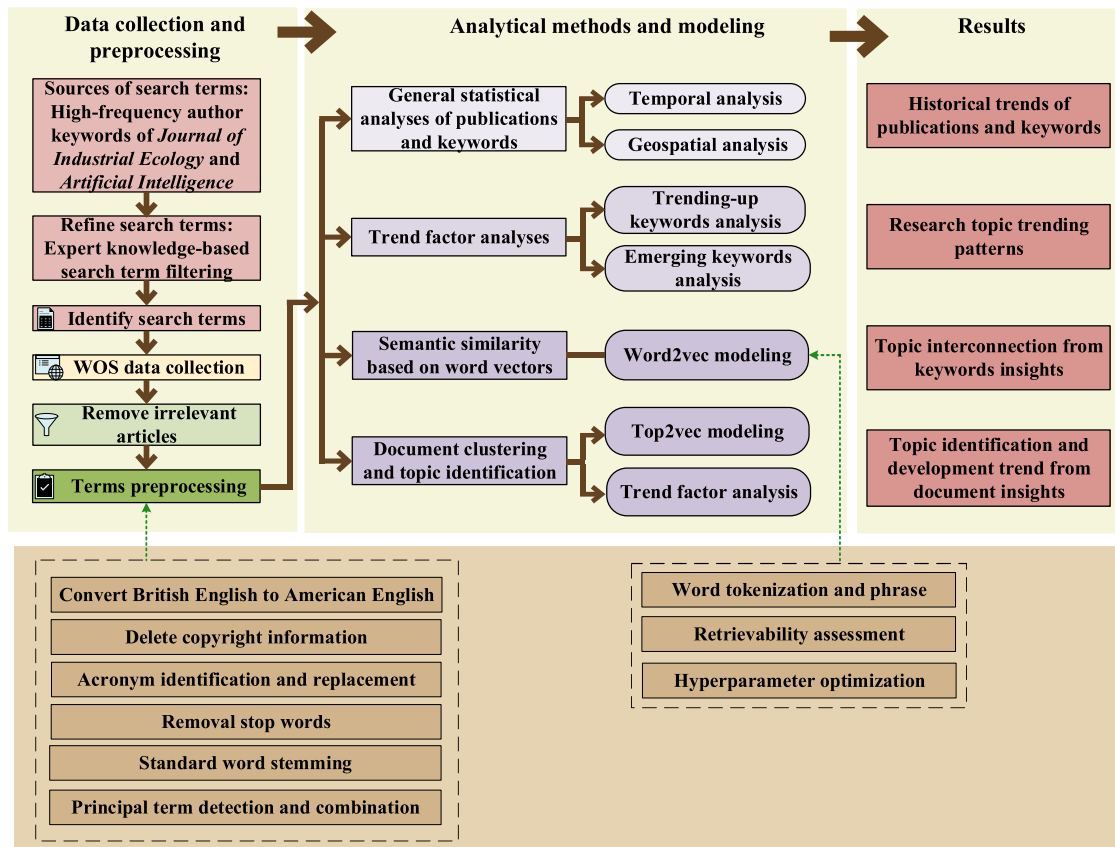
This work analyzed 1068 publications at the intersection of IE and AI to explore topic development patterns and interconnections using general statistics, trend factors, semantic similarity, and topic modeling methods. Specifically, we reduced textual data noises and analyzed variations in publication volume by country and the frequency of author keywords over time. Subsequently, we investigated the temporal variations of trending and emerging topics. Furthermore, we applied word embedding (word2vec modeling) and topic modeling (top2vec modeling) to analyze topic interconnections and to identify clusters (topics) of related documents.

## 2 | METHODS

Figure 1 illustrates the research framework for this study. We first describe the data collection and processing procedures. We then analyze the data using general statistics and NLP techniques to explore the development patterns and trends at the IE–AI intersection. The analysis comprised four phases, as follows: (1) statistical analysis of the number of national publications and keyword frequency to understand historical development patterns; (2) keyword analysis using trend factors to identify trending and emerging topics; (3) semantic similarity analysis of keywords through word2vec modeling to map interconnection features of the topics; and (4) application of top2vec topic modeling to identify document-based topics and explore topic trends.

### 2.1 | Data collection and preprocessing

To conduct the analysis within the specified domains of IE and AI, we implemented a dual-pronged approach. This method involved an extensive review of the literature and consultations with domain experts, ensuring a comprehensive and precise selection of terms pivotal for the analysis. Initially, we focused on author keywords that appeared more than 10 times in the *Journal of Industrial Ecology* (for IE-related terms and domains) and *Artificial Intelligence* (for AI-related techniques). These journals were selected due to their long publication history and broad coverage of topics relevant to our research, transcending limitations to specific subfields such as ML or LCA. Leveraging expert knowledge in both fields (IE and AI), we carefully filtered out terms not specific to our primary domains of interest. The resulting list of author keywords thus constituted the refined search terms. To further validate our selection of AI-related terms, we consulted published review papers and a seminal textbook in the AI domain (Contreras & Vehi, 2018; Kotu, 2019; Russell & Norvig, 2021).



**FIGURE 1** Flow diagram of the systematic methodology developed and used in this study.

Details of the retrieved content are presented in Supporting Information S1. After the initial search, 1517 publications with document types limited to “article or review” were retrieved (Web of Science data updated to October 12, 2023). Additionally, research papers irrelevant to integrating AI with IE were excluded. Finally, a total of 1068 bibliographic records were identified for further analysis (Supporting Information S2). Detailed information about data preprocessing is presented in Supporting Information S1.

## 2.2 | General statistical analyses

General statistical analyses of publications and keywords can help visualizing temporal changes and geospatial variations in the literature integrating AI with IE from 2000 to 2023. We focused on the *publication year* and *corresponding address* of 1068 publications. The corresponding addresses were identified using the “re” module in Python due to the fixed relative data positions for countries and regions within these address details. When publications had multiple corresponding addresses, the geographic counts of publications were determined by the frequency of their home countries/regions (e.g., China [2] and the United States [1]), expressed as a proportion of the total (e.g., China [2/3] and the United States [1/3]).

Based on the processed data, the frequency of author keywords was calculated. Furthermore, a normalized frequency ( $F_{yrs}$ ) was introduced, representing the ratio of the number of publications that studied an author keyword ( $f_{yrs}$ ) to the total number of publications ( $N_{yrs}$ ) in the same period (e.g., years  $i, \dots, j$ ). When the time interval is a particular year (e.g., year  $i$ ), the ratio is named normalized annual frequency, representing the ratio of the number of publications that studied an author keyword ( $f_i$ ) to the total number of publications ( $N_i$ ) in year  $i$ . This ratio was designed to reflect the temporal evolution of author keywords from a perspective that allows for fair comparison (Equation 1). For clearer understanding, this ratio is typically multiplied by a constant (1000) to indicate how often a keyword has been studied per 1000 publications over time.

$$F_{yrs} = 1000 \times \frac{\sum_{yr=i}^j f_{yrs}}{\sum_{yr=i}^j N_{yrs}} \text{ (if } i \neq j) = 1000 \times \frac{f_i}{N_i} \text{ (if } i = j) \quad (1)$$

## 2.3 | Trend factor analyses

In this study, we used trend factors to identify the trending and emerging topics. Specifically, we divided the data into so-called “early period” (2000–2015, 16 years) and “recent period” (2016–2023, 7 years and 10 months). The trend factor was calculated by the logarithmic value of the ratio of

normalized frequencies in the recent ( $F_{\text{recent}}$ ) and early ( $F_{\text{early}}$ ) periods (Equations 2 and 3) (Zhu & Ren, 2023). Consequently, trend factor values may extend from negative infinity to positive infinity. A trend factor approaching positive infinity signifies that the topic (or keyword) has emerged only recently. In contrast, a trend factor nearing negative infinity indicates that the topic was prominent in earlier periods but has diminished or even disappeared in prevalence in recent times. We used a bubble plot to visually represent the temporal trends of keywords (frequency  $\geq 3$ ). A keyword is considered increasingly trending when  $TF \geq 0.5$  and  $F_{\text{recent}} \geq 4$  (Zhu & Ren, 2023).  $-0.5 \leq TF < 0.5$  demonstrates a stability trend, and  $TF < -0.5$  represents a trending down.

$$F_{\text{early}} = 1000 \times \frac{\sum_{2000}^{2015} f_{\text{yrs}}}{\sum_{2000}^{2015} N_{\text{yrs}}} \quad \text{and} \quad F_{\text{recent}} = 1000 \times \frac{\sum_{2016}^{2023} f_{\text{yrs}}}{\sum_{2016}^{2023} N_{\text{yrs}}} \quad (2)$$

$$\text{Trend factor} = TF_{\text{early period}}^{\text{recent period}} = \log\left(\frac{F_{\text{recent}}}{F_{\text{early}}}\right) \quad (3)$$

In addition, we identified emerging topics based on two additional trend factors,  $TF_{2000-2019}^{2020-2023} \geq 0.5$  (early: 20 years and recent: 3 years and 10 months) and  $TF_{2016-2019}^{2020-2023} \geq 0.5$  (early: 4 years and recent: 3 years and 10 months), respectively.

## 2.4 | Word2vec modeling and analyses

Word2vec was employed to construct semantic relational networks based on keywords, thereby elucidating the interconnected nature of the topics. This model, which is based on neural networks, acquires semantic relationships among vocabulary items within extensive text corpora, generating distinctive word embeddings within a continuous, high-dimensional vector space. Words that share similar contexts are positioned close to each other within the vector space. Fundamentally, word2vec converts unstructured textual data into structured data, represented numerically as vectors. The semantic similarity within a specific research scope between two words is assessed by quantifying the cosine similarity ( $\text{sim}(\alpha, \beta)$ ) between their vectors (e.g.,  $\alpha$  and  $\beta$ ) as shown in Equation (4).

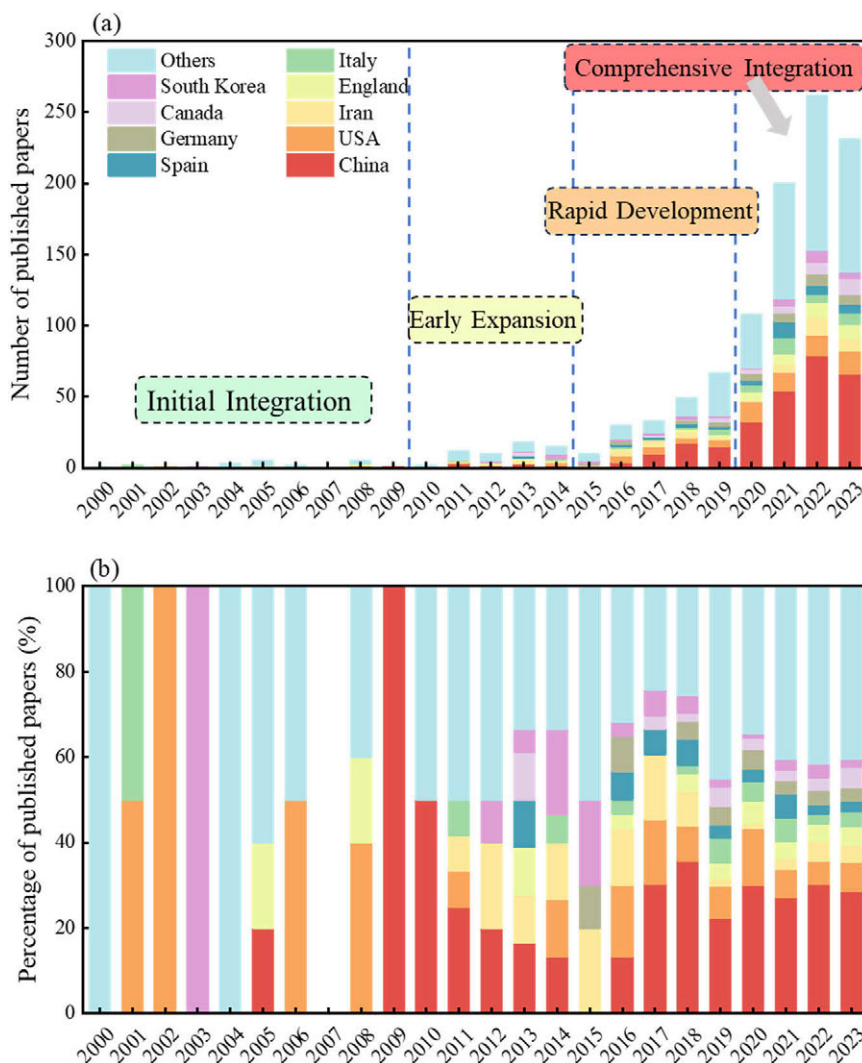
$$\text{sim}(\alpha, \beta) = \cos \theta = \frac{\alpha \cdot \beta}{\|\alpha\| \|\beta\|} \quad (4)$$

Word2vec-based analyses were conducted using the *Gensim* package in Python (Řehůřek & Sojka, 2010). Three fields of data (title, abstract, and author keywords) were used for modeling. Although author keywords lack context, they often effectively represent the article's main themes. Integrating these with the title and abstract enhances the model's ability to capture core semantics, thus improving subject comprehension. Details on data preprocessing are described in Supporting Information S1. Details about "word tokenization and phrase," "retrievability assessment," and "hyperparameter optimization" methods were referenced from Zhu and Ren (2023). We generated a 250-dimensional word2vec model containing over 7289 terms, of which 2880 appear with a frequency greater than 10. After filtering out meaningless and general terms (e.g., express, occupy, and best), we retained 365 terms (frequency  $> 10$ ) for further analysis.

## 2.5 | Top2vec modeling and analyses

Top2vec modeling was employed to discern document-based topics. Concurrently, the results from these topics were integrated with trend factors to investigate patterns of topic development. Top2vec, an unsupervised topic modeling technique, leverages hierarchical clustering to systematically categorize documents into distinct topics. This method facilitates the discovery of representative knowledge within expansive text datasets (Angelov, 2020). This approach is implemented in the *top2vec* Python library. The first step is to "create semantic embeddings," which involves jointly embedding word and document vectors in a higher-dimensional space using word2vec and doc2vec. The second step is "dimensionality reduction of embedding vectors." Uniform manifold approximation and projection (UMAP) is commonly utilized for this purpose due to its ability to preserve both local and global structures of high-dimensional data. In the third step, hierarchical density-based spatial clustering of applications with noise (HDBSCAN), a density-based clustering approach, is used to identify clusters of documents in two dimensions. The fourth step involves determining topic vectors as the centroids (arithmetic mean) of all document vectors belonging to a dense cluster in the original dimensional space. The words closest to the topic vector are defined as the topic words. Supporting Information S2 summarizes the documents corresponding to each topic.

To identify trending and emerging topics, we calculated the trend factor for each topic (Figure 7). The selection of time points aligns with those used in the trend factor analyses of the author keywords. We defined the trend factor thresholds:  $TF_{2000-2015}^{2016-2023} \geq 0.5$  indicates trending, a value between  $-0.5$  and  $0.5$  suggests a stable trend, and  $TF_{2000-2015}^{2016-2023} < -0.5$  signifies trending down. Therefore, the subsequent analysis will examine topic patterns by integrating the top2vec results with the temporal evolution of the topics.



**FIGURE 2** Temporal and geospatial variations of research articles and reviews in integrating industrial ecology with artificial intelligence. (a) Number of published papers. (b) Percentage of published papers. Underlying data for this figure are available in Table S4 of Supporting Information S2.

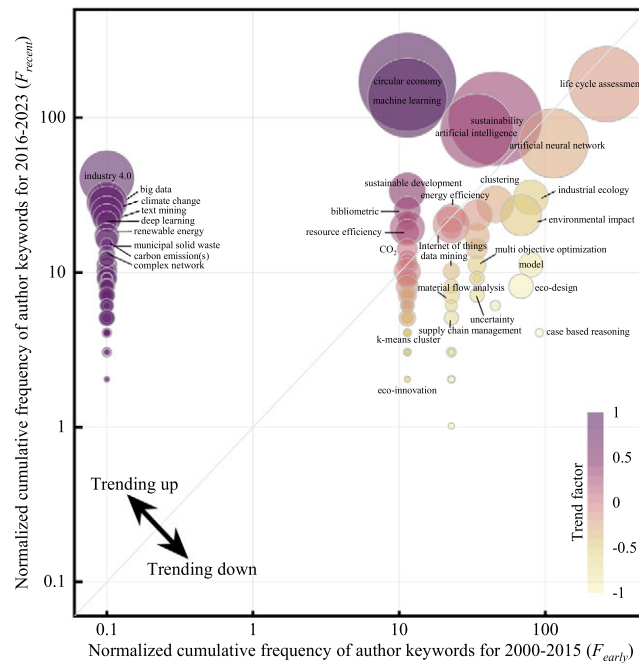
### 3 | RESULTS

#### 3.1 | Historical trends of publications and keywords

The integration of AI with IE has distinctly evolved through four phases, as delineated by temporal trends in the volume of related publications (Figure 2). The number of papers gradually increased after 2015, with rapid growth from 2020 onward. Approximately 69.4% of the papers were published in the last 3 years. These papers published were from 73 countries and regions, with the five most significant contributors being China (mainland) (291, rounded to the nearest whole number), the United States (85), Iran (51), England (43), and Italy (39). China accounted for about 30% of the publications from 2017 to 2023, becoming the most significant contributor. Meanwhile, publication output from the United States and Iran has decreased.

Figure 3 illustrates the temporal trend of the top 50 most frequently used author keywords, as determined by their normalized annual frequency. Before 2010, the annual number of publications was fewer than 10, primarily focusing on terms such as *LCA*, *sustainability*, and *artificial neural networks*. These terms appeared in studies at a frequency ranging from 200 to 1000 papers (per 1000 papers). They have continued to be prominent in research since 2011. Research in *circular economy* (CE) and *ML* began in 2013 and 2015, respectively, and these topics have gradually gained popularity. The focus on *environmental impact* peaked between 2014 and 2016. Terms with similar trends include *artificial neural network*, *clustering*, *model*, *eco-design*, *multi-objective optimization*, *input-output model*, *eco-industrial park*, *data mining*, and *case-based reasoning*. In the last 5 years, *AI* and *sustainability* have become increasingly prevalent. It is worth noting that the normalized annual frequency may decline even with an upward trend in the number of annual publications, such as *LCA*. This is because other topics are being discussed more frequently and rapidly within the same period. Vertically, *LCA*, *CE*, *ML*, and *AI* are the main contributors to the annual publications. Detailed information about high-frequency author keywords is presented in Supporting Information S1.



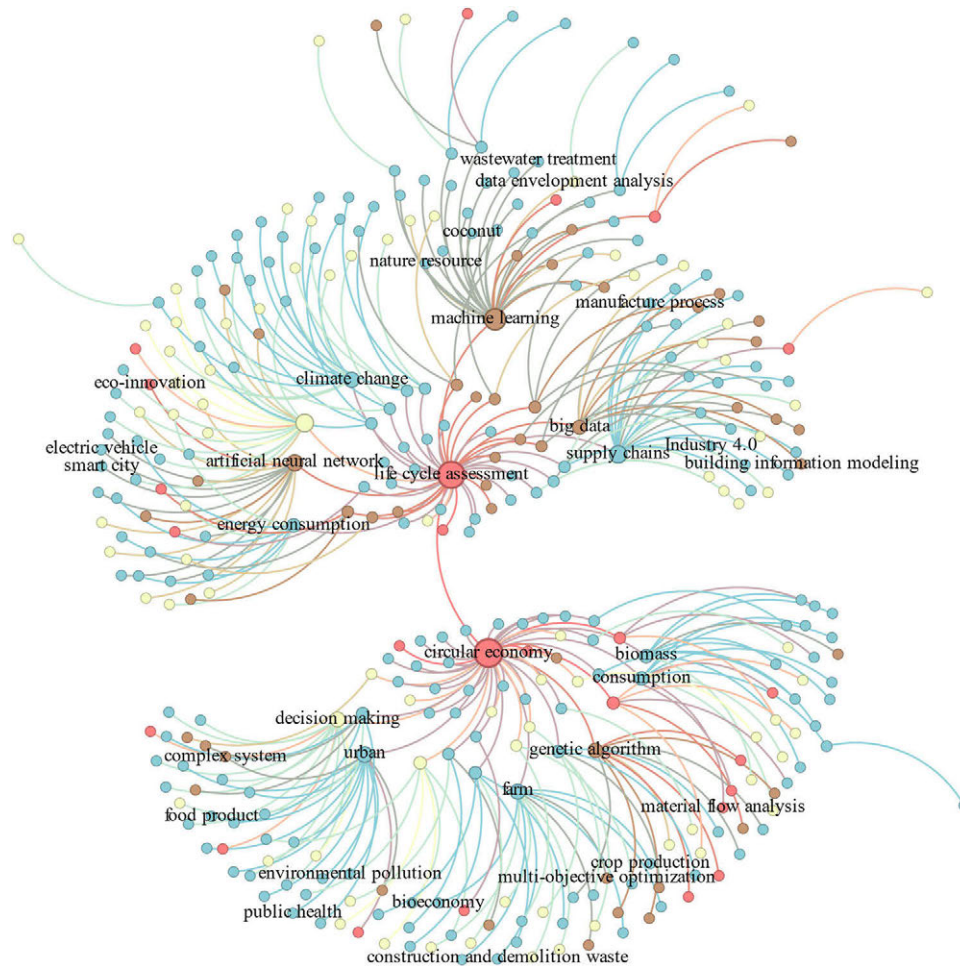


**FIGURE 4** The trend factor of author keywords (255 with frequencies  $\geq 3$ , represented as bubbles). Note: The normalized cumulative frequencies in the early (2000–2015) and recent (2016–2023) periods ( $X$ -axis and  $Y$ -axis) determine the position of the bubbles. Due to using logarithmic coordinates, the bubbles along the  $Y$ -axis have been deliberately adjusted to placement at  $X = 0.1$  for clearer visualization. The color of the bubbles indicates the value of the trend factor; bubbles in purple are more likely to exhibit an upward trend, while those in yellow suggest a downward trend. The size of each bubble represents the geospatial popularity of the author keywords, defined by the number of countries and regions researching them. For example, the keyword “artificial neural network” is represented by a normalized cumulative frequency of 113.64 for 2000–2015 ( $X$ -axis coordinates) and 68.30 for 2016–2023 ( $Y$ -axis coordinates). The trend factor for this keyword is  $-0.22$ , which influences the bubble’s color. The geospatial popularity is 34. Underlying data for this figure are available in Table S6 of Supporting Information S2.

Among the 176 trending candidates, only 99 satisfy  $F_{recent} > 4$ . After excluding several keywords that are too general (such as *recycling*, *digitization*, and *construction*) or geographically related (*Iran*), 71 relatively more trending keywords were retained. Their detailed temporal variations are shown in Supporting Information S1. These 71 topics can generally be categorized into three groups: IE method (e.g., *multi-regional input–output analysis*), IE subjects, and AI techniques (e.g., *NLP*) (Supporting Information S2). The research subjects of IE include categories such as waste management (e.g., *wastewater treatment*), biomass-related topics (e.g., *biochar*), and climate-related topics (e.g., *climate change*).

Among the 71 trending keywords, 69 were absent from 2000 to 2015, except for *CE* and *ML*. *CE* was first introduced by Zhou et al. (2013), who developed an evaluation system for *CE* focused on iron and steel enterprises. The keyword re-emerged in 2017, with its normalized annual frequency increasing from 91 to 208 over the past 7 years. D’Amato et al. (2017) (highly cited status) conducted a bibliometric review using *ML* to reveal the interconnections and distinctions among the concepts of *CE*, the green economy, and the bioeconomy, highlighting *CE*’s role in addressing industrial urban processes aimed at decoupling resource consumption from economic output. Similarly, Rajput and Singh (2019) (highly cited status) comprehensively analyzed the connection between *CE* and *Industry 4.0*, proposing that *AI*, services, and policy are key enablers. A similar pattern is observed in *ML*, traced back to Slapnik et al. (2015), who utilized *ML* to estimate characterization factors in *LCA*. *ML* was prominently applied again in 2017, as noted earlier in D’Amato et al. (2017).

The significance of the 69 author keywords that have emerged over the recent 8 years ( $F_{early} = 0$ ) cannot be overstated—for example, *Industry 4.0*, *big data*, and *climate change*. The term *Industry 4.0* was first mentioned by Xu and Duan (2019), who explored the use of big data and cyber-physical knowledge to optimize resource efficiency in *Industry 4.0*. However, the concept of *Industry 4.0* originated from a German government-supported project for advanced manufacturing in 2011. This origin explains why *Industry 4.0* has been widely adopted by researchers from 27 countries and regions, making it one of the trending topics over the last 8 years (detailed information about the geospatial popularity of each keyword is presented in Supporting Information S2). Analysis of temporal trends in trending keywords (Supporting Information S1) reveals that a significant portion of research integrating *AI* and *IE* focuses on critical issues such as climate change, energy, solid waste treatment, and carbon emissions. Notably, the application of the trending topic of *complex networks*, in conjunction with *input–output analysis*, has been employed to investigate the flow characteristics of energy or materials across various sectors and countries (Gao et al., 2018; Liu et al., 2023; Wang et al., 2017). In addition, eight new emerging topics (i.e., *support vector machine*, *product service system*, *global warming potential*, *decision support system*, waste



**FIGURE 5** Topic interconnections based on the word2vec model for the top 365 frequent keywords (frequency  $\geq 11$ ). Note: We represent the links between the nodes using a maximum spanning tree, which is applied using Kruskal's algorithm to retain the main structure of the original network graph. A maximum spanning tree is a subgraph within an original undirected weighted graph. It includes all nodes and maximizes the sum of edge weights while ensuring connectivity among all nodes without forming loops. The weights of the edges represent the cosine similarity between the two nodes (keywords), and the size of each node correlates with its degree. Keywords are categorized into four groups: research subjects (represented by blue bubbles), IE methods (pink bubbles), AI techniques (brown bubbles), and other topics (yellow bubbles), each distinguished by a specific color. Only some labels are displayed for clarity; this does not imply that other bubbles without labels are unimportant.

electrical and electronic equipment, *supply chain management*, *sustainable product development*, and *life cycle*) have been identified, with detailed information available in Supporting Information S1.

### 3.3 | Topic interconnection from keywords insights

Providing a more granular analysis, we further assessed the intersection of AI techniques and common IE methods/subjects. For this analysis, we used the word2vec method. LCA and the CE, at the heart of the maximum spanning tree (Figure 5), serve as the focal points for the upper and lower parts of the network diagram, respectively. LCA and CE exhibit strong similarities (99.6%), frequently appearing in similar contexts. LCA provides quantitative tools and methodologies to support and validate the sustainability of CE strategies (Yang et al., 2023). In turn, CE offers a practical framework that leverages LCA results to promote the sustainable development of industrial systems and processes.

At the intersection of AI and IE, the most striking aspect is that AI transcends the limitations of traditional methods, reshaping the link between LCA and CE (Rolnick et al., 2023). For example, data-driven machine learning models predict product yields, provide data for environmental impact assessments, and thereby promote sustainable practices throughout the production chain (Hajabdollahi Ouderji et al., 2023; Yadav et al., 2023). Artificial neural networks can create simulation models of complex systems, enabling more accurate predictions of resource flow pathways and their potential environmental impacts (Ascher et al., 2022; Nabavi-Pelesarai et al., 2017b; Velidandi et al., 2023). Additionally, convolutional neural networks, a subset of artificial neural networks, are mainly used for waste classification and recycling in smart city and electric vehicle domains,

significantly reducing reliance on human resources (Maiurova et al., 2022; Meng et al., 2022). Big data improves the computational accuracy of traditional industrial ecology models (e.g., LCA and material flow analysis) and data-driven machine learning models in predicting the environmental impacts and economic benefits of various circular strategies (Ji et al., 2021, 2023). It also enhances transparency and controllability across different stages of the CE. Genetic algorithms and multi-objective optimization help balance conflicting goals, such as minimizing environmental impact and resource consumption while maximizing economic benefits (Abokersh et al., 2020; Lim et al., 2013). The advancement of AI continues to drive IE toward greater efficiency, sustainability, and intelligence.

In terms of research objects, supply chain, urbanization, climate change, resource efficiency, wastewater management, and energy consumption are key research areas integrating AI and IE. Additionally, the integration of AI has expanded the scope of research to include complex systems, smart cities, and supply chains, allowing traditional IE methods to model and analyze large-scale and multi-dimensional systems more feasibly.

### 3.4 | Topic identification and development trends from document insights

This study used top2vec modeling to identify document-based topics and integrated trend factors to explore topic development patterns. Notably, word2vec, discussed in Section 3.3, primarily focuses on the interconnectedness between keywords based on semantic similarity, while top2vec is a type of topic modeling that extracts topics from many documents. We identified 18 distinct topics (Figure 6) and determined trending topics (i.e., Topics 3, 12, 2, and 14) and a new emerging topic (i.e., Topic 17) based on their evolutionary patterns, which are likely to dominate future research (Figure 7).

The trending topics focus on the application of AI techniques for CE, particularly for waste management and biomass-to-energy. Topic 3 explores the role of AI and digital technologies, such as big data, blockchain, and the Internet of Things (IoT), in advancing the CE (Akram et al., 2022; Chauhan et al., 2022; Feng et al., 2022; Gebhardt et al., 2022; Rusch et al., 2023). Topic 12 concentrates on AI techniques for waste classification, such as the automatic classification of construction demolition waste using a deep convolutional neural network model (Lin et al., 2022b), a recyclable waste classification model that incorporates deep residual networks with transfer learning (Lin et al., 2022a), and the mechanical recycling of plastic bottles with shrink sleeves through ML algorithms (Bernat, 2023; Chen et al., 2023b). Topic 2 focuses on biomass energy and employs AI to predict the environmental and economic performance of various biomass feedstocks, along with other characteristics (Cheng et al., 2020a, 2020b; Culaba et al., 2022, 2023; Li et al., 2023a; Yadav et al., 2023). First studied in 2005 (Bloom, 2005), Topic 14 briefly disappeared from scholarly attention before being revisited in 2017 (Koop & Van Leeuwen, 2017; Nabavi-Pelesaraei et al., 2017a). It utilizes ML and neural networks to analyze and predict factors influencing municipal solid waste generation and environmental impacts (Duan et al., 2020; Hoy et al., 2022; Liu et al., 2021; Magazzino et al., 2020; Paulauskaite-Taraseviciene et al., 2022).

For emerging topics, Topics 12 and 17 have been identified, with Topic 12 previously classified as trending. Initially explored in 2014 (Tambouratzis et al., 2014), Topic 17 utilizes advanced methods such as convolutional neural networks, genetic algorithms, and ML to predict and improve the properties and environmental sustainability of concrete and other construction materials (Abuodeh et al., 2020; Lv et al., 2022; Shobeiri et al., 2023; Zandifaez et al., 2023). Given the rapid increase in the IE–AI literature subsequent to 2020, we have redefined an “early period” spanning 2016–2019 and a “recent period” spanning 2020–2023. Our results indicate that Topic 17 alone can be classified as an emerging topic. While it initially appeared briefly in 2014 (Tambouratzis et al., 2014), Topic 17 gained prominence in the research community in 2018 (Hannula et al., 2018). For a detailed description of other topics, please refer to Supporting Information S1.

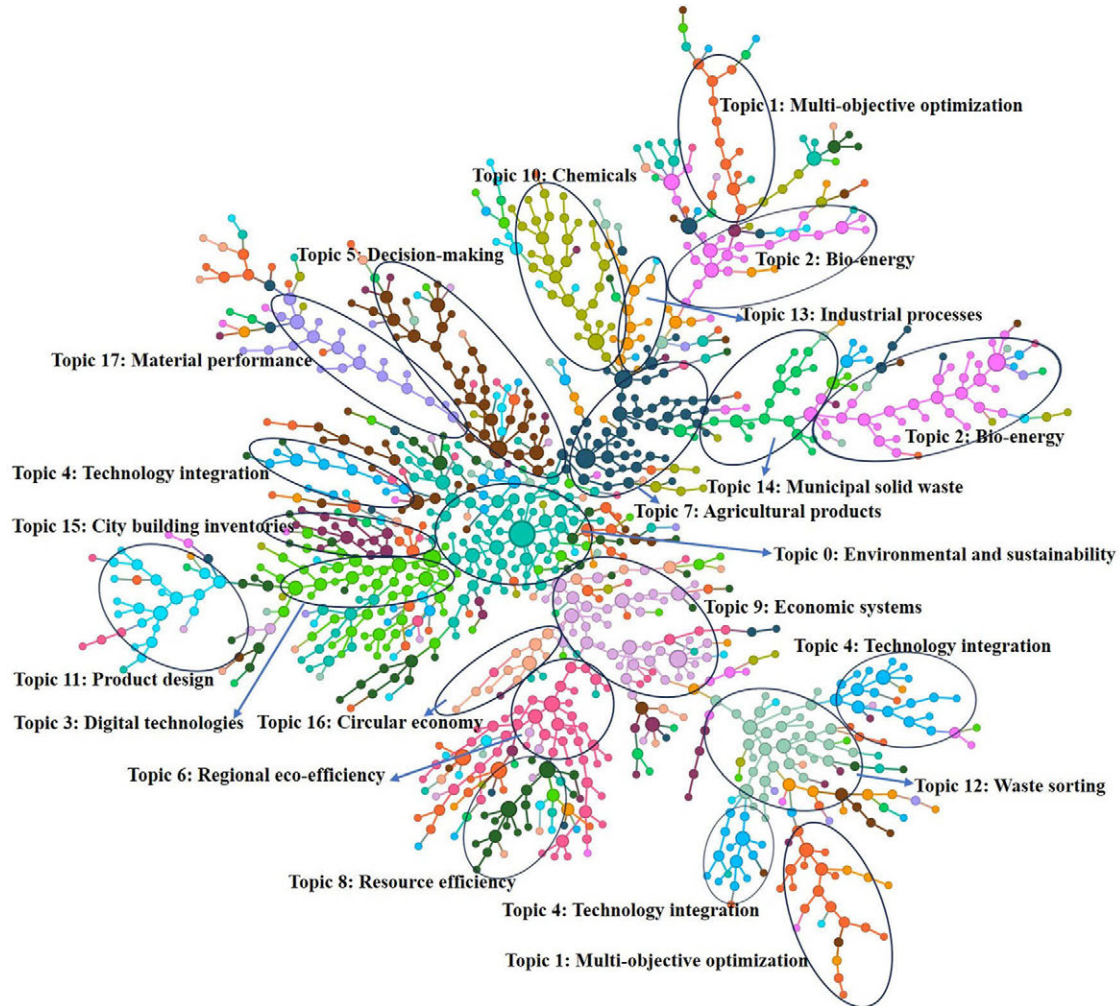
Furthermore, it is crucial to emphasize that Topic 0 is the core of the maximum spanning tree. The pivotal literature (Xu & Feng, 2021), which is the central node with a cosine similarity of 0.60 to the topic vector, plays an essential role in connecting various segments of the network. Topic 0 broadly explores how innovative technologies and methodologies can enhance environmental sustainability (Chen et al., 2022; Dayeen et al., 2020; Romero-Silva & De Leeuw, 2021; Tanveer et al., 2022; Xu & Feng, 2021).

## 4 | DISCUSSION

This study examines the interconnection and distribution of topics at the intersection of IE and AI using word2vec and top2vec-enhanced data mining and pattern analysis. The integration of these fields is directly linked to advancements in science, technology, and engineering. Based on our findings, we track the evolution of the IE–AI intersection and examine the prospects and challenges ahead.

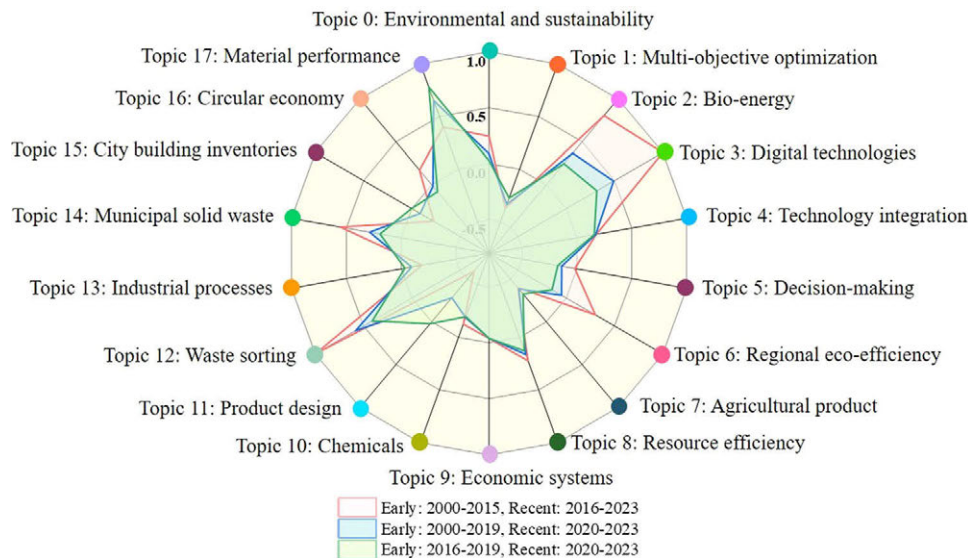
### 4.1 | The development path of the integration of AI with IE

The periodic changes in the number of publications suggest phased progress in employing AI techniques within the IE research (Figure 2). The underlying assumption is that advancements in AI models, computing power, and data availability (Russell & Norvig, 2021) have enabled their integration



**FIGURE 6** Topic recognition based on the top2vec at the document level (1068 documents). Note: 1068 documents were divided into 18 distinct topics, each containing between 29 and 103 documents. We summarize the top five topic words and document counts for the 18 identified topics in Supporting Information S2. The links between the nodes (documents) are represented using a maximum spanning tree, which employs Kruskal's algorithm. This approach is chosen because it retains the main structure of the original network graph. A maximum spanning tree, defined as a tree within an undirected weighted graph, includes all nodes and maximizes the sum of edge weights to ensure connectivity among all nodes without forming loops. Nodes belonging to the same topic are displayed in the same color. The weights of the edges between nodes indicate the cosine similarity between the two documents. The size of the nodes correlates with their degree. The topics covered include: Topic 0—Literature review in environmental and sustainability; Topic 1—Multi-objective optimization for solving complex problems; Topic 2—Artificial intelligence in bio-energy; Topic 3—Digital technologies in the circular economy; Topic 4—Technology integration and optimization; Topic 5—Consideration of environmental loads in early decision-making; Topic 6—Regional eco-efficiency; Topic 7—Assessment and forecasting of agricultural product indicators; Topic 8—How businesses can improve resource efficiency; Topic 9—Flow and network properties in economic systems; Topic 10—Predicting the environmental impacts of chemicals; Topic 11—Innovation in the product design and development phase; Topic 12—Artificial intelligence for waste sorting; Topic 13—Optimization of selected industrial processes; Topic 14—Projections of municipal solid waste-related indicators; Topic 15—Material flow analysis, geographic information system, and big data are used to analyze city building inventories; Topic 16—Circular economy in the EU; Topic 17—Predicting and improving concrete performance. Underlying data for this figure are available in Table S7 and S8 of Supporting Information S2.

into IE, supporting an increasing array of IE-related processes, methods, and quantifications (Figure 8). During the so-called initial integration phase (2000–2010), artificial neural networks and clustering algorithms began to gain widespread attention and application in LCA, input–output analysis, and industrial symbiosis. Their integration could resolve complex challenges through systems thinking and enhancing the sustainability of industrial systems (Deutz & Gibbs, 2008; Kraines et al., 2005; Wernet et al., 2008). The subsequent early expansion phase (2010–2015) saw data mining, multi-objective optimization, and support vector machines expand AI's role in enhancing complex system analysis and sustainable eco-design in IE (Liang & Zhang, 2011; Manfren et al., 2011; Yang & Chen, 2011). In the rapid development phase (2015–2019), advanced AI techniques like ML and NLP accelerated the development of smart cities and improved life cycle cost analysis in IE (D'Amato et al., 2017; De Clercq et al., 2019; Vondra



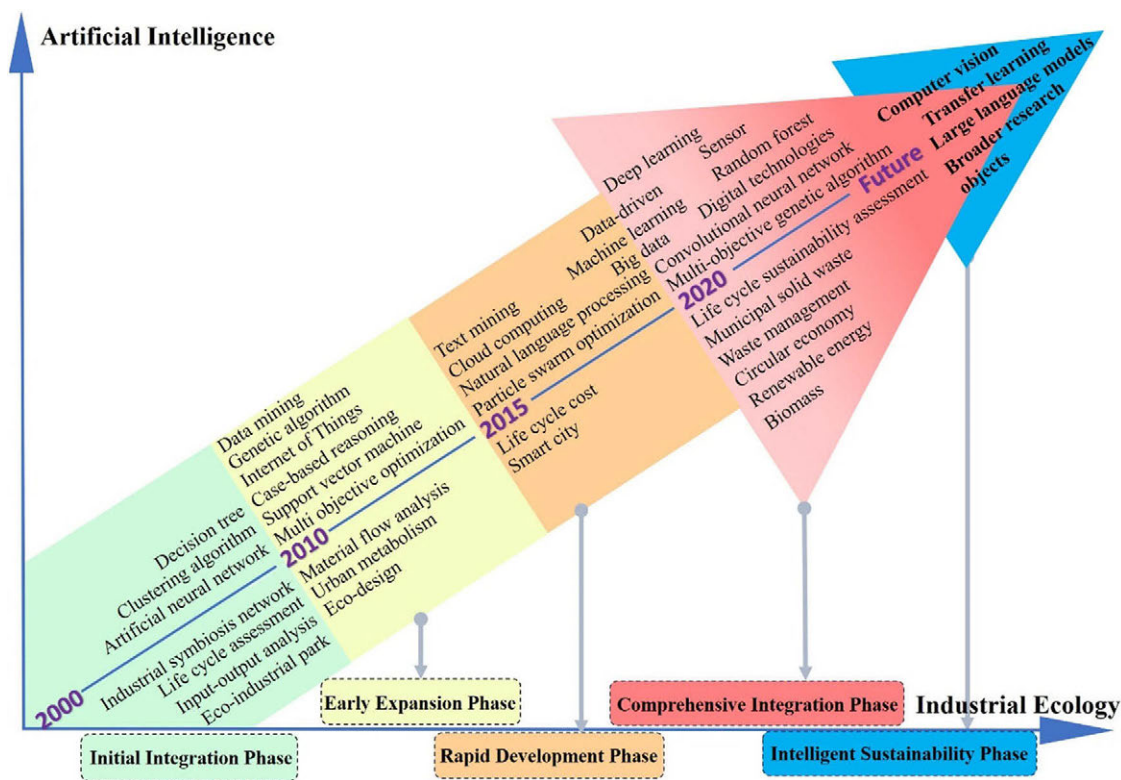
**FIGURE 7** Trend factor analysis of each topic across different periods. Note: The selection of periods aligns with those used in the trend factor analysis of the authors' keywords, as detailed in Section 3.2, referencing (Zhu & Ren, 2023). The scale of the axis represents the trend factor. Topics 3 and 12, which first emerged in 2016 with a trend factor of positive infinity, are positioned at coordinates equal to 1 on the graph for display clarity. The topics covered include: Topic 0—Literature review in environmental and sustainability; Topic 1—Multi-objective optimization for solving complex problems; Topic 2—Artificial intelligence in bio-energy; Topic 3—Digital technologies in the circular economy; Topic 4—Technology integration and optimization; Topic 5—Consideration of environmental loads in early decision-making; Topic 6—Regional eco-efficiency; Topic 7—Assessment and forecasting of agricultural product indicators; Topic 8—How businesses can improve resource efficiency; Topic 9—Flow and network properties in economic systems; Topic 10—Predicting the environmental impacts of chemicals; Topic 11—Innovation in the product design and development phase; Topic 12—Artificial intelligence for waste sorting; Topic 13—Optimization of selected industrial processes; Topic 14—Projections of municipal solid waste-related indicators; Topic 15—Material flow analysis, geographic information system, and big data are used to analyze city building inventories; Topic 16—Circular economy in the EU; Topic 17—Predicting and improving concrete performance. Underlying data for this figure are available in Table S9 of Supporting Information S2.

et al., 2019). During the comprehensive integration phase (2020–2023), cutting-edge AI technologies (e.g., deep learning and big data) focused on extracting knowledge insights from data and further improving the capability to emulate human problem-solving approaches in the context of the CE (Li et al., 2023b; Zocco et al., 2022).

Overall, since 2020, research that integrates AI with IE experienced rapid growth (Figure 2). The evolution of AI within IE is primarily reflected in the diversity of research subjects, which now include emerging areas such as waste management, renewable energy, and biomass (Figures 4 and 7). These topics reflect increasing concerns over environmental sustainability and public health (Adamović et al., 2018; Hassoun et al., 2023; Kumar et al., 2021; Lau Hiu Hoong et al., 2020; Zhou et al., 2022). Moreover, the development of smart sustainable biorefineries, bio-waste to bioenergy, and bioenergy with carbon capture and sequestration underscores the drive toward a circular bioeconomy (Banerjee, 2023; Goswami et al., 2022; Guo et al., 2019; Li et al., 2022, 2023a). Presumably, changes in research focus may be further attributed to the implementation of laws and regulations, such as the European Green Deal (European Commission, 2019), the outline of the 14th Five-Year Plan (2021–2025) for National Economic and Social Development (National Development & Reform Commission, 2021), Japan's green growth strategy (Ministry of Economy, Trade & Industry, 2020), Horizon Europe (European Commission, 2018), and China's New-Generation Artificial Intelligence Development Plan (The State Council of the People's Republic of China, 2017).

## 4.2 | The prospects and challenges

Trending topics, including big data, data-driven methods, digital technologies, and NLP (a subset of AI) as illustrated in Figures 4 and 8, are interconnected. They play crucial roles in data analytics and developing intelligent solutions that address sustainability issues in production and consumption systems. Big data offers extensive and diverse datasets that are essential for training language models in NLP. These models use data-driven techniques such as deep learning to interpret and generate human language. Additionally, digital technologies supply the necessary storage, processing, and analytical capabilities to meet the computational demands and maintain the technical infrastructure required for data-driven models and NLP applications.



**FIGURE 8** The development trends in the integration of artificial intelligence and industrial ecology. Note: This result is based on the normalized annual frequency of author keywords.

LCA is a prevalent research methodology within IE, as illustrated in Figure 5. This method can be effectively integrated with various AI techniques to tackle environmental and sustainability challenges in industrial systems and processes (Chen et al., 2023c; Nabavi-Pelesarai et al., 2018; Tanhadoust et al., 2023; Zhou et al., 2023). However, the life cycle inventory phase, which is notably the most time-consuming and labor-intensive aspect of LCA, encounters significant challenges due to missing data. This limitation impedes the scalability of LCA methodologies. In general, methods to address missing data still rely on aggregated data to represent industrial systems averages at various scales (Xu et al., 2015). Advances in automation of the life cycle inventory through data mining (Cashman et al., 2016), ML, and artificial neural networks (Liao et al., 2020) are becoming increasingly available. As AI technologies advance, data-driven decision-making will progressively incorporate the spatial, temporal, and demographic heterogeneities inherent in industrial systems. However, challenges related to data availability and the complexity of data extraction persist, representing significant obstacles for researchers. Open-access online platforms for data sharing, such as the one developed by the TianGong Team (TianGong database, 2023), may facilitate more accurate model development and enhance informed decision-making by providing open, free, and traceable life cycle data.

Pre-trained large language models (LLMs), such as ChatGPT and Llama, are advanced models trained on vast datasets to understand, generate, and interpret human language with remarkable accuracy (Rillig et al., 2023). For example, Kaiwu—AI for sustainability constitutes a platform where LLMs are employed to promote environmental innovation (TianGong, 2023). Recent studies have explored the applications of ChatGPT within the context of Industry 5.0 (Wang et al., 2023a) and digital CE (Verma, 2023).

LLMs demonstrate promising potential in processing and analyzing datasets pertinent to IE. However, these models also raise important debates regarding model biases, transparency, and interpretability. Zhu et al. (2023) highlighted various limitations and potential challenges when deploying ChatGPT in environmental research. Furthermore, the growing complexity and popularization of AI techniques are leading to increasing concerns about resource consumption and environmental impacts (Donati et al., 2022; George et al., 2023).

Moreover, the acquisition of real-time data to satisfy the requirement for simulations, monitoring, optimization, and prediction processes—enabled by digital twins—is now feasible. The deployment of a digital twin architecture, including sensors and IoT devices in industrial processes, is imperative to broadly realize CE and sustainability (Figure 8) (Baduge et al., 2022; Suvarna et al., 2020; Tzachor et al., 2022a, 2022b; Zhao et al., 2024). Computer vision and robotics have also emerged as effective data capture methods, particularly in complex and hazardous environments. For example, underwater data collection can be conducted using robotic sensor networks (Hollinger et al., 2012), and vision-based mobile robotic systems facilitate autonomous data collection in construction environments (Asadi et al., 2020). Sensors and computer vision technologies are increasingly utilized for data collection and to address broader industrial challenges, such as integrating these two techniques to generate 3D

surface maps of urban stocks (Arbabi et al., 2022). Nonetheless, developing a material stock monitoring system that provides accurate, real-time information about the types, masses, and locations of materials within a designated area remains challenging. Zocco et al. (2022) examines how enhancing IE research with computer vision can foster sustainable manufacturing, proposing a novel material measurement system to improve the management of material stocks in a CE. Future research should persist along this trajectory.

As computer vision matures further, it will be able to detect pollutants across environments. The technology is already leveraged to accurately estimate pollutants' quantity, composition, and origins, and categorize microplastic litter in water bodies (Jia et al., 2023). A rising area of interest, Topic 12—Artificial intelligence for waste sorting—demonstrates a significant application of this technology. It employs a deep convolutional neural network model to automatically classify construction and demolition waste (Lin et al., 2022b). Similarly, a model that integrates deep residual networks with transfer learning for recyclable waste classification (Lin et al., 2022a) underscores the growing trend and utility of computer vision. Computer vision is also capable of identifying the wear state of products, thereby enabling timely intervention and maintenance (Walk et al., 2023).

Robotics have become instrumental in advancing waste management systems, thereby playing an essential role in the evolution of smart cities. Specifically, industrial robot arms are adept at precisely grasping and categorizing waste materials based on their content, enhancing the efficiency and effectiveness of the recycling processes (Kshirsagar et al., 2022; Maiurova et al., 2022). Robotics have been further employed in fungal fermentation systems for the collection and transfer of substrates and chemicals. However, the exploration of their functionalities at higher technology readiness levels is still pending (Wainaina & Taherzadeh, 2023). In the realms of Industry 4.0 and the CE, the application of robotics is increasingly pervasive. Consequently, it is imperative to consider the environmental implications of this expansion seriously (Laskurain-Iturbe et al., 2021).

### 4.3 | Research limitations

While this study attempts to narrow gaps in the literature and identify research hotspots at the emerging IE–AI intersection, we acknowledge several limitations in our approach. Search terms were derived from high-frequency author keywords in the *Journal of Industrial Ecology* and *Artificial Intelligence*. Given the expansive scope of these fields, which encompass hundreds of relevant journals and books, it is not feasible to cover every possible source. Consequently, our selection may not capture all pertinent literature in these domains. Regarding data, the dataset for 2023 is incomplete, as the study commenced in October 2023. However, we believe that the data collected is representative of the year. Moreover, future studies should incorporate additional databases to ensure data comprehensiveness and consider exploring the network of citations in the literature may yield more insightful conclusions.

In terms of methodology, although word2vec and top2vec efficiently extract topics from large text volumes, they have difficulty capturing deeper semantic structures and complex topic hierarchies. Word2vec identifies word similarity by training a model to recognize co-occurrence patterns within sentences or phrases. However, it lacks the capacity to fully capture complex contextual relationships. Top2vec generates topics by clustering similar text vectors, but it also struggles to capture finer semantic nuances. Replacing word2vec and top2vec with context-aware embedding models, such as transformers (e.g., BERT) and LLMs, could enable more granular topic extraction and uncover hierarchical relationships between topics. BERT uses a bidirectional transformer architecture, enabling it to capture the contextual information of words within a single text fragment (Callaghan et al., 2021). Trained on extensive text corpora, LLMs exhibit strong contextual understanding, enabling them to detect subtle thematic shifts and semantic transitions in lengthy and complex scientific literature (Tshitoyan et al., 2019; Zhu & Ren, 2023). This capability aids in uncovering complex topic hierarchies.

## 5 | CONCLUSION

NLP has emerged as a potent methodology for uncovering the intrinsic relationships between textual data and scientific advancements. To the best of our knowledge, this is the first instance where word2vec and top2vec (NLP techniques) have been employed to explore the application of AI within the domain of IE. We focused on exploring the directions and characteristics of integrating AI techniques with IE's main tenets, practices, and processes. This research intersection saw 1068 published papers between 2000 and October 2023, involving researchers from 73 countries and regions. We identified 71 relatively trending keywords, 69 of which (such as *Industry 4.0* and *big data*) emerged only in the recent period (2016–2023), with the exceptions of *CE* and *ML*. The word2vec modeling revealed that the specific focus of IE and AI methods varies according to the research subjects in question. For example, LCA combined with artificial neural networks was primarily applied to smart cities and electric vehicles. LCA integrated with ML was extensively utilized in natural resource management, energy use, fossil fuels, and plastic waste research. Furthermore, we performed a trend factor analysis on document-based topics, identifying four trending topics and one newly emerging topic. Employing digital technologies and optimization algorithms, such as big data, AI, and the IoT, to predict the yields, characteristics, and environmental impacts of products (or waste), as well as to refine processes, reduce costs, and enhance efficiencies, represents an emerging direction of development. Finally, we reviewed the development path of AI and IE for collaborative problem-solving and envisioned future research opportunities. LLMs, sensors, robotics, and computer vision can, and ought to play significant roles in data-driven decision-making processes in IE. Meanwhile, computer vision

and robotics are emerging as pivotal instruments in a wide array of domains, including waste management. We anticipate that future research will produce an increased volume of scholarly studies and practical applications at the IE–AI intersection.

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## CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

## DATA AVAILABILITY STATEMENT

The data that supports the findings of this study are available in the supporting information of this article.

## ORCID

Yongyue Gong  <https://orcid.org/0009-0009-1312-409X>

Heming Wang  <https://orcid.org/0000-0003-3487-0912>

Heinz Schandl  <https://orcid.org/0000-0001-6399-4231>

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## SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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