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Review article

A state-of-the-art review of digital twin-enabled human-robot collaboration in smart energy management systems

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ABSTRACT

Digital twin (DT) and human-robot collaboration (HRC) have shown great potential in smart energy management systems (SEMS) with the development of industrial digitisation. Despite recent applications, the mainstream topics and future research directions of DT-enabled HRC in SEMS remain unexplored. Furthermore, no review study has combined a systematic literature review and science mapping analysis to comprehensively summarise this topic. This study conducts a state-of-the-art review of DT-enabled HRC in SEMS, as well as identifies mainstream topics, research gaps, and future research directions. Using Scopus as an electronic database, this study obtained 126 articles for quantitative discussion through scientometric analysis. Subsequently, a qualitative discussion that concentrated on the research objectives was conducted. The results revealed influential findings related to publication trends, journal sources, co-occurrence of keywords, countries/regions, and document analyses. Additionally, this paper highlighted four mainstream topics, including: (1) artificial Intelligence (AI) enhancement for DT-enabled HRC in SEMS, (2) optimisation and enhancement based on DT, (3) improvement of HRC, and (4) development of the Industrial Revolution. Moreover, it summarised the research gaps and future research directions based on these results. This review study could help researchers in related fields understand the progress of current research and discover directions for further study.

1. Introduction

The advancement in information and communication technologies has led to the development and use of various systems in smart facilities, such as energy monitoring and energy consumption devices, for energy management. This has had a positive impact on power grids, resulting in the emergence of smart energy management system (SEMS) [1]. Lund et al. [2] demonstrated that the concept of smart energy systems has evolved from the primary signal electricity sector to an integrated system that encompasses various energy sectors and classifications. Based on this idea of the overall energy system, SEMS has brought many opportunities to improve the energy supply and develop the operation of traditional energy systems by collaborating with all sectors [3,4]. Furthermore, SEMS has facilitated the efficient utilisation of emerging energy sources, the integration of diverse renewable energy resources, intelligent substations, battery energy management, cyber-security applications, electric vehicle charging stations, distribution equipment, and among others [5–7]. Recent years have seen a growing concern for reducing energy consumption and carbon footprint, leading to the design and application of SEMS in various industries to enhance energy efficiency and reduce energy costs [8].

As a complex and changeable system, Lund et al. [2] introduced the requirements for the simulation and design of SEMS. These requirements include extending across all parts of SEMS, maintaining a high temporal resolution to account for seasonal variations and accurately reflect storage utilisation, and having the capability to calculate the input, output, and contents of each storage option chronologically. Currently, various energy monitoring devices in SEMS can support the coverage of each sector [9]. Maley and Romanosky [10] emphasised the importance of control sensors in energy systems. However, the lack of a framework to integrate and collaborate on different types of energy resources and facilities is also an existing issue. Lasemi et al. [11] introduced a

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framework for the multi-energy system that integrates various types of renewable energy systems, adapting to the uncertainty of renewable sources, demands, and energy market spot prices, among other factors. Caputo et al. [12] suggested a framework based on digital twin (DT) to study complicated assembly line systems with uncertain variables connected in non-linear ways. It provides new ways to simulate systems that are always changing.

Meanwhile, real-world applications have demonstrated many approaches to SEMS-based technologies. For example, [1] proposed a SEMS framework that focuses on monitoring and calculating smart grid parameters via the Internet of Things (IoT), enabling smart meters to provide efficient energy management. Yousefi [13] developed a SEMS for a residential home with a photovoltaic array (PV) and plug-in electric vehicle (PEV), which was able to reduce the cost of electricity and help make a tradeoff with PEV battery aging. Huang et al. [5] studied a SEMS platform that combined the advantages of an interactive user interface and hardware (i.e., an AI chip) to increase renewable energy utilisation and efficiency. Taken together, SEMS is an approach that addresses energy challenges and provides new opportunities for enhancing energy storage, collaboration, and management by combining with relevant emerging technologies [14]. Yu et al. [15] found that a DT-enabled SEMS can fundamentally shift the way an industry operates to minimise specific energy consumption and increase renewable energy integration across all time horizons.

Recent research has focused on human-robot collaboration (HRC) approach as a significant emerging concept, while automatic systems and production have emerged as major trends in the development of various industries [16]. Some industries like manufacturing plants [17], healthcare [18], inspection and facility management [19] have typically identified robots as having higher efficiency and repeatability [20], as well as the ability to handle increasingly complex environments [21]. Nevertheless, in traditional industrial robot technology, there are several limitations to mechanical action. Sun et al. [22] introduced a single structure, making it challenging to complete assembly tasks alone and requiring the robot program to be rewritten. In contrast, human workers have more flexibility and autonomous decision-making abilities that can respond to changes in their environments [23]. Therefore, through the collaboration between robots and humans, robotic precision complements human flexibility, which enables efficient task delivery [24,25]. Iqbal and Riek [26] developed the idea that the collaboration of humans and robots, involving side-by-side cooperation in the same workplace, could finish complex and flexible operations with higher precision. While the advantages of the HRC have been known in many industries, previous studies have revealed several limitations of this technology based on its ad-hoc, piecemeal, and sporadic nature [27]. On the one hand, due to the weak ability of the robot's perception and cognition, the current HRC technology cannot make decisions and respond to issues as quickly as humans [22]. On the other hand, the inability to collectively consider information from all robots and the lack of an effective human-robot interface cause some difficulties in planning tasks and decrease teamwork efficiency [24]. Despite certain limitations, Grieves et al. [28] demonstrated the widespread belief that DT can significantly enhance the potential of HRC.

Grieves [29] coined the term DT to describe a system that includes a physical part, a digital (or virtual) replica, and a connection between the two domains. Lu et al. [24] proposed that DT commonly represents a virtual replica of a physical entity, and its significant capabilities of predictive analysis and simulation based on real-time data can impact the real world. DT technology constructs a model in virtual space, integrating geometry, information, and algorithms. This model can synchronously monitor, analyse, and optimise real-time data [30], providing feedback to its physical system [31–33]. DT, as a virtual system that can exert influence on physical entities, has the potential to improve HRC [24] and build a framework for complex systems [12]. Besides, in recent years, DT technologies focused on improving real-time data synchronisation and user interaction have gradually matured and improved [34]. For the development of HRC, DT can capture real-time data and achieve continuous monitoring by humans to ensure robots' functioning and timely response to environmental changes [24]. DT-enabled HRC has stronger adaptability due to the ability to collect and simulate information [35]. In addition, Caputo et al. [12] reported that DT can inform decision-making through its interaction and simulation abilities. Moreover, DT technology finds application in the management of complex and intelligent systems, such as assembly-commissioning systems [12], medical equipment manufacturing systems [35], industrial energy management systems [15], and building information management systems (Lee, 2021). The concept of DT has rapidly developed in recent years, aligning with Industry 4.0′s goal of realising a digital factory [12]. When combined with other technologies, DT presents a promising future application [36–38]. For example, a human digital twin (HDT) dynamic deployment framework based on edge computing can simultaneously optimise long-term deployment strategies and short-term resource scheduling strategies at different time scales according to task accuracy requirements, user mobility, and system resource conditions, thereby promoting human-centred task execution [39,40]. Moreover, various fields have extensively studied the combination of DT with blockchain (BC) technology to enhance information security, as it offers a reliable method for cyber-physical integration [41,42]. In summary, DT technology has become an efficient tool that can link the physical system with its virtual equivalent and has the potential to develop HRC and manage systems across their whole life cycle [28].

Many previous reviews of DT-enabled technologies in SEMS, such as Ghenai et al. [43] and Billey and Wuest [44], were done manually, which means that they could be subjective and biased. Ghenai et al. [43] summarised a three-layer DT system architecture and categorised its application cases in industrial robot collaboration, but did not use tools such as bibliometric analysis or comparability indicators to provide quantitative analysis results. Billey and Wuest [44] adopted a bibliometric analysis approach to map the research landscape of DT-HRC, employing tools such as VOSviewer to identify major research clusters and trends. However, it does not follow systematic literature review methodology, as it lacks clearly defined inclusion and exclusion criteria, search protocols, or a structured quality assessment of the selected articles. Weil et al. [45] and Do Amaral et al. [46] conducted a systematic literature review of the current findings of DT technology in the energy industry. However, these studies were limited to a few areas, such as using DT in the subsystems of energy generation, transmission, storage, and consumption. Amaral et al. [46] suggested that existing research could broaden its scope. Collectively, prior research has not applied the research methodology, which combines a systematic literature review and a science mapping approach. Furthermore, no study has proposed a DT-enabled HRC approach in SEMS, and there are no existing frameworks that combine DT, HRC, and SEMS. This study combines a systematic literature review and science mapping approach to conduct state-of-the-art research on DT-enabled HRC in SEMS, as well as improve the theoretical and conceptual underpinnings for further studies in this field. Therefore, this study aims to conduct a systematic literature review and science mapping analysis of DT-HRC in SEMS. The specific research objectives are to (1) analyse the annual trends in research publications and peer-reviewed journals on a DT-HRC in SEMS, (2) conduct a scientometric analysis on the co-occurrence of keywords, countries/regions, and document analysis; (3) identify the mainstream research topics on a DT-HRC in SEMS; and (4) recommend research gaps and suggest future research directions on a DT-HRC in SEMS.

The remainder of this paper is structured as follows. Section 2 reviews the previous related research on DT-HRC, and DT-enabled HRC in SEMS. Section 3 introduces the research methodology that combines a systematic literature review and science mapping analysis. Section 4 presents the results, while Section 5 discusses the mainstream research topics, research gaps, and future research directions. Lastly, Section 6 outlines the conclusions, implications, limitations, and further studies.

2. Related works

This section discusses the extant studies of (1) DT-HRC; (2) previous reviews of DT-HRC; (3) concept of SEMS; and (4) DT-HRC in SEMS.

2.1. Existing studies of DT-HRC

In recent years, especially due to the influence of COVID-19, the requirement for efficiency and safety in manufacturing has been increasing, which promotes the development of a DT-HRC. According to Lv et al. [35] and Lu et al. [24], the development of a DT-HRC has gained momentum in recent years. Malik and Bilberg [47] combined DT with HRC to assess and enhance safe cooperation between human operators and robots for assembly work. The simulation-based approach (SBA) and layer-based approach (LBA) are two categories of DT approaches that Ramasubramanian et al. [48] reviewed and integrated with HRC. The SBA builds the DT-HRC model that can evaluate performance and address issues before operation phases [49], provide virtual commissioning in HRC scenarios [50], help test safety [51], and save time and cost [52]. The LBA provides a design of DT-HRC in three general layers, which include the physical layer, virtual layer, and connection layer/-information processing layer [53]. LBA is suitable for the combination of DT with existing systems based on real-time data monitoring and simulation [54]. Existing research indicates that real-world applications of DT-HRC have brought about numerous changes across various industries [12]. A significant application of DT-HRC lies in the manufacturing industry, including assembly, industrial workplaces, and controlling industries. While DT technologies are widely used in manufacturing, recent research has shown their potential in human-centered fields [55]. For example, Chen et al. [56] explored how DT can be applied in personalised healthcare, using mobile artificial intelligence generated content (AIGC) and multimodal sensing to support real-time health monitoring. They also highlighted how DT can be combined with generative AI and IoT, enabling real-time health monitoring and personalised medical support. Table 1 displays some applications of DT-HRC in different industries.

2.2. Existing review studies of dt-hrc

Industry 4.0, which focuses on the flexible automation and customisation of products by interconnected smart facilities, served as the backdrop for the development of the DT-HRC concept [67,68]. According to a study of DT-HRC technology from 2010 to 2022, Feddoul et al. [69] found that more people using and studying DT technologies unlocked their full potential that wasn't possible before for industrial uses. This made it easier for people and robots to work together. Establishing the DT of manufacturing equipment can improve the behaviour, design, further diagnosis, and prediction of faults or damages in robots [70]. Qiu et al. [71] proposed that the integration of DT and intelligent assembly technology is poised to become a significant development trend in the manufacturing of complex products. In addition, DT could support robotics in the construction industry [72]. In summary, the development of DT has indicated that it has the potential to integrate with HRC in other fields or industries instead of just manufacturing [48]. Various studies in different areas have reported on the capabilities of the DT-HRC technology [23]. Table 2 shows previous review studies of DT-HRC.

Table 1
Application areas of DT-HRC research.

Application areas	Research areas	Sources
Assembly and disassembly (Manufacturing)	Production line monitoring and optimisation; Predictive maintenance; Robot path planning; Task scheduling	[35,47, 57–59]
Construction	Robot on-site construction work; Facility management	[24,60]
Industrial workplace (Manufacturing)	Workplace design and maintenance; Remote collaboration and interaction	[12,61]
Healthcare	Modelling of physiological systems; Medical decision-making systems; Disease simulation and prediction; Personalised health management	[18,55,56, 62,63]
Controlling industry (Manufacturing)	Predictive control; Process control, and equipment scheduling; Task planning	[64,65]
Energy	Green manufacturing; Optimisation of renewable energy systems such as solar and wind power; Energy consumption optimisation	[24,66]

2.3. Concept of SEMS

The initial development of SEMS might have originated from the demand for power usage efficiency, real-time control, and user participation in the power system field [73]. With the emergence and advancement of smart grids, digital technologies have been combined with traditional power networks, enabling SEMS to evolve from conventional energy management to distributed, user-participatory, and intelligent management [74]. SEMS could currently be regarded as an integrated platform based on information and communication technologies, as well as intelligent control algorithms [75,76]. It can monitor, analyse, and optimise energy systems in real time, and is widely used to support energy efficiency improvements and intelligent decision-making in various scenarios, such as buildings [77], factories [78], and power grids [79]. Against the backdrop of growing energy consumption, escalating environmental concerns, and rapid technological advancement, SEMS offers a revolutionary approach to energy management. By integrating advanced technologies such as machine learning (ML), artificial intelligence (AI), and DT, SEMS enables more efficient, intelligent, and sustainable operation of energy systems, providing novel solutions for future energy challenges [80].

2.4. DT-HRC in SEMS

In the current global scenario for SEMS, with the rising demand for electricity and the requirement to reduce carbon emissions, DT has had a crucial impact on optimising the performance of existing energy systems [46]. The combination of DT and SEMS can take various forms and have different effects. Bayer and Pruckner [81] proposed a DT-enabled smart energy system as a template to provide decision support for either system operator based on real-time data. Furthermore, Yu et al. [15] summarised the applications of energy DT throughout a site's lifecycle in industrial energy management systems. The digitalisation of energy sectors has led to the development of DT technology applications in SEMS, rooted in the fields of automation and robotics [43]. Nevertheless, the existing studies show that the integration of DT technology, HRC, and SEMS tends to be separate and intermittent. Table 3 illustrates various sectors within SEMS, their utilisation of DT or HRC, and the extent of their integration in prior studies.

Table 3 divides the degrees of combination between DT and HRC into three levels. The single level indicates that neither DT nor HRC has advanced in these fields. The level of co-existence means that both DT and HRC have had some examples of applications in these fields. Lastly, the level of collaboration indicates that DT and HRC have engaged in joint research in various fields. There is a limited body of previous research that attempts to connect both DT-HRC and SEMS, primarily focusing on several distinct fields. Although some articles have studied DT and HRC within the energy sector, their integration is limited. Therefore, this study develops the potential of DT-HRC in SEMS based on existing studies.

3. Research methods

This review study deployed a "mixed-method review approach",

Table 2
Previous review studies of DT-HRC.

Application scenarios	Research areas	Research methods	Key findings	References
Critical design aspects (i.e. Objectives, associate technologies, and application scenarios)	In industrial collaborative environments (such as assembly lines, collaborative welding, and logistics handling), modelling, optimising, and enhancing HRC tasks based on DTs.	Categorical literature review and science mapping review	Identifying the application scenarios, associated technology and digital twins development prospective of DT in HRC systems	[23]
The sustainability functions of Industry 4.0	DT-HRC promotes sustainability in environmental, economic and social dimensions at all stages of the supply chain.	Interpretive structural modelling technique	There are sophisticated precedence relationships among different sustainability functions of Industry 4.0.	[67]
Manufacturing	DT-HRC applications across the whole lifecycle (Design, scheduling, monitoring, control, maintenance) in smart manufacturing.	Categorical literature review	For the literature concerning the highest development stage, there is hardly any literature about DT, whilst there is more literature about DM and DS.	[68]
The operating process of manufacturing	DT implementation for dynamic monitoring, control, and optimisation of manufacturing HRC operations	Quantitative review and categorical literature review	The function and challenges of digital twins in HRC scenarios and the exactness of the DT in the physical system.	[48]

Table 3
The application of DT and HRC in SEMS with their interaction level.

Application in SEMS	DT	Sources	HRC	Sources	Integration level
Renewable resource system (data capturing and processing)	✓	[82,83]	✓	[84]	Co-existence
Renewable resource system (decision-making support)	✓	[85]			
Intelligent system management	✓	[86]			
Building energy management	✓	[24, 87–89]	✓	[24]	Collaboration
Industrial energy management	✓	[90]	✓	[59,91]	Collaboration

which combines a "quantitative review (i.e., science mapping analysis)" and a "qualitative review (i.e., systematic literature review)". Mixed methods are regarded as being able to combine the strengths of quantitative and qualitative methods [92]. Meanwhile, mixed methods could also reduce bias and subjectivity in research, as well as help ensure that the statistical analyses are based on a realistic academic setting [93]. First, the study employed a systematic literature review as an evidence-informed research methodology to minimise bias and enhance overall reliability [94]. The systematic literature review in this study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [95]. These guidelines gave steps for finding literature and screening articles as demonstrated in previous studies [96–99].

Thereafter, the science mapping review was applied in the bibliometric analysis of this study, which could quantitatively show the research status and publication trend of this emerging subject by assessing academic performance from different perspectives [100]. The VOSviewer tool, which is one of the most common and useful software approaches in library and information science [101,102], was used to visualise these knowledge maps. Then, a qualitative discussion was adopted to qualitatively illustrate the main current directions and depth of research in the field of DT and HRC in SEMS. Overall, this approach involved five steps: (1) source recognition and article search, (2) article screening and review of eligibility, (3) included articles, data extraction and quality assessment, (4) science mapping review, and (5) qualitative discussion. Fig. 1 shows an overview of the research method.

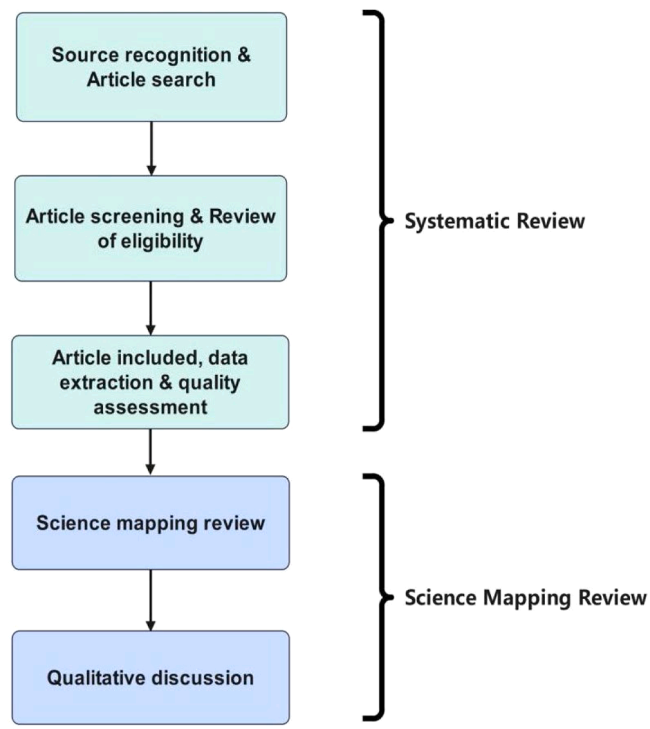

Fig. 1. An overview of the research method.

analysis, Scopus has become one of the most crucial and reliable databases for citations, bibliometric analysis, and abstracts due to its broad coverage of journals, particularly its advantages in including the most recent research findings [104,105]. In certain specific fields, such as biomedicine [106] and engineering [107], Scopus has demonstrated a more stable and impartial performance. In addition, the user interface and search capabilities of Scopus are also particularly well-suited for conducting bibliometric analyses [108–110]. The keywords "digital" AND "twin" and "human-robot" OR "human-computer" OR "man--machine" OR "machine AND intelligent" and "energy" OR "system" were used to retrieve literature samples in Scopus, which got 565 documents. Table 4 presents the complete research string. Then, these articles were further selected by a constrained structured query in Scopus.

3.1. Source recognition and article search

Data used for systematic review and science mapping analysis were retrieved from the Scopus database, which is an influential and multidisciplinary citation database [103]. In the field of scientometric

3.2. Article screening and review of eligibility

This paper conducted the initial screening of the literature by adding limitation strings to the Scopus database. It restricted the source type to journals, set the document type to articles, and finalised the publication

Table 4
Keywords and literature search results.

String	Results
(TITLE-ABS-KEY (digital AND twin) AND TITLE-ABS-KEY (human-robot OR human-computer OR man-machine OR machine AND intelligent) AND TITLE-ABS-KEY (energy OR system))	565
AND (LIMIT-TO (SUBJAREA, "ENGI") OR LIMIT-TO (SUBJAREA, "ENER")) AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (PUBSTAGE, "final")) AND (LIMIT-TO (SRCTYPE, "j")) AND (LIMIT-TO LANGUAGE, "English"))	142
Manual screening by reviewing keywords in titles and abstracts	134
Manual screening by eligibility criteria	126

Note: The publication years of articles had no limit, and the Scopus search was conducted in January 2024.

stage to confirm the research value of the chosen documents. Currently, research studies related to SEMS, particularly those integrating DT technologies and HRC, are predominantly concentrated in the fields of engineering and energy [111,112]. Additionally, over the past ten years – prior to 2023, SEMS-related studies have primarily been published in engineering and energy journals [76]. Therefore, this paper restricted the subject areas to engineering and energy, which aligned with the study's topic. Finally, this paper limited the language of the articles to English. After screening, we identified and retained 142 documents. Next, this paper applied further screening to these articles, ensuring that each title or abstract included at least one of the identified keywords. This paper then reviewed and considered 134 articles for a detailed review to determine their eligibility.

Following PRISMA guidelines, based on the purpose of the study, a specific definition of the selection criteria in the systematic literature review helps to ensure the credibility and reproducibility of the analysis [113]. This study primarily aims to analyse the research trends of DT-HRC in SEMS, thus, a review of titles, abstracts, and full texts was conducted to determine eligibility and eliminate irrelevant articles. Table 5 displays the specific criteria. Finally, this paper included 126 articles for the next analysis, as shown in Table 6.

3.3. Included articles, data extraction, and quality assessment

After screening and eligibility steps, 16 irrelevant articles were removed, and there were eventually 126 articles that were defined as eligible. Meanwhile, to achieve the best relevance and validity, a quality assessment of articles based on the following questions was adopted, and the checklist of questions was constructed based on Kitchenham and Charters [120].

- Are the objectives of the articles clear and relevant to the topic of this study?
- Are the design and steps of the studies consistent with the objectives?
- Are the methods and results of the articles clearly reported?
- Are there any new contributions in the articles?
- Do these articles clearly define the limitations of the studies?

After all steps, 126 selected articles were used for data extraction.

Table 5
The criteria for the systematic literature review.

Criteria	Instruction	References
No system-related (NSR)	The article focuses on isolated research subjects or fails to consider the analysis of the object of study in the context of a system.	[114,115]
No robot/machine related (NRR)	The article discusses the DT but considers virtual performance and lacks connection to devices, machines, or robots.	[116,117]
Non-HRC related (NHR)	The article discusses DT and related machines but does not have a relation to collaboration or interaction with human.	[118,119]

Table 6
Results of the eligibility identification of articles.

Searching or screening steps	The number of included articles
Search within Scopus with research string	142
Initial screening	134
Removing articles that lack keywords in the title or abstract	
Eligibility review	
Excluding articles for NSR reasons	131
Excluding articles for NRR reasons	128
Excluding articles for NHR reasons	126 (Final included articles)

Three types of general information were extracted from each article for the next science mapping review, including citation information, bibliographical information, and abstract and keywords. These data from 126 articles were downloaded in a .csv (comma-separated values) file, which could be imported into VOSviewer.

3.4. Science mapping analysis

In this study, the fourth step was to import the data from these final 126 articles into VOSviewer for bibliometric analysis. VOSviewer could make and show bibliometric maps using any kind of co-occurrence data, make it easy to see how bibliometric networks are connected based on distance, and have a huge impact on bibliometric maps [102,121,122]. VOSviewer employs a clustering algorithm based on modularity optimisation. This algorithm divides the network into groups by maximising the density of intra-group connections, ensuring that elements in each cluster are closely connected, which makes it suitable for community detection in bibliometric and network analyses [102]. The normalisation method adopted in the software is the association strength normalisation method. This method is suitable for measuring the relative strength between two items (such as keywords, authors, etc.), eliminating the bias caused by different frequencies of occurrence, thereby better reflecting their actual co-occurrence relationship [123]. Therefore, this paper performed the scientometric analysis, including both co-occurrence and citation analysis, using VOSviewer. This step would also serve as the foundation for the subsequent qualitative discussion. This section implemented the co-occurrence analysis of keywords, the co-occurrence analysis of countries/regions, and the co-citation analysis of documents, resulting in the generation of networks.

3.5. Qualitative discussion

The results of the co-concurrence analysis in Section 3.4 guided the qualitative discussions in this section. This paper presented a comprehensive review of the screened literature to delve into the mainstream topics of DT-HRC in SEMS, explore recent research trends, and suggest future research directions.

4. Results

4.1. Annual publication trend

Fig. 2 presents the annual article publication trend between 2017 and 2024. According to Fig. 2, the overall trend of annual publications is increasing from 2017 to 2023. Although the number of articles published so far in 2024 is lower than in 2023, the search was unable to show a downward trend because it included articles from before January 2024. This study also observed a flat and slightly declining trend from 2017 to 2019, which is associated with the advancement of digital technology. Next, the emergence and development of Industry 4.0 are transforming industries towards intelligence and digitisation [124]. Especially since COVID-19, people have realised the importance of automated manufacturing and HRC [35]. As a result, HRC based on

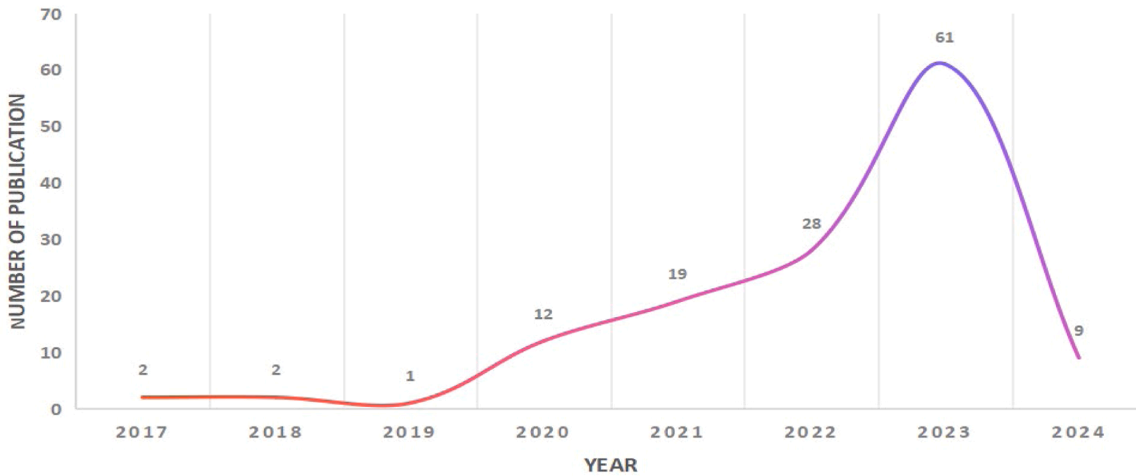

Fig. 2. Annual publication trend of articles. **Note:** articles that were published in 2024 include only those retrieved in the Scopus database until January 2024.

digital technology, has gradually increased in research and application. Since 2020, there has been a gradual increase in the number of articles published, with the most rapid increase occurring from 2022 to 2023, with an increase of approximately 117.86 % over the previous year. The second significant increase is between 2019 and 2020, when the number of articles rose from the lowest point of 1 in 2019 to 12 in 2020, an increase of 110 %. After this, the number of studies starts to grow gradually from a steady state. In conclusion, the studied topic anticipates a continued growth in research on DT-enabled HRC technologies in industrial or energy systems in the future.

4.2. Sources of journals

72 journals published the 126 selected articles for this study, with Table 7 showing the top 15 journals. By analyzing the sources of the journals, the journals with a high number of publications are mainly from China, the United Kingdom, and the United States, which suggests that these countries are currently more interested in relevant research. According to Table 7, the journals cover a wide range of fields, including manufacturing, energy, communications, and so on, demonstrating that the systematic application of DT-enabled HRC technology has potential in many fields. The journal with the largest number of publications, 12.5 %, is Applied Sciences (Switzerland), which deals with various aspects of applied natural sciences. In addition, 25 journals published two or more articles, indicating a wide dispersion of journals covering research in this area.

Table 7
Top 15 journal sources and their shares.

Source title	Count	Percentage
Applied Sciences (Switzerland)	9	12.50 %
Journal of Manufacturing Systems	7	9.72 %
Sensors	6	8.33 %
IEEE Access	5	6.94 %
IEEE Journal on Selected Areas in Communications	4	5.56 %
Journal of Cleaner Production	4	5.56 %
Energies	3	4.17 %
International Journal of Advanced Manufacturing Technology	3	4.17 %
Journal of Intelligent Manufacturing	3	4.17 %
Reliability Engineering and System Safety	3	4.17 %
Robotics and Computer-Integrated Manufacturing	3	4.17 %
Sustainability (Switzerland)	3	4.17 %
Automation in Construction	2	2.78 %
Buildings	2	2.78 %
CIRP Annals	2	2.78 %

4.3. Keywords co-occurrence analysis

Firstly, a CSV file containing 126 related documents was imported into VOSviewer for co-occurrence analysis, and “author keywords” were selected. Secondly, 48 keywords met the threshold out of a total of 465 by setting the minimum number of occurrences of a keyword to 2. Next, the selected number of keywords was set to 25, and semantically repetitive keywords like “digital twin” and “digital twins” were combined. After these screenings, 24 keywords were selected, and the results of keyword co-occurrence analysis are shown in Fig. 3.

According to Fig. 3, keywords are nodes in the network graph, and the size of the area of the node reflects the size of the frequency of keyword occurrence. For example, the keyword “digital twin” has the highest number of occurrences with the largest nodes. Besides, the connecting lines between nodes represent co-occurrence relationships in the keywords, with closer proximity between nodes representing stronger co-occurrence relationships. Different colours in the keyword co-occurrence analysis network indicate the classification of the keywords into different clusters. Six clusters were clearly grouped as shown in Fig. 3. For instance, ML belongs to the same cluster as internal elements, deep learning (DL), and human-robot collaboration, a reflection of their frequent combination in research, indicating a closer internal connection.

Table 8 presents the top 15 keywords of the DT-enabled HRC research. Table 8 also displays the links to the keywords and their total strength. Moreover, this paper ranked the list of keywords based on the total link strength, as this indicates the degree of connection between the keywords and a specific area, typically associated with the research topic [108]. For example, the keywords “Industry 4.0″ and “machine learning” were considered to have a stronger connection to the DT-enabled approach. In addition, according to Table 8, there are some frequently occurring keywords, including “digital twin,” “industry 4.0,” “machine learning,” and “artificial intelligence,” with the most commonly used keyword being “digital twin." This suggests that Industry 4.0 will greatly facilitate the development and application of the DT concept. Meanwhile, DT is also contributing to Industry 4.0′s process. Secondly, the integration of AI with DT has stimulated its development in various areas.

The average publication year reveals recent research trends and themes. DL emerges as the latest trend, closely trailed by reinforcement learning (RL) and IoT. In contrast, AI and cyber-physical systems have become traditional research topics.

When analyzed in conjunction with Fig. 3 and Table 8, the mainstream research topics in DT-HRC in SEMS could be defined based on these 6 clusters, which were shown as follows.

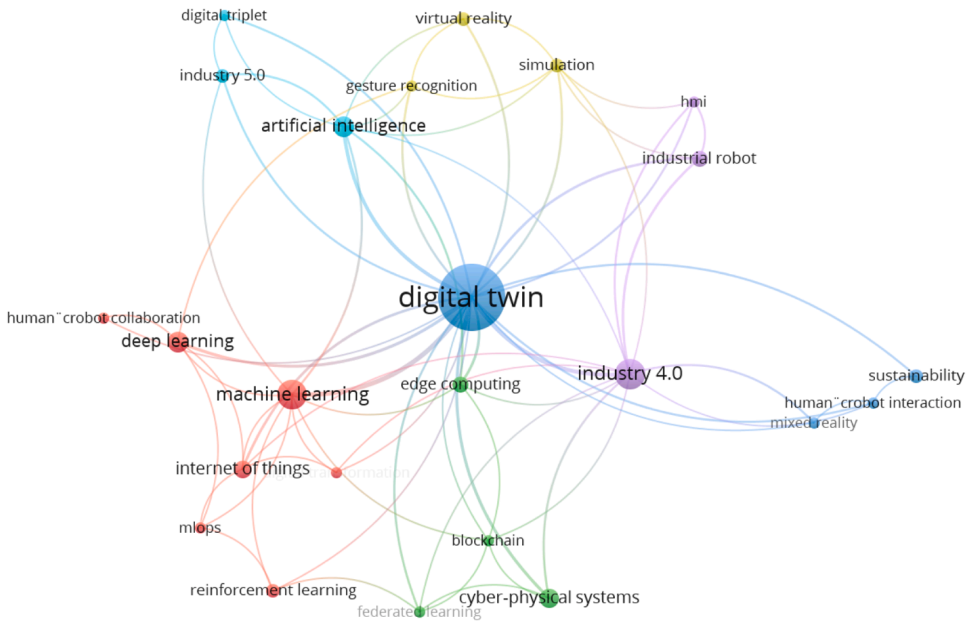

Fig. 3. Keywords co-occurrence network of DT-HRC in SEMS.

Table 8
Top 15 keywords of DT-enabled HRC research.

Keyword	Cluster	Occurrences	Average publication year	Links	Total link strength
Digital twin	5	76	2022.11	22	65
Industry 4.0	2	15	2022.00	13	25
Machine learning	1	14	2021.86	10	21
Artificial intelligent	3	7	2021.29	9	17
Deep learning	1	7	2023.29	6	9
Industrial robot	2	4	2022.00	4	9
Cyber-physical systems	4	6	2021.33	4	8
Internet of things	1	5	2022.40	6	8
Edge computing	4	4	2022.00	5	8
Simulation	6	3	2021.67	7	8
Industry 5.0	3	3	2022.33	4	6
Virtual reality	6	3	2022.33	4	5
Reinforcement learning	1	3	2022.67	4	4
Digital triplet	3	2	2021.50	3	4
Sustainability	5	3	2022.33	2	3

1. Integrating DT with intelligent learning and HRC (Red Cluster) – The DT approach could enhance ML and combine it with HRC, forming a major research cluster. DT-HRC can generate realistic, controllable simulation data through virtual modelling, which helps to increase the training sample required for ML, especially for rare scenarios or high-risk tasks [125]. Similarly, the reliance of DL on large amounts of labelled data can potentially be addressed by DT-HRC systems. Additionally, the simulation feedback provided by the DT enhances the generalisation ability of the model in real-world scenarios [126]. Moreover, related research could also be extended to reinforcement learning [127] and further integrated with the IoT [128] to enhance machine intelligence and overall system performance.
2. DT in the context of Industry 4.0 and smart manufacturing (Purple Cluster) – In these articles, the discussion of DT in the context of Industry 4.0 is also a major topic. The DT concept could meet the goals and requirements of smart manufacturing in Industry 4.0, such as the integration of the physical and digital worlds, real-time monitoring and optimisation, intelligent decision-making, and adaptive control [129]. Meanwhile, research articles in this cluster were also relevant to industrial robotics. DT can provide a virtual simulation environment for industrial robot systems, helping to analyse collaborative behaviour and task progress in real time, thereby effectively improving collaboration efficiency and system responsiveness [130].
3. AI-driven DT for Industry 5.0 and digital triplets (Light Blue Cluster) – AI-driven enhancement is also a popular area to combine with the DT approach. AI, especially ML and DL algorithms, can empower DT models to recognise patterns from historical and real-time data, transforming them from passive simulations to systems capable of predicting system status and user behaviour [90]. Furthermore, the potential of this topic in human-machine automation collaboration also links it to Industry 5.0 [131] and the concept of the digital triplet [132], which emphasises not only the integration of physical, digital, and human elements, but also the creation of systems capable of intelligent adaptation, personalised interaction, and continuous improvement.
4. Risk management and information security (Green Cluster) – As human-machine collaboration systems become increasingly complex, ensuring safety and data integrity has become a key research focus. Jin et al. [133] suggested combining DT with edge computing to enhance risk analysis in HRC. Similarly, research on blockchain [134] and cyber-physical systems [135] could also contribute to the field of risk management and information security by implementing tamper-proof data exchange, decentralised access control, and real-time threat detection in the interconnected components of the DT-HRC system.
5. Sustainability and energy systems (Blue Cluster) – In addition, based on the potential of DT and human-robot interactions for energy management, research on sustainability has also developed into a main cluster [136]. The real-time monitoring, full lifecycle management, and intelligent task planning capabilities of the DT-HRC system can effectively improve resource utilisation and enable more accurate energy monitoring and control [24]. At the same time, mixed reality technologies can also enhance the practice of DT in industrial or energy systems. The DT framework can combine augmented reality (AR) with IoT sensors to enable remote monitoring of photovoltaic systems, demonstrating the potential for

enhanced user interaction and operational efficiency in digital transformation applications in the energy sector [137].

6. Simulation and interaction technologies (Yellow Cluster) - Finally, there is also some research on simulation and gesture recognition in human-computer interaction. DT-supported systems can provide real-time connectivity and improved accuracy, thereby making simulation results more closely resemble real systems [138]. By integrating with gesture recognition systems to build digital replicas of humans, DT can provide users with more personalised, high-precision services [139]. Moreover, related computing and interaction research could also be applied to virtual reality (VR) [140] to provide technical support for it.

4.4. Countries/regions co-occurrence analysis

This paper selected the minimum number of documents for a country in VOSviewer to 3, while there was no limit to the minimum number of citations for a country. Finally, 14 countries out of 44 were included. Fig. 4 displays the countries/regions co-occurrence network, while Table 9 displays the quantitative analysis of selected countries.

Fig. 4 reveals that Asia, particularly China, boasts the largest area of nodes. However, the lines connecting these nodes are longer than those in Europe, North America, and Africa, indicating a closer relationship in this field of research. Table 9 shows that China has the largest number of articles, which have 63 documents, and occupies 50 % of the total included articles. It could demonstrate that China is currently at the forefront of theoretical contributions in this field. This is followed by the United Kingdom, with 15 documents, or 11.9 % of the total included articles. Next are the United States (9.52 %), Germany (7.14 %), and Italy (7.14 %). It could be seen that among the countries with the highest number of publications, the developed countries have a higher proportion and are mainly concentrated in East Asia, Europe, and North America. As a result, it illustrates the stronger tendency of developed economies to transition to digitalised HRC management systems in the context of Industry 4.0. Meanwhile, the average publication year indicates that research in this area in different countries is focused on the period from 2021 to 2023, which demonstrates the interest in this area of research in recent years. In addition, total link strength indicates that although Finland has fewer articles, it has a high total link strength, which shows that it is more relevant to this research area.

Table 9
Top 14 countries/regions in DT-HRC in SEMS.

Country/region	Documents	Average publication year	Links	Total link strength
China	63	2022.10	10	23
United Kingdom	15	2022.20	9	17
German	9	2021.22	7	8
Canada	6	2022.33	4	7
Italy	9	2022.44	6	6
Finland	4	2022.00	5	6
United States	12	2021.67	4	5
Singapore	4	2022.50	2	5
India	3	2021.00	4	4
Sweden	3	2022.00	2	4
Japan	5	2022.60	3	3
United Arab Emirates	3	2023.00	2	3
Netherlands	3	2022.00	3	3

4.5. Document analysis

Document analysis could reflect articles' value and contribution based on the number of citations they receive. VOSviewer set the minimum number of citations for a document at 29, resulting in 25 articles meeting the threshold of 123 total articles. Table 10 presents a summary of some highly cited articles.

Table 10 shows that the article by Rasheed et al. [144] has the highest number of citations, with 700 citations and 5.10 normalised citations, indicating its high academic value. The article's early publication and subsequent growth in the number of studies in this field may

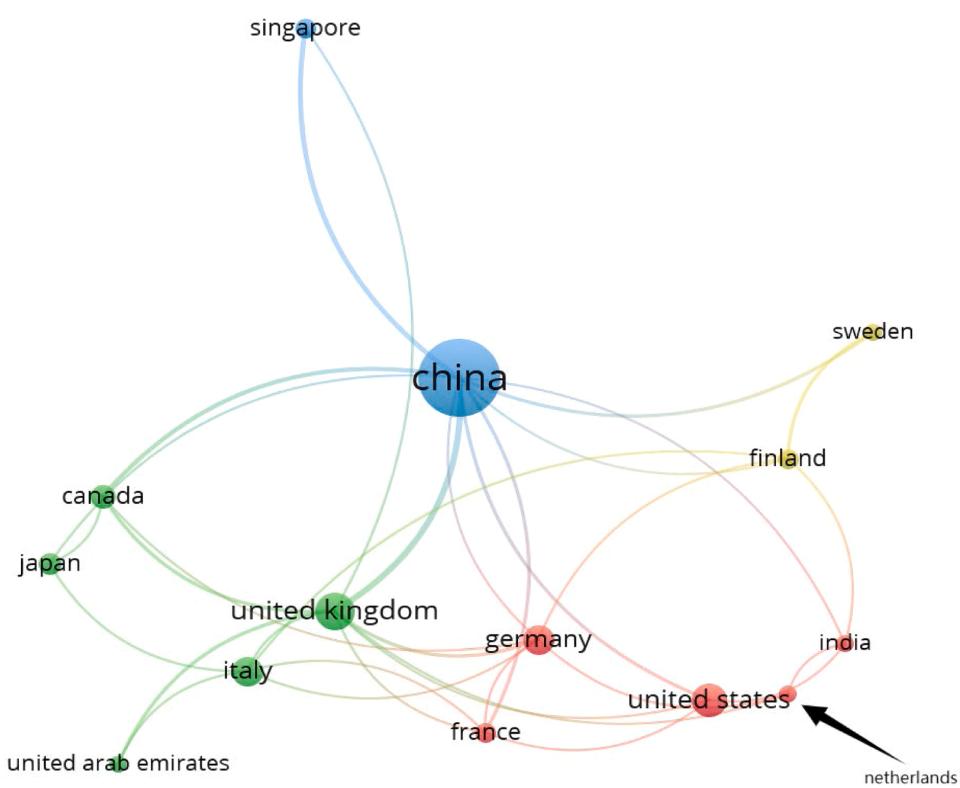

Fig. 4. Network of countries/regions co-occurrence analysis on DT-HRC in SEMS.

Table 10
Top 15 highly cited articles with their normalised citations.

Articles	Titles	Citations	Normalised citations
Feng et al. [141]	Digital twin-driven intelligent assessment of gear surface degradation.	97	18.37
Zhang et al. [142]	A multi-access edge computing enabled framework for the construction of a knowledge-sharing intelligent machine tool swarm in Industry 4.0.	34	6.44
Liu et al. [143]	Digital twin-enabled collaborative data management for metal additive manufacturing systems.	76	5.76
Rasheed et al. [144]	Digital twin: values, challenges and enablers from a modeling perspective.	700	5.10
Xia et al. [145]	Intelligent fault diagnosis of machinery using digital twin-assisted deep transfer learning.	149	3.50
Hu et al. [135]	Review and perspectives on driver digital twin and its enabling technologies for intelligent vehicles.	42	3.18
Sun et al. [59]	Artificial Intelligence of Things (AIoT) enabled virtual shop applications using self-powered sensor enhanced soft robotic manipulator.	131	3.08
Khan et al. [146]	Digital twin perspective of fourth industrial and healthcare revolution.	33	2.50
Fan et al. [147]	A digital-twin visualised architecture for Flexible Manufacturing System.	81	1.90
Luo et al. [148]	A hybrid predictive maintenance approach for CNC machine tool driven by digital twin.	238	1.73
Agostinelli et al. [149]	Cyber-physical systems improving building energy management: digital twin and artificial intelligence.	73	1.72
Wu et al. [150]	Battery digital twins: perspectives on the fusion of models, data and artificial intelligence for smart battery management systems.	171	1.25
Liu et al. [151]	Digital twin-driven rapid individualised designing of automated flow-shop manufacturing system.	229	1.00
Brenner and Hummel [152]	Digital twin as enabler for an innovative digital shopfloor management system in the ESB logistics learning factory at Reutlingen - University.	129	1.00
Chen et al. [153]	A human-cyber-physical system toward intelligent wind turbine operation and maintenance.	42	0.99

be the reasons for that. Moreover, this study offers a comprehensive and universal overview of the development of DT and the prospects for related technologies, potentially contributing to its high citation count. However, articles in Table 10 were ranked in order of normalised citations, a measure of the article's level of attention in the field. The top articles by Feng et al. [141] have 18.37 normalised citations, which means that the research on DT-supported smart machine health management systems has gotten a lot of attention. Furthermore, research studies on the DT framework and industrial management system combined with smart devices are at the top of Table 10, suggesting their contributions and influence in this field [141,142,154]. Moreover, the results show research trends on DT to enhance information and data capture and processing, such as smart sensors [59] and smart devices [135,145].

5. Discussion

5.1. Summary of mainstream research topics

According to the author's keyword co-occurrence analysis, there are six main clusters of different keywords, which represent different research directions and topics. However, the keywords within various clusters are not isolated, but rather interconnected, forming a relationship network collectively. The analysis in the review led to the identification of the mainstream research topics on DT-HRC in SEMS.

5.1.1. Artificial intelligence (AI) enhancement for DT-enabled HRC in SEMS

This topic mainly overlaps with Clusters 1 (Red), 3 (Light Blue), and 4 (Green). Focusing on AI technologies like ML, RL, and DL can enhance the machine and system's data analysis, interpretability, and interaction capabilities, thereby meeting the needs of data analysis, monitoring, interaction, and other functions in the human-robot collaboration process. Recent years have seen a common use of AI in energy and engineering systems, demonstrating its significant role in DT optimisation [155].

ML algorithms can automatically learn the behaviour of individual machines, thereby analyzing and optimising the performance of the entire system. Huang and Liu [156] reported the potential of ML for enhancing real-time data monitoring in DT-based intelligent systems, which could help achieve remote management. Moreover, combining ML with the scientific computing and model order reduction method, known as scientific ML, enhances the machine's capacity for intelligent computing and prediction, enabling it to adjust to the dynamic DT model [157]. Zhao et al. [158] also used ML in building condition analysis, developing the model's functionality for prediction and decision support, and providing a good example of the fusion application of ML and DT. Additionally, Kobayashi and Alam [155] focused their research on the interpretability and interactivity of AI and ML approaches. Kobayashi and Alam [155] focused on the interpretable and explainable model in DT-based energy and engineering systems, providing explainable AI (XAI) and interpretable ML for precise prediction and reliable decision support to human operators.

RL is a branch of ML that is concerned with learning from interaction. The RL-enhanced model could learn from the layer of user interaction, providing responses, model analysis, and optimisation based on perceived user behaviours [159]. Therefore, several articles have focused on RL, providing optimisation for intelligent systems based on data from the layer of interaction. Li et al. [159] demonstrated the optimisation for a mobile communication network by developing RL in the open radio access network model. Additionally, Zhou et al. [160] developed a federated RL framework, which they extended to various mobile network types such as intelligent transportation. This framework provides efficient model training based on data from suitable clients, thereby enhancing information safety. On the other hand, DL is also a significant research topic in AI. DL has the potential to automatically extract representative features from raw data, indicating the operating condition, thereby monitoring equipment health conditions and improving machine fault diagnosis [145].

5.1.2. The optimisation and enhancement based on DT-enabled approach

DT has shown great potential in improving many aspects of HRC and SEMS, such as simulation, monitoring, modelling, and other areas. A significant portion of research concentrated on the DT-enabled approach. This topic primarily relates to Clusters 1 (Red), 2 (Purple), and 5 (Blue), emphasising DT-driven optimisation, predictive maintenance, and sustainability enhancement.

By building the DT model for the key component in the system, the whole performance of the system could be optimised. The gearbox in the power transmission system is susceptible to damage in non-stationary operating environments, and the construction of a DT model for the gearbox could facilitate monitoring and health condition prediction for this specific component [141]. To improve the management of lithium-ion batteries, Wu et al. [150] developed a battery DT, which could help to achieve a longer working life for lithium-ion batteries in smart energy management. Zhou et al. [161] focused on the critical components in the piping system, optimising the corrugated compensators with a DT-based approach, which could improve the fault diagnosis process and the piping system's risk management.

DT not only enhances the performance of the equipment and machine, but also enhances its interaction with other components in the system. DT could help with machine health management in manufacturing. For example, it could be used to find adaptation faults in the triplex pump [162] and plan for industrial alternating current machine maintenance [163]. Kim and Okwudire [164] developed a DT optimisation approach for numerical computer control machines, which could maximise machine operating speed by enabling machines to select process parameters autonomously. Moreover, DT could also enhance the data acquisition capability of the equipment, achieving intelligent energy management [165].

The industry commonly uses DT for quality control and production state monitoring. By analysing the dynamic characteristics of the production process, a DT model to control processing and machining errors could be developed [166] The microelectronics assembly industry requires precise control over the printed circuit board's location, and a DT model could achieve this by accurately perceiving the object's position [167].

In an intelligent system, DT has the potential to optimise various aspects of constructing DT models of machines in a manufacturing system through monitoring and energy consumption, thereby enhancing smart energy management [165]. The DT approach could construct a simulation system of the intelligent industry system, which would improve the sustainability of the whole system and provide decision-making support [168]. Dan et al. [169] introduced a DT-based approach to the bridge intelligent management system, which has the potential to evaluate traffic loads and enhance infrastructure management. Moreover, DT has the potential to improve the design process of intelligent manufacturing systems, including the automated flow-shop manufacturing system [151] and the accelerated design and evaluation of the manufacturing production line [170]. Moreover, Brenner and Hummel [152] reported a case study of a DT-enabled intelligent manufacturing system, which introduced the concept of a DT-enabled digital management system, including hardware and the required software.

Compared to the DT-enhanced system, the industry has conducted extensive research on the integration of DT entities, focusing not only on overall performance but also on the level of signal units. Apostolakis et al. [171] developed an optimised framework for different phases of the intelligent network workflow in the context of 6 G, which included appliances DT, services DT, and environment DT. Shi et al. [172] developed a DT framework for the assembly quality control system, which would achieve production quality monitoring and prediction by building a virtual DT model of each assembly action.

In recent years, DT technology has rapidly developed. ElMaraghy and ElMaraghy [173] introduce the concept of Cognitive DT (CDT), which represents the transformation of DT from a digital model to a cognitive model, suitable for the new adaptive cognitive manufacturing system. The concept of the digital triplet is also a result of DT development. Apart from the physical and virtual layers, the digital triplet incorporates a layer of human intelligence activities into the DT concept, allowing for the consideration of human ingenuity and creativity [132]. Gichane et al. [174] introduced a digital triple model of a three-floor elevator system, which could provide better and more intelligent decision-making support.

The primary focus of DT research is on optimising systems and industries. In the face of increased pressure on healthcare due to population growth, DT can improve the healthcare system in aspects of building patient models, training, and result prediction [146]. Semeraro et al. [175] demonstrated a guideline for introducing a Li-ion battery DT in battery energy storage systems. In addition, Rojek et al. [136] also reported the sustainable potential of DT in manufacturing and maintenance systems.

5.1.3. *The improvement of human-robot collaboration*

HRC means that human operators and robots could complete a common objective together with great interaction at the cognitive and physical levels [176]. Several industrial sectors have already introduced and applied HRC as an approach in line with the concept of Industry 4.0. This topic is associated with Clusters 1 (Red), 2 (Purple), and 6 (Yellow), centering on enhancing human-robot interaction and cognitive collaboration.

The key step in HRC is the collaboration process between humans and robots. While identifying the uncertainties in the HRC process, Zheng et al. [177] provided a collaborative intelligence approach to address the three main types of uncertainties and improve collaboration in the HRC assembly task. Wang et al. [178] developed the HRC in intelligent manufacturing based on visual question-answering technology to improve production safety and persistence. In addition, several studies have focused on enhancing HRC through the implementation of Industry 4.0. Gallala et al. [137] developed the HRC approach with Industry 4.0 enabling technologies, improving the HRC programming method, and enhancing the interaction capability of non-expert operators.

For HRC works, a common cognitive model translates data from the environment and human operators into information that robots can use [176]. The Robotics Recognition Enhancement category summarises the approach that enhances the recognition process. Zhong et al. [179] focused on the high complexity and uncertainty of human actions, building a human model that improved human locomotion mode identification for robots. Additionally, they developed an enhanced robot sensor. Sun et al. [59] extended the recognised shapes of objectives by introducing an intelligent soft robotic manipulator, which fused multiple types of smart sensors. On the other hand, Peruzzini et al. [180] introduced a system that could collect and analyze data from workers, providing the knowledge to improve the human operator's performance, which in turn developed the design of human-centered industrial systems.

5.1.4. *The development of the industrial revolution*

This topic spans Clusters 2 (Purple), 3 (Light Blue), 5 (Blue), and 6 (Yellow), focusing on Industry 4.0/5.0, smart manufacturing, and digitisation-driven transformation. The digital revolution has brought digital transformation to various industries, which is known as Industry 4.0 [67]. The current development of Industry 5.0 has become the goal of sustainable transformation of the industry [181].

Intelligent system management is a critical component of industrial intelligence and digitalisation development. Agostinelli et al. [149] suggest building a three-dimensional data model for the intelligent energy management of residential districts through the combination of IoT, ML, and DT. Besides smart energy management, Meng and Wang [182] also integrated ML and DT to forecast the load requirements in solar-based smart grids. Park et al. [183] also constructed an optimisation model for microgrid operation based on the fusion of ML and DT, which could potentially reduce electricity consumption. Furthermore, Industry 4.0 enhances data and information safety management. Edge computing (EC) and ML can enhance data privacy protection in mobile networks [127]. IoT and DT in the smart building management system, indoor safety could be enhanced by analyzing the data from IoT sensors [184].

With the progress of digitisation in industry, the interaction between human operators and machines is also an important research direction. Charissis et al. [138] have significantly improved information processing efficiency and driving safety by integrating complex information in the car cabin and interacting with the driver using AR-enhanced technology. Su et al. [139] introduced the gesture recognition approach into the DT model, developing a new information interaction framework based on human gestures.

With the development of the intelligent industry, smart production has been a key focus under the Industry 4.0 concept. Previous studies have constructed a federated learning-enabled platform for smart Industry 4.0 manufacturing, utilising IoT devices for data acquisition and a DT-enabled cyber physical system (CPS) to capture equipment characteristics [134]. In the smart manufacturing concept, all the smart manufacturing concept aims to optimise and intelligently manage all stages of industrial production, including the design phase [185], production quality [186], and device maintenance [187]. Computer vision and IoT could provide high-precision monitoring for foundation pits in the construction industry, thereby enhancing the safety management of construction [188]. Intelligent manufacturing could also build the energy demand model of the manufacturing process, potentially reducing energy consumption and promoting sustainable industrial production [189].

Transportation and supply are also important aspects of the industry. The Industry 4.0 concept could develop intelligent logistics by identifying goods based on MV and introducing DT for data analysis and intelligent distribution [190]. In the oil industry, ML could provide a prediction of the risk of oil pipelines, which could play an important role in the oil pipeline maintenance system [191].

Beniiche et al. [181] formulated the concept of Society 5.0, a framework for Industry 5.0 that prioritises mass manufacturing and a smart, sustainable society. The development of a human-cyber-physical system (HCPS) could address the complexity of future wind turbines, preparing them for the requirements of Industry 5.0 [153]. Mo et al. [131] introduced a DT-enabled human-machine interface sensor that could improve finger gesture recognition, supporting patients with reduced mobility or future users of human-robot collaboration in Industry 5.0.

5.2. Research gaps on DT-enabled HRC in SEMS

5.2.1. The combination and practice of AI and DT

The integration of AI and DT has demonstrated potential in various areas. However, the integration of AI and DT still has a lot of room for development. For the smart grid system, the integration of DT and AI is highly dependent on high-quality real-time data streams. However, in actual power grid systems, data may be missing, noisy, or delayed, which can reduce modelling accuracy [130]. Furthermore, in smart grids, the absence of unified standards and interoperability protocols for DT and AI technologies has led to limited interaction between different platforms and manufacturers, hindering collaborative development across the entire industry [192]. In the construction industry, while incorporating ML algorithms into DT modelling has the potential to predict a building's operational status, these combined DT techniques are still in their infancy, with most approaches lacking empirical evidence [158]. A study by Li et al. [157] focused on the integration of ML and DT for intelligent computing and prediction models, hasn't significantly advanced DT. It only applies DT technology at the modelling level, without developing additional functions like real-time data analysis and uncertainty quantification. There is still significant potential for combining DT and AI, including enhancing the integration of DT in ML and RL [160] and developing additional combination strategies between DT and DL [145]. Additionally, Lombard et al. [193] built a DT-AI platform for location-based service data in a complex healthcare organisation, demonstrating the need for more case studies in various areas to evaluate the research.

5.2.2. The development of DT in data processing, availability, and model-driven pattern

Current applications of DT have increased the demand for DT to process data in complex situations. Although the simulation of fully automated machines has been demonstrated, the current computing capability of DT cannot meet the requirements during complex high-speed machining operations [194]. The need for a real-time, synchronised link between DT and physical entities necessitates further enhancement of DT's communication network [195]. In addition, cybersecurity risks in network- or cloud-based DT often receive insufficient attention, necessitating significant improvement [196]. Several studies have combined other technologies with DT; the integration approach also has more room for development. For instance, the potential for further development in the advanced data analytics of DT, which is based on advanced ML technology, remains untapped [197].

As the number of DT applications in various industries has increased, their availability and generalisability are in higher demand. Firstly, the industrial DT application lacks a standardised and transparent approach for data processing, data storage, and database management across areas and industries [150]. Standardised DT models are also necessary for the same type of industrial product, which could reduce redundancy and heterogeneity and improve efficiency [195]. Simultaneously, the need for the DT approach to be generalisable has emerged. Despite focusing on the same product in the assembly industry, a significant change in the product structure can invalidate the DT model's assembly process [195]. In the study of enhancing machine fault detection, the proposed DT framework lacks advanced transfer learning algorithms to enable generalisation of the findings to other machines [162]. Finally, simplicity is another aspect of improving DT availability. The current DT model is complex, which makes model establishment and calibration difficult [141]. Although Lin et al. [168] have introduced a container virtualisation approach for DT models, the containers cannot adapt well to various operating systems and environments.

The study also discussed the limitations of the DT-driven pattern. To develop hybrid models, a single physical or data-driven model is not sufficient to meet the higher needs, necessitating the development of a fusion drive model [150]. A machine-to-machine learning approach could support the physics-based research on the next data-driven DT model, adding value to the physics-based dynamics model of industrial equipment [164]. In a data-driven DT model, there are also challenges in quickly and accurately determining the actual state of physical entities based on DT model results [169].

5.2.3. Highly accurate, adaptable, and interactive HRC approach

In recent years, HRC has faced a complex fusion application in multiple scenarios, which demands better performance from HRC [198]. Firstly, current research has demanded more operational precision from HRC. Zhong et al. [179] have constructed a digital model of human locomotion modes to enhance the accuracy of human operation recognition technology. However, their enhancement to HRC only focuses on improved model identification, not on enabling the robot to respond by directly recognising the model's data. Despite research in the assembly industry aimed at improving HRC efficiency and accuracy, the research model's generalisation to other areas and systems is limited, and the general framework remains lacking [199]. Secondly, there is a need to improve HRC's adaptability to complex and changing work scenarios. In intelligent manufacturing, there is a lack of attention to the uncertainty in HRC work from human operators, tasks, robots, the environment, and other factors [177]. Complex steps are frequently encountered in the HRC system's adjustment process due to varying needs. Programming traditional industrial robots typically requires proficiency in proprietary languages (such as RAPID, KRL, etc.), which are difficult for non-expert workers to learn. It is also necessary to consider the actual hardware device status and environmental impact, which vary significantly in different industrial scenarios [200]. Although Park et al. [201] streamlined the programming process for integrating new machines into entire systems, complex tasks still rely on underlying custom programming. Further research is still required to streamline the process of adjustments and modifications to the HRC. Moreover, there is a growing demand for enhanced sensor functionality. According to Sun et al. [59], sensors should be able to determine the state of an object, such as freshness, based on data such as image, colour, and temperature. Finally, there is a lack of research that focuses on the convenience and experiential aspects of the interaction process in HRC. The development of collaborative robots should keep pace with human-operator interaction capabilities, and current research needs to focus more on enhancing the collaborative capabilities of non-professionals and unskilled operators [137]. Peruzzini et al. [180] have proposed an approach that can improve operator-perceived comfort and interaction efficiency, which has yet to see industrial application.

5.2.4. More reliable, interactive, and sustainable industrial systems

In the context of Industry 4.0, the development of digitalised production and management necessitates further development of trustworthy and intelligent management systems. Although intelligent monitoring and management systems have been demonstrated, the risk management of these systems should not be overlooked [202]. In the current intelligent management platform, the wireless channel plays an important role in connecting smart devices, which still face a risk of information safety and connection reliability [134,203]. Besides, with the development and promotion of Industry 4.0, many studies are beginning to focus on the improvement of interactivity in intelligent systems. Researchers need to focus more on simplifying human-machine interface interaction [138]. Researchers have investigated the incorporation of gesture recognition in human-computer collaboration, but their research relies on manually segmented datasets, failing to automatically segment gesture data and achieve user recognition [139]. Although much research has combined AR or VR with HRC processes to enhance interaction, Zhang et al. [204] suggest that there is still a lack of multimodal interaction modes in human interaction systems, such as visual and verbal. Lastly, enhancing the industry's sustainability could pave the way for the concept of Industry 5.0. Despite the advancement of smart grid, further research is necessary to integrate decentralised and complex energy resources into the smart grid systems, such as establishing energy storage for electric vehicle charging stations [205]. The circular economy in smart manufacturing systems also needs to be considered and researched in the future [189].

5.3. Future research directions of DT-HRC in SEMS

The science mapping analysis and systematic review identified the future research directions of DT-HRC in SEMS. Fig. 5 shows the percentage distribution of various research trends, while Fig. 6 presents the future research directions of DT-HRC in SEMS.

DT-enhanced approaches have primarily focused on optimisation and modelling, accounting for 21 % and 6 % of the main research objectives, respectively. According to the current research trend, one of the main goals of modern research is to improve the availability and standardisation of DT-enabled systems. This is because there are gaps in the way DT model data is processed. Furthermore, the research gap regarding the driven pattern of DT has also been discovered and reported in studies aimed at modelling improvement. In the future, optimising and standardising DT-related approaches in specialised industry areas to meet the needs of intelligent manufacturing and management will be one of the directions of research. As a result, future research directions regarding various aspects of the DT-enabled HRC approach in SEMS can be defined as follows:

- Integration of DT models and ML with real-time data.

Our review reveals that most ML and DT combinations only operate at the level of modelling and model-based ML. In contrast, further development of the data-based ML in the DT system could improve its efficiency and accuracy. Therefore, future research could establish a deep connection between ML and DT, enabling ML approaches to directly apply raw data from DT for analysis, instead of limiting them to surface-level model learning.

- The analysis of AI-enhanced DT of industrial applications in real cases.

Although there are an increasing number of studies focused on the integration of AI and DT, the experience and data from practical cases are still lacking. Therefore, it is important to verify the theories based on further case studies of industrial applications. Future research could focus on how the AI-enhanced DT approach can be used in industry, using case studies to show how it works and how to analyze its effects. This could help the research go beyond the theoretical and experimental stages.

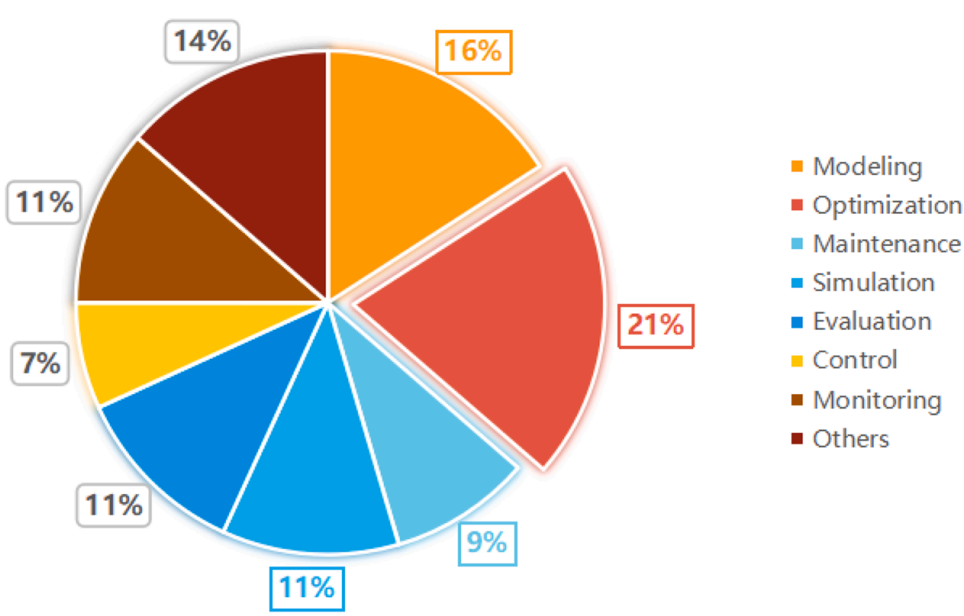

Fig. 5. Distribution of research trends on DT-HRC in SEMS.

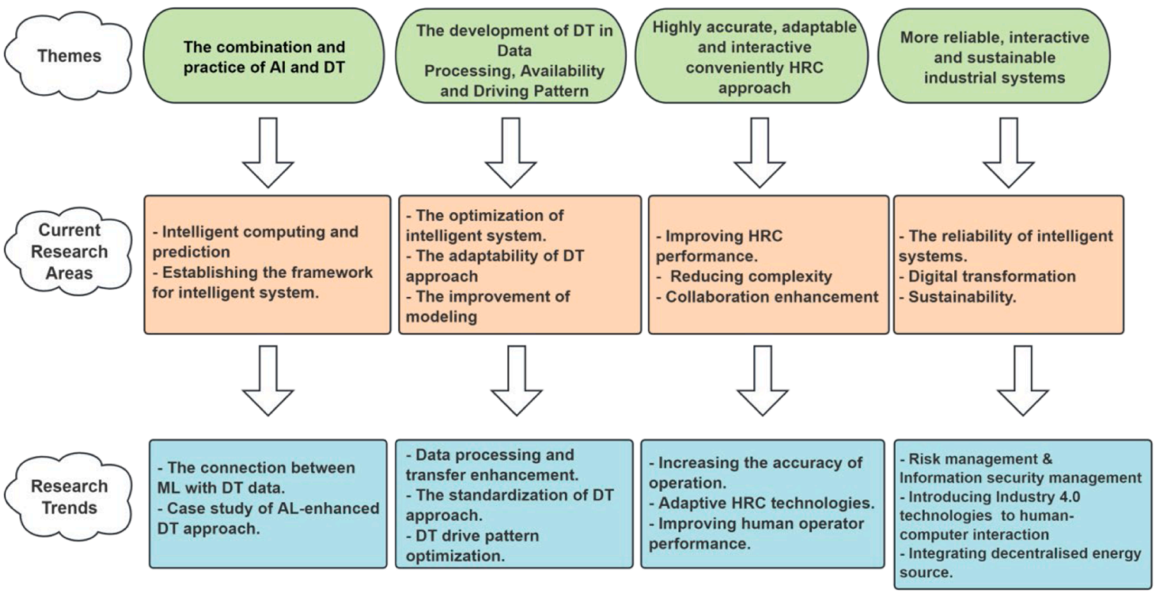

Fig. 6. Future research directions of DT-HRC in SEMS.

- Enhancing the data processing and data transfer efficiency of DT.

In this review, some studies focused on DT have illustrated that the data processing and transfer capabilities of the current DT model are sometimes insufficient, which has limited the wide application of DT in industry. Future research can meet the needs of higher and more complex data analyses by developing enhancements to the data processing and algorithms in the DT model. Future research could also focus on improving the ability of DT data transmission to address the current issue of latency in data transmission.

- Developing standardised, simplified, and transferable learning DT methods.

The availability of DT systems has also limited the industrial application of the DT-enhanced approach. For the current application of the DT approach, the complexity of the construction and modification of the DT-enabled system is one of the limitations of its application. Future research could establish a framework for a standardised DT approach and simplify the process of DT modelling, which could reduce work redundancy and promote the use and diffusion of DT methods.

- Optimising the drive pattern of the DT or developing a hybrid drive approach.

Some research has pointed out the advantages and shortcomings of the two main driving patterns of DT. Researchers in the future could try to fix the problems with both physical-driven and data-driven DT to meet more stringent requirements and complicated application scenarios. They could also create a modelling method that works with both drive modes and is suitable for a variety of use cases.

- A general approach to improving the accuracy of HRC operations.

Although the HRC approach has a wide application in various industries, the accuracy of its operation process is sometimes unsatisfactory in manufacturing or other industries. Future research should construct a general enhancement approach to enhance the accuracy of HRC, such as developing a more efficient cognitive model and enhancing data recognition capabilities, to meet the increased operational requirements and expand the application of the HRC approach to more industry sectors.

- Developing adaptive HRC technologies applied to different work scenarios.

Some studies have also revealed that in real-world applications, the process of modifying the HRC program is intricate and challenging. For example, the introduction of new machines to the HRC system is challenging to complete in a short time. Therefore, future research should focus on migrating developed HRC methodologies to different domains, building HRC frameworks for different work scenarios, or improving HRC's ability to cope with complex changes in the same scenario.

- Enhancing the interaction capability of human operators in HRC.

To achieve the best practice of HRC, some researchers propose that the performance of human operators should also be considered, especially in some complex application scenarios. Current studies have also pointed out that human operators sometimes cannot keep pace with the rapid development of robots. As a result, in the future, researchers could focus on improving the human operator experience in HRC, developing collaborative methods for non-technical people, or improving the operator experience in the HRC process. Furthermore, attention should be given to socio-technical barriers, such as the high cost of workforce training, the need for standardised interoperability frameworks, and resistance to technological adoption. Addressing these challenges is essential to ensure the inclusive, sustainable, and effective deployment of HRC systems across diverse industrial sectors.

- Improving equipment risk management and information security management in an intelligent management system.

Researchers have focused on the safety and security of the system and its devices in the smart management system, as they are crucial for the system's reliability and stability. However, the development of risk management and security, particularly information security, remains incomplete. Therefore, future studies should also focus on risk management in intelligent systems to provide device monitoring and prediction, as well as improve information security management in transfer and sharing processes.

- Enhancing human-computer interaction processes in smart systems by combining Industry 4.0 technologies such as AI and gesture recognition.

This review reveals that the integration of multiple Industry 4.0 technologies has become a prevalent trend in the industry. Furthermore, smart systems require innovation and improvement in their interaction methods. Smart management systems should introduce and develop various Industry 4.0 technologies, such as computer vision, VR, AR, and so on, to adapt to different requirements and achieve different functions, thereby enhancing machine cognition and human understanding during interactions.

- Enhancing sustainability in smart manufacturing and improving energy management by integrating decentralised energy sources.

Based on this review, smart production and management systems have had better development and application in the manufacturing industry. However, more research is needed to further develop the smart management of energy consumption in manufacturing. Future research could focus on manufacturing sustainability by reducing consumption, increasing energy efficiency, and integrating various decentralised renewable energy sources.

6. Conclusions

Nowadays, DT technologies have been well developed and extended to other fields. The awareness of HRC has also increased, particularly after experiencing labour shortages during the COVID-19 pandemic. Furthermore, SEMS has become a popular concept that could combine various technologies for efficient and intelligent energy management. Despite their usefulness, current studies in these areas lack a comprehensive review of combining DT and HRC approaches in SEMS. Therefore, this study combines a systematic literature review with a science mapping approach to conduct a state-of-the-art review of the DT-enabled HRC approach in SEMS. In this study, 126 articles were obtained from the Scopus database by following PRISMA guidelines and were then used to conduct scientometric analyses. The results indicate a general upward trend in the number of studies in this field from 2017 to 2023, with a notable increase in published articles, particularly after 2022, suggesting a growing interest in this field in recent times. The countries/regions co-occurrence analysis reveals that developed countries contribute more to the studied topic, potentially due to their higher level of industrialisation. Furthermore, the keyword co-occurrence analysis identified six main research clusters. Moreover, the document citation analysis suggested that current research is increasingly focused on the development of DT-related technologies. Additionally, the results discussed four mainstream research topics that cover research areas, including AI, DT, HRC, and the development of the Industrial Revolution. Lastly, the qualitative discussion highlighted the existing research gaps and suggested future research directions.

For the theoretical contributions, this review study analysed relevant articles published in this field, considering publication trends, journal sources, keywords, countries/regions, and documents. It also identified the mainstream research topics and existing gaps in current studies and provided a theoretical framework for future research. Recent years have witnessed the rise in intelligent energy management systems supported by several technologies. The integration of DT with optimisation analytics technologies like AI and interaction enhancement technologies like VR has demonstrated its potential. The entire HRC process is undergoing enhancements and upgrades, with a growing focus on the capabilities of human operators. Moreover, the development of Industry 4.0 and Industry 5.0 has led to the integration of advanced technologies to meet the needs of different aspects of intelligent systems, and some research has focused on decentralised resource management, such as electric vehicles, to improve sustainability, which has the potential to develop as a new research area. In terms of practice and policy contributions, this study is the first state-of-the-art review of the DT-enabled HRC approach in SEMS, which integrates the systematic literature review and science mapping analysis. The results and findings of this study could provide insights to related researchers and practitioners in the same industry on the latest research and application of DT and HRC in SEMS. For instance, the results of the publication trend can assist practitioners in understanding the level of interest in this field, while the country-specific findings can guide researchers in their search for relevant literature. Additionally, the identified mainstream research topics could provide practitioners and policymakers with a clear understanding of the current application of DT-HRC in SEMS. The provided future research could help future researchers identify their research topics and explore new research directions, which would contribute to the existing body of knowledge.

However, there are also some limitations to this study. First, this study only selected related literature from the Scopus database, which may not have adequately represented all relevant studies. As such, future research could potentially improve these discrepancies by incorporating literature from other databases like the Web of Science, PubMed, and Science Direct. Second, the search strategy was limited to articles written in English and those within engineering and energy subject areas. Therefore, future research could incorporate other languages and relevant research from different disciplines.

CRediT authorship contribution statement

Shichang Fu: Writing – original draft, Methodology, Formal analysis, Data curation. **Maxwell Fordjour Antwi-Afari:** Writing – review & editing, Supervision, Project administration, Methodology, Conceptualization. **Shahnawaz Anwer:** Writing – review & editing, Visualization, Validation. **Zhen-Song Chen:** Writing – review & editing, Visualization, Validation. **Heng Li:** Writing – review & editing, Visualization, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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