Evolution of Knowledge Structure in an Emerging Field Based on a Triple Helix Model: the Case of Smart Factory

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Received: 4 September 2021 / Accepted: 16 September 2022 / Published online: 6 October 2022
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Abstract
As an important emerging field of science and technology, smart factories have received attention from academia, industry, and the government. Currently, although some scholars have examined the research trends in the field of smart factories, we have not found any research on the analysis of the knowledge output of relevant organizations among smart factories. An urgent problem is whether cooperation between organizations with different characteristics will affect the overall development of intelligent factories. This study aimed to perform a comprehensive analysis of the knowledge content and structure of a smart factory and the characteristics of its knowledge production structure. We also evaluated whether the triple helix structure was stable, and whether the research topics of different issues were similar. The triple helix model was used to study three aspects of the knowledge structure of a smart factory: university, government, and industry. Furthermore, the research contents of different organizations were analyzed in detail using network analysis. It was found that research funding at the national level leads to a knowledge spillover effect. After 2015, a triple helix knowledge structure was formed in the field of smart factories, which maintained a certain stability until 2020. The output of triple helix cooperation research has a significant impact. University research focuses more extensively and intensively on technology, government research on macro aspects, and Industry 5.0 has become a hotspot in industry research. The government needs to provide new platforms to integrate and promote the development of smart factories.

Keywords Smart factory · Triple helix · Industry 4.0 · Industry 5.0 · Knowledge management
**Introduction**

The term “Fourth Industrial Revolution—Industry 4.0” has attracted much attention in the industrial and academic circles in recent years. Similar to the three previous industrial revolutions of great significance in the history of modern human development, it is gradually driving the rapid development of the modern industry to the smart manufacturing mode. As the carrier of smart manufacturing, the core of Industry 4.0—smart factory—has been described as a fully interconnected flexible manufacturing system that uses the connection operation and continuous data flow of the production system to learn and adapt to the new requirements through transmission receiving and processing the data necessary to complete all the tasks required for the production of various types of goods (Lasi et al., 2014; Sjödin et al., 2018).

Modern machine factories originated in Britain during the first Industrial Revolution. Britain was the first to complete the bourgeois revolution and carried out the enclosure movement that created a large number of surplus labor. Furthermore, the development of natural science, especially the development of Newtonian mechanics and mathematics, laid a scientific theoretical foundation for the emergence of modern machines. The vigorous development of manual workshops created conditions for the invention and application of machines, thus promoting the emergence of machine factories (Daemmrich, 2017; Ó Gráda, 2016).

The American Ford company founded by Henry Ford in the early twentieth century (production line) introduced the mass production mode, which was another step toward the development of factories (Paxton, 2012; Williams et al., 1992). It further established and consolidated the capitalist system and provided a political guarantee for the further development of capitalism and new technological innovation. Capital accumulation under the production of big machines and commodity export to and plunder of the colonies provided a strong material foundation for the new technological innovation. Breakthroughs in natural science were quickly transformed into technology. The great achievements of the nineteenth-century electromagnetic theory (such as Faraday’s electromagnetic induction theory) provided the theoretical basis for the wide application of electricity (Mokyr, 1998).

After the end of the Second World War, wartime military technology was rapidly converted for civilian use, which promoted the emergence and development of the Third Industrial Revolution. As the organizer and promoter of science and technology, the state greatly accelerated the pace of transforming science and technology into productive forces (Carlsson et al., 2007). Einstein’s theory of relativity and other natural scientific theories have developed rapidly and made a series of breakthroughs. Into the mid and late twentieth century, the use of statistical principles and methods to achieve product quality management and the wide use of robots for the development of factories provide a new approach; factories began to enter the era of automation (Öztürk, 2017).

The concept of Industry 4.0 officially appeared in Germany in 2011 (Büchi et al., 2020). Industry 4.0 is considered as a new industrial stage in which the integration and product connectivity in vertical and horizontal manufacturing
processes can help enterprises achieve higher industrial performance (Dalenogare et al., 2018). The German government has announced plans to build smart factories to promote Industry 4.0, which is conducive to the realization of smart manufacturing. It is a joint project involving multiple government enterprises and academic circles (Kang et al., 2016). Other governments around the globe also realize the importance of smart manufacturing (Reischauer, 2018) and are taking steps in this direction, such as Advanced Manufacturing Partnership in the USA, Made in China 2025 in China, future of manufacturing in the UK, the New Industrial France in France, and Innovation in Manufacturing 3.0 in South Korea.

In the context of Industry 4.0, the term “smart factory” is widely used by industry practitioners and academic researchers (Strozzi et al., 2017). Smart factory research from the concept (Mladineo et al., 2019) to performance (Büchi et al., 2020) and application (Won & Park, 2020) has grown exponentially over the past decade. To realize Industry 4.0, it is necessary to realize the horizontal integration of the value network among enterprises, the end-to-end integration of the engineering value chain, and the vertical integration within the factory. While actively addressing the technical challenges, the smart factory of Industry 4.0 can be realized by widely applying the existing enabling technologies (Wang et al., 2016a). One of the main features of Industry 4.0 is the vertical integration of various components within the factory to achieve a reconfigurable and flexible manufacturing system, namely the smart factory (Wang et al., 2016b). Industry 4.0 makes factories smart by applying advanced information and communication systems and future-oriented technologies (Sanders et al., 2016). Intelligence comes from data, and a comprehensive analysis of manufacturing data is helpful to manufacturing. Digital twinning paves the way for the physical integration of manufacturing information, which is an important means to realize a smart factory (Qi & Tao, 2018). Cyber technology used in smart factories integrates independent systems, increasing the precision and complexity of production techniques (Chen et al., 2017). Smart factories and supply networks that rely on information technology can better respond to national interests and strategic needs, fundamentally improve performance by promoting global competitiveness and export to provide sustainable employment, and promote manufacturing innovation, which can revitalize the industrial sector (Davis et al., 2012).

Smart factory research receives a significant amount of support from the academia, industry, and government. Issa et al. (2017) proposed synergistic technology matching between firms’ financial and technological systems and government-supported project management systems. Researchers have studied the phenomenon of academic commercialization, which has also been widely discussed, such as industry-learning integration, academic entrepreneurship, and technology incubation (Curi et al., 2012; Galán-Muros et al., 2017; Hülsbeck et al., 2013). Government strategies for smart factories should be refined and elaborated to facilitate the establishment of economic and social systems that can respond flexibly to changes in industrial structure (Sung, 2018). The impact of cooperative relationships among academia, industry, and government on the overall development of smart factories, the stability of triple helix relationships, and the differences in topics of concern among different organizations need to be studied further in the smart factory knowledge structure, to promote the positive development of the smart factory field.
The “Literature Review” section examines previous research, thoroughly analyzes the research background, describes the state of the art, identifies gaps, and raises questions regarding this research. The “Methods” section introduces data sources, the triple helix method, and network analysis. The “Results” section presents the outcomes of our analysis. The final section discusses the study’s contributions, limitations, and conclusions.

**Literature Review**

A smart factory is an important part of the Fourth Industrial Revolution as an emerging field (Malik & Kim, 2020). The study of knowledge structure can help to grasp the current situation and trends in an emerging field (Miyata et al., 2020). A research field comprises various knowledge units, and the interrelationship between these units forms a system known as the knowledge structure (Cheng et al., 2020). Early knowledge structure researchers conducted qualitative analyses of knowledge structures. They frequently presented opinions and suggestions based on their own research experience and professional knowledge, but deviations are unavoidable, given the background of individual cognition (Yoon et al., 2018). Digital technology has advanced rapidly since the year 2000. The Web of Science, Scopus, and other databases contain a wealth of academic information, allowing researchers to conduct more objective quantitative research. Quantitative analysis has been developed in the field of knowledge structure analysis (Min et al., 2021). With the advancement of knowledge structure analysis, various research methods have been applied, such as keyword frequency analysis, co-occurrence analysis, social network analysis, triple helix analysis, citation analysis, and topic modeling analysis (Amado et al., 2018; Cheng et al., 2018; Kim & Hastak, 2018; Zhu & Park, 2020). Cheng et al. (2020), for example, built a “keyword—citation – keyword” network structure using citation links, which can mine more significant topics in the knowledge structure. Yoon et al. (2018) studied current technologies in the IoT and forecasted topic trends in the field using keyword frequency analysis and co-occurrence analysis. Miyata et al. (2020) investigated the knowledge structure of library and information science using a topic modeling method, and discovered the transition factors of the knowledge structure.

In terms of smart factory knowledge analysis, Strozzi et al. (2017) used a bibliographic network analysis method to quantitatively analyze the emerging topics of knowledge. Yang et al. (2018) compared Korean and international studies on smart factories using topic extraction and provided suggestions for Korean research strategies. Osterrieder et al. (2020) reviewed the relevant literature and divided smart factory research into eight distinct themes. Although previous studies have examined the topic trends of smart factory field knowledge, the study of organization-related knowledge structures remains insufficient. An urgent problem to be solved is whether cooperation between organizations with different characteristics will affect the overall development of intelligent factories.

As mentioned in the introduction, from the first industrial revolution to the third industrial revolution, factories underwent three levels of transformation. Each was accompanied by government support, industry development, and the scientific
theories of scholars. Currently, the output and influence of knowledge related to smart factories continue to grow and have received significant attention in academia and industry (Strozzi et al., 2017). Government strategies for smart factories should be refined and elaborated to facilitate the establishment of economic and social systems that can respond flexibly to changes in the industrial structure (Sung, 2018). Currently, industry and academia in developed countries are trying to find new ways to cooperate for the co-creation of value (Compagnucci & Spigarelli, 2020; De Silva & Wright, 2019). Reischauer (2018) discussed an innovation system model called the Industry 4.0 triple helix innovation model that covers industry, academia, and political circles. However, the author only mentioned this model without in-depth analysis and discussion.

This study uses the triple helix model to comprehensively analyze the knowledge structure of smart factory research from three aspects: university, government, and industry. The research contents of different organizations are analyzed in detail, and the goal is to grasp the developmental status of smart factory and evaluate the helix stability degree of cooperation among research institutions related to the smart factory. Through a comprehensive analysis of the knowledge content and knowledge structure of the smart factory, the characteristics of the current knowledge production structure of the smart factory and the analysis of the structure formation are examined, and valuable suggestions are put forward to better promote the healthy development of the field of the smart factory.

We posed three research questions:

RQ1: How is the distribution and influence of the relevant research on smart factories in the triple helix structure?
RQ2: Is the triple helix structure of relevant research on smart factories stable in the last decade?
RQ3: What are the research topics for different types of organizations? What are the implications of the similarities and differences for future research on smart factories?

Methodology

Data sources

The data used in this study were extracted from the Web of Science (WoS) database, which, together with Scopus, is the most commonly used database of the index used by the most influential multidisciplinary academic literature digests worldwide. The WoS database is the leading citation database for most citation analysis research thus far and is also an internationally recognized database reflecting the level of scientific research (Zhu & Liu, 2020).

The number of articles and journals included in Scopus is higher than that in WoS but the journals included in WoS are of higher quality and are commonly used as research database sources for scientific researchers (Christian et al., 2017; Danilo
& Mário, 2020; Pranckutė, 2021; Strozzi et al., 2017; Victor et al., 2021). To maintain the consistency of data sources and structure, this study only considered the WoS data.

**Search Keyword Selection**

This study aims to study smart factory in the context of Industry 4.0. Therefore, we chose “smart factory” as the first keyword. Since several literature materials often use manufactory to replace factory (Strozzi et al., 2017), we also selected “smart manufactory” as the keyword, and the command to execute the search was as follows: “TS = “Smart factor*” OR TS = “Smart manufactur*” OR (TS = “Industry 4.0” AND TS = factor*) OR (TS = “Industry 4.0” AND TS = manufactur*).”

**Date of Publication of the Data**

As mentioned above, since the German government announced the launch of Industry 4.0 as one of the key initiatives of its high-tech strategy in 2011 (Büchi et al., 2020), the concept of smart factory has gradually emerged in the scientific literature. On April 19, 2021, we collected journal data from the WoS database between 2011 and 2020. This time period was chosen because 10 years have passed since the proposal of Industry 4.0, and governments around the world have begun to make efforts to accelerate the arrival of the era of smart factories. We only considered papers published in English and retrieved 2409 articles.

**Triple Helix Model**

A new mode of production is emerging based on the links between academia, industry, and government, proposing to model this complex system as a “triple helix” of university-industry-government relations. This “triple helix” is likely to become a key component of any national or multinational innovation strategy (Etzkowitz & Leydesdorff, 1995).

The triple helix is a new evolutionary model that includes sociological concepts of meaning processing and interactive knowledge generation. It is a tool that helps explain the current shift from epistemology to the knowledge economy (Leydesdorff & Etzkowitz, 2003). The triple helix is complex and can fully explain the innovation dynamics of social reproduction (Etzkowitz & Leydesdorff, 1998, 2000).

The triple helix of university-industry-government relations highlights the growing trilateral network between science, industry, and government actors and the blurring of boundaries between the three fields (Etzkowitz & Leydesdorff, 1998, 2000; Etzkowitz et al., 2000; Raman, 2005). The demand for continuous innovation promotes the system to become a knowledge-based system, forming a triple helical network of university-industry-government relations (Park et al., 2005).

Park and Leydesdorff (2010) used the article from the WoS database to perform a network analysis of the triple helix interaction in South Korea. Kwon et al. (2012) added a foreign R and D institution actor to the traditional triple helix institutional
actor to determine whether foreign actors led to an enhancement in the triple helix synergies in the South Korean research network. They argued that the direct policy of the government to stimulate interaction between South Korea and developed countries weakened the synergies.

Steiber and Alänge (2013) taking Google as an example, examined the applicability and practical value of the triple helix model in exploring the process of enterprise formation and growth; this is because the triple helix plays an important but constantly changing role in different stages of enterprise formation and growth. Rosenlund et al. (2015) studied the triple helix model from the perspective of participants and used the concepts of social capital and trust to further illustrate this point, emphasizing the importance of the human side of the triple helix structure.

Lee and Kim (2016) divided the industries involved in the triple helix institution into three types of companies—large enterprises, small and medium-sized enterprises, and venture capital firms—and studied the interaction of R and D networks among different types of firms. Zhu and Park (2020) analyzed the knowledge in the field of blockchain by using the triple helix structure and found that the degree of the triple helix in blockchain research was lower in Asia than in non-Asian countries, and Asian researchers needed to expand the cooperative relationship with the industry.

Due to the forces of integration and differentiation, it can be expected that the systematicness of the innovative mode of the triple helix model of the university-industry-government relationship will still be in the transitional stage (Leydesdorff, 2012), and the quadruple helix (Carayannis & Campbell, 2009), quintuple helix (Carayannis & Campbell, 2010), and N-tuple helix (Park, 2014) appeared successively. For example, Zhu and Park (2021) used the quadruple helix model to study the network information transmission of COVID-19 and found that multi-helix information sources are insufficient in public health emergencies; especially, educational institutions should be more actively involved in the release of information.

For academic and methodological reasons, one may wish to extend the model incrementally and gain explanatory power as needed, but helix expansion requires substantial specification of the operability of potentially relevant data and sometimes further development of relevant indicators. If there is no such perspective, the triple helix model should be carefully extended to the N-tuple helix (Leydesdorff, 2012). Several researchers have investigated the triple helix model formed by universities, industries, and governments and proved its reliability and operability. Therefore, this study adopts the triple helix model to conduct research.

In this study, the specific method of the triple helix model is as follows. First, we sorted out all the collected data and classified all the institutions where the authors worked. The schools and institutes of the schools were divided into U (university). Enterprises are classified as I (industry), while government research institutes and administrative organs were classified as G (government). Next, we marked the institutional helix attribute of each piece of data. A paper is defined as helix if it is composed of multiple institutions. If a paper has multiple authors, but only distributed in the universities, it is defined as U, and does not have the helix attribute. If there is a joint participation of schools and enterprises in an article, it is defined as UI (university and industry), which is a double helix. Strand and Leydesdorff (2013) proposed an index—$T_{uig}$—to evaluate the helix degree.
\( T_{uig} \) is the stability index for evaluating the triple helix. The specific algorithm is as follows. The distribution according to Shannon’s definition of uncertainty is calculated first:

\[
H_u = -\sum_u p_u \log_2(p_u)
\]

Thus, it can be deduced that the distribution of the double helix case \( H_{ui} \) is as follows:

\[
H_{ui} = -\sum_u \sum_i p_{ui} \log_2(p_{ui})
\]

For each unit of the two helices, the overlap and the overlapping part are adjusted and changed when the helix changes; the transmission between the two units can be represented by the T index, that is:

\[
T_{ui} = H_u + H_i - H_{ui}
\]

If \( T_{ui} \) is zero, the two units are completely independent without coincidence. In other words, no spiralization is formed; while the index of \( T_{ui} \) is regular, indicating that the two units have an overlapping spiralization effect. Similarly, the calculation method of the triple helix can be deduced to obtain \( T_{uig} \):

\[
T_{uig} = H_u + H_i + H_g - H_{ui} - H_{ug} - H_{ig} + H_{uig}
\]

\( T \) values for the triple helix can be positive, negative, and zero. For the triple helix, the system is often the existence of complex uncertainties at the network level. When the index \( T_{uig} \) is negative, the uncertainty of this complex system is reduced. The greater the absolute value of a negative number, the smaller the uncertainty of the system. We can judge the stability of a triple helix complex system by \( T_{uig} \).

**Network Analysis**

To excavate the respective research characteristics of universities, governments, and industries, this study explored the article data of the university, government, and industry. Using the network analysis method, the visual keywords of each paper’s data network and the network centricity index were analyzed. The network centrality index evaluates the influence of each node in a network.

The nodes in this study are keywords, and the link is the number of common occurrences between keywords. The study adopts degree, closeness, and betweenness centralities. Degree centrality is an index that evaluates the number of other nodes directly linked by a node in the network (Kim & Hastak, 2018). The greater the index, the greater is the influence. Closeness centrality is an indicator that evaluates the shortest path of a node to other nodes in the network (Aloni et al., 2020). When the indicator value is small, the keyword reaches other keywords at a short distance and has a great influence. Betweenness centrality is a description of the influence of node’s role as a bridge, that is, the ability of other nodes to connect with each other through this node (Aloni et al., 2020; Kalgotra et al., 2020).
greater the betweenness, the greater is the influence. This study used UCINET 6 to calculate network centrality. Furthermore, we conducted cluster analysis on the keyword network through VOSviewer. We found the community of keywords for the topics using clustering. By analyzing the community’s theme, we were able to identify the research focus of universities, governments, and industries.

**Results**

We analyzed and answered questions 1, 2, and 3 in subsections R-1. and R-2., R-3, and R-4 and R-5, respectively.

**R-1 Distribution of the Smart Factory Research in Universities, Industries, and Governments**

Figure 1 shows the distribution of published research on the smart factory in the fields of government, industry, and university. In terms of the amount of research published by government, industry, and university worldwide, China, the USA, Italy, Germany, and South Korea rank first, second, third, fourth, and fifth, respectively. Universities in Chinese Mainland have the highest number of publications; that is, research in the field of the smart factory has been active in Chinese universities.

![Fig. 1 Distribution of publication volume in the field of smart factories](image-url)
from 2011 to 2020. Although the USA ranks second to China in terms of total publications, it stood first in terms of government publications. South Korea, China, and Italy also had the high number of government publications. In terms of industry, Germany has the largest number of publications, followed by Spain.

R-2 Distribution of the Average Number of Articles and Citations of the Helix Structure Each Year

Table 1 presents the distribution of the published research and citation rate of each index of the triple helix each year; N is the number of articles, and IF is the average number of citations. Although the survey period ranges from 2011 to 2020, no publication was found for 2011 during the data collection. Therefore, the data were calculated from 2012. The first published papers were in the fields of universities and universities–industries cooperation (one each) (Table 1). The citation rates of both the papers were high (60 and 33, respectively). The first paper from industries appeared in 2013, and the citation rate of this paper was 29. The first paper of government was published in cooperation with universities in 2014, and a separate paper was published in 2015. Interestingly, the double and triple helix cooperation structure was fully formed in 2015. As Table 1 presents, both helix and non-helix publication volumes showed an upward trend over time. Especially in universities, the number of publications has increased sharply in the past 5 years. In terms of the citation rate, the citation rate of articles with government participation is relatively high, especially those with the triple helix cooperation among government, industry, and university. The citation rate of articles in the last 2 years is 55 (2019) and 71 (2020).

The dynamic performance of cooperation among government, enterprises, and schools continues to increase. Universities dominate the helix structure. Although the industry is the center of the implementation of smart factory, the research and development capacity of the university is far higher than that of the industry. The cooperation between the government and industries has not been very obvious. There were no more than two articles in some years, but the number of citations was high. The influence of the cooperation work between the government and industries cannot be ignored. Cooperation between the government and industries will also boost the smart factory sector.

R-3 Stability Analysis of the Triple Helix Structure

We sorted out the sources of all the articles and calculated the annual $T_{uig}$ index. Figure 2 shows the $T_{uig}$ values from 2015 to 2020. The $T_{uig}$ from 2011 to 2014 was 0; the triple helix did not form during these years. $T_{uig}$ was $-69.76$ in 2015 during which the triple helix system had the lowest uncertainty. $T_{uig}$ has been between $-25$ and $-40$ from 2016 to 2020. This indicates that although the number of research articles has continued to increase since 2015 and the universities’ research has taken the leading role, the triple helix structure of the whole research system still maintained certain stability.
Table 1: Distribution of the average number of articles and citations of the helix structure in each year

| Years | G I N | U I N | IG N | UI N | UIG N | IF | N IF |
|-------|-------|-------|------|------|-------|----|------|
| 2012  | 0.00  | 0.00  | 0.00 | 0.00 | 0.00  | 1  | 0.00 |
| 2013  | 0.00  | 29.00 | 0.00 | 27.00 | 0.00  | 0.00 | 0.00 |
| 2014  | 0.00  | 29.00 | 33.50| 1.00  | 34.00 | 1  | 0.00 |
| 2015  | 3 23.67| 0.00  | 41.00| 0.00  | 33.00 | 3  | 0.00 |
| 2016  | 5 10.00| 51.00 | 6 15  | 33.14 | 21.00| 0  |
| 2017  | 4 25.00| 39.41 | 6 35.33| 29.50 | 25.50| 0  |
| 2018  | 0 38.75| 45.62 | 17.80| 32.50 | 32.50| 2  |
| 2019  | 0.00 | 20 17.80| 39.74| 53.00 | 53.00| 0  |
| 2020  | 0 11 21.18| 802  | 53.86| 46.54 | 53.90| 8  |

IG: IG: U G, UI: UI: UIG: IF
R-4 Keyword Co-Occurrence Network

We used the network analysis method to analyze the co-occurrence of keywords. Keywords are nouns or phrases that can reflect the core content of an article (Xiang et al., 2017). To optimize the visualization effect, we display the appropriate keywords on the visualization results according to the number of keywords appearing together in each field. The minimum number of co-occurrence of keywords in universities is 10, and that in governments and enterprises is 1. The frequency of keywords determines the size of the visualized nodes. The larger the node, the higher is the frequency of the keyword in the smart factory publication. Link represents the relative strength of co-occurrence between keywords. Keywords in the same color can be classified as similar themes.

From the overall network analysis results of universities in Table 2, the degree, closeness, and betweenness centralities of Industry 4.0, smart manufacturing, internet of things, cyber physical systems, and smart factory are found to be the best. These keywords are also the most frequent words. The research related to these keywords plays an important role in the university network.

The co-occurrence keyword network in Fig. 3 clearly illustrates the largest cluster of six. The topics in each cluster are similar. By analyzing the characteristics of each cluster, we mined and summarized the topic of each cluster. In the red cluster, the keywords include “Industry 4.0,” “case study,” “digital factory,” “digitization,” and “manufacturing,” which we classify under the topic “smart factory concept and case study.” In the green cluster, keywords such as “internet of things,” “cloud computing,” “edge computing,” “wireless sensors,” “security,” and “5G” were classified under “computing and communication.” The dark blue cluster is named “supply chain and logistics,” and includes keywords such as “blockchain,” “circular economy,” “logistics,” “supply chain,” “multi-agent system,” “supply chain...
management,” and “sustainability,” among others. In the yellow cluster, keywords such as “additive manufacturing,” “3D printing,” “advanced manufacturing,” “automation,” “human–robot collaboration,” “integration,” and “robotics” are classified under “smart manufacturing.” Furthermore, there is the purple cluster, and the nattier blue cluster. Both groups are related to “big data and machine learning.” The purple cluster indicates more “predictive maintenance,” and the nattier blue cluster denotes more “fault diagnosis.”

According to the results of the government network analysis in Table 3, the five keywords with the highest degree centralities are “smart manufacturing,” “Industry 4.0,” “artificial intelligence,” “standards,” and “internet of things.” These five

| No | Keywords                          | Degree | Closeness | Betweenness |
|----|----------------------------------|--------|-----------|-------------|
| 1  | Industry 4.0                     | 1008.00| 75.00     | 417.31      |
| 2  | Smart manufacturing              | 443.00 | 80.00     | 335.17      |
| 3  | Internet of things               | 353.00 | 88.00     | 224.61      |
| 4  | Cyber physical systems           | 316.00 | 95.00     | 169.91      |
| 5  | Smart factory                    | 213.00 | 95.00     | 167.90      |
| 6  | Big data                         | 155.00 | 107.00    | 73.82       |
| 7  | Industrial internet of things    | 158.00 | 108.00    | 70.66       |
| 8  | Digitalization                   | 85.00  | 116.00    | 48.97       |
| 9  | Cloud computing                  | 137.00 | 114.00    | 39.25       |
| 10 | Sustainability                   | 76.00  | 120.00    | 34.82       |

Fig. 3  Topic network visualization in universities
key words also have the highest frequency of occurrence. The keywords with lower closeness centrality are “smart manufacturing,” “artificial intelligence,” “internet of things,” “standards,” “COVID-19 recovery,” “flexible manufacturing,” and “supply chain recovery.” The keywords with higher betweenness centrality are “smart manufacturing,” “artificial intelligence,” “standards,” “machine learning,” and “internet of things.”

In Fig. 4, we extracted the six largest topic groups. The first is “macro prospects,” which include “capability development,” “digital transformation,” “disruptive innovation,” “global value,” “industrial network,” “industrial 4.0,” and “upgrading.” The second is “computing and machine learning,” which includes “artificial intelligence,” “cloud computing,” “computational modeling,” “deep reinforcement learning,” and “transfer.” The third is “smart factory application,” which includes “big data,” “COVID-19 recovery,” “smart cities,” “flexible manufacturing,” and “supply chain recovery.” The fourth is “sustainability of the smart factory,” which includes “global production networks,” “industrial development,” “leapfrog technology,” “moveable production system,” “sustainable development,” and “sustainable production,” among others. The fifth is “manufacturing and production systems,” which includes “model-based systems engineering,” “production systems,” “smart manufacturing,” and “SYSML” (Systems Modeling Language). The sixth is “digital design and analysis,” which includes “big data analysis platforms,” “computer aided design,” “simulation,” and “die casting process.”

According to the industry network analysis results presented in Table 4, the keywords with the highest degree centrality are “Industry 4.0,” “smart manufacturing,” “smart factory,” “big data,” and “additive manufacturing.” These also have the highest frequency of occurrence. The keywords with lower closeness are “Industry 4.0,” “smart manufacturing,” “smart factory,” “big data,” and “additive manufacturing.” The keywords with higher betweenness centrality are “Industry 4.0,” “smart factory,” “smart manufacturing,” “big data,” and “machine learning.”

As before, we extracted the six largest industry topics (Fig. 5). The first topic is “Industry 5.0 and industrial processes,” which includes “adaptive processes,” “augmented reality,” “gamification,” “image vision,” “Industry 5.0,” “process re-engineering,” and “process workflow simulation.” The second topic is “smart
Fig. 4  Topic network visualization in the government

Table 4  Centrality analysis of network (industry)

| No | Keywords                               | Degree | Closeness | Betweenness |
|----|----------------------------------------|--------|-----------|-------------|
| 1  | Industry 4.0                           | 159.00 | 621.00    | 17,317.41   |
| 2  | Smart factory                          | 53.00  | 722.00    | 5728.73     |
| 3  | Smart manufacturing                    | 57.00  | 716.00    | 5066.08     |
| 4  | Big data                               | 44.00  | 725.00    | 2534.62     |
| 5  | Machine learning                       | 11.00  | 808.00    | 1568.00     |
| 6  | Digitalization                         | 28.00  | 784.00    | 1444.41     |
| 7  | NDT (non-destructive testing) 4.0      | 15.00  | 855.00    | 1350.00     |
| 8  | Additive manufacturing                 | 35.00  | 756.00    | 1283.95     |
| 9  | Cyber-physical systems                 | 20.00  | 763.00    | 1212.61     |
| 10 | Digital twin                           | 17.00  | 806.00    | 939.48      |
manufacturing,” which includes “automation factory,” “high precision,” “auto-
mation,” “lean precision,” “lean manufacturing,” and “virtual manufacturing.”
The third is “smart systems,” which includes “discrete event systems,” “digital
twin,” “human–machine interface,” and “micro-service architecture.”. The fourth
is the “computing communication and sustainable supply chains,” which includes
“the cloud,” “control system,” “client devices,” “edge computing,” “internet of
things,” “microcomputers,” “sustainable supply chain management,” and “smart
waste management.” The fifth is the “smart inspection and smart produce,” which
includes “high speed inspection,” “metrology,” “produce service innovation,”
“rapid prototyping,” “additive manufacturing,” and “3D printing.” The sixth is
the “application and prospects,” which includes “automation,” “digitalization,”
“employment,” “technological change,” and “work of the future.”

R-5 Similarities and Differences for Different Types of Organizations

Figure 6 presents a visualization of the different topics of university, industry, and
government. We found that smart manufacturing, computing, supply chain, data
analysis, and sustainability are hot topics in all three areas. University does more
research on new concepts and cases and has formed two large-scale groups for big
data and machine learning. One focuses heavily on predictive maintenance, and the other on fault diagnosis. In industry and government research, big data and machine learning do not occupy a particularly large proportion and do not form a separate mega-group. The topics of Industry 5.0 and the transformation of industrial processes are more prominent in the research of industries, which is different from that of universities and governments. The prospect of smart factories is a common hot topic for the government and industries, among which the former focuses more on technology application and prospect and the latter on the macro prospect.

Discussion

In the overall distribution of the triple helix structure of smart factories, universities occupy the leading position and lead in terms of productivity of knowledge innovation. Although the industry is the primary center in the implementation of the smart factory, the R and D ability of universities is far higher than that of the industry. The cooperation between government and industry has not been obvious, but the number of citations is also not low. Collaboration between government and industry will also boost the field of smart factories. China is the leader in the regional distribution of smart factories. The rapid progress of science in China as a whole is mainly due to the large amount of public science and technology funds provided by the Chinese government (Asad et al., 2019; Hu, 2019). Among them, the National Natural Science Foundation of China’s 2016 budget of 26.8 billion Yuan ($3.9 billion at that time) accounts for almost one-third of China’s basic research funding (Cyrano’ski, 2018). Among the 2409 articles, 757 were funded and NSFC of China provided the largest amount of funding (146 articles), followed by the European Commission (91
articles), Department of Health Human Services (75 articles), and National Institutes of Health (70 articles). Research spending at the national level brings knowledge spillovers. In terms of the nature of the funded units, China receives a large proportion of state funding in the field of universities, Germany in the field of industry, and the USA in the field of government, with a relatively high output of research knowledge.

Universities are frequently producers and disseminators of new knowledge or technology in the triple helix model, whereas industry is the actual producer and service provider. Although the government has a role of control and supervision, it is also one of the government’s responsibilities to promote collaboration between universities and industry (Etzkowitz & Leydesdorff, 2000; Leydesdorff, 2000). In 2011, Germany formally proposed Industry 4.0 of which smart factory is the core (Mabkhot et al., 2018; Wagire et al., 2019). In 2012, the first articles related to smart factory appeared in universities and under the cooperation between universities and industries. These articles introduced the fields of mass customization and industrial internet of things (Ngiiatedema, 2012; Wang et al., 2013). Notably, mass customization is needed for market development. The emergence of technologies in the field of smart factory (such as industrial internet of things and big data) makes mass customization possible (Miqueo et al., 2020). In 2013, Germany was committed to realizing the industrial transformation of automation through Industry 4.0 to maintain its leading position in the manufacturing industry. In 2014, South Korea implemented various strategies such as the mid- and long-term master plan to prepare for the smart information society. In 2015, Japan was the first country to take Industry 4.0 as a national strategy, actively using its powerful robotics technology to increase industrial competitiveness and accelerate the social and economic system. In the same year, China also pushed forward the “Made in China 2025 Plan” in the thirteenth five-year plan (Li, 2018; Min et al., 2019). The overall knowledge structure of smart factory evolved from double helix to triple helix for the first time in 2015, forming a complex structure. The formulation of policies by governments around the world provided a guarantee for the comprehensive formation of the double helix and triple helix cooperation between universities, industries, and governments in the field of smart factories in 2015.

Our study found that the citation rate of the triple helix collaborative research between universities, industry, and government in 2019 and 2020 was very high, with the average citation rate per paper reaching 71.38 in 2020. Triple helix cooperation research produces good benefits and has high impact. More triple-helix collaboration could help the industry as a whole. Governments have an important role to play in stimulating the capacity of firms to absorb, improve, and create new technologies, as they are responsible for providing the infrastructure and creating the appropriate institutional platforms for communication and knowledge dissemination (Broström, 2010). These platforms can facilitate triple helix collaboration. Moreover, according to the results of the triple helix index, although the number of studies continued to increase after 2015 and the universities’ research took the leading role, the whole research system still maintained certain stability of the triple helix structure.

According to the content analysis results, although universities, industries, and governments share many similar research topics, they also have their own unique
topics. The circumstances and positions of the three are different, which objectively leads to this phenomenon. Universities’ research contains concepts and case studies, in addition to a variety of technologies; especially, the number of studies on big data and artificial intelligence is higher compared that done by the government and industry. The government is unique in terms of conducting research on the macro prospect. It is important to note that Industry 5.0 and industrial processes are relatively large subjects in the enterprise theme. The characteristics of Industry 5.0 mode are mainly people-oriented, logistics, production process, and customer interaction, which are all in transition (Carayannis et al., 2020). For example, customization can lead to a shift in the process, and gamification, visualization, and augmented reality experiences can also provide a people-oriented purchase experience for customers.

In the early stage of Industry 4.0, production is the mainstay; therefore, more attention is paid to the improvement of the relationship between technology and production, for example, smart factory. However, with the increasing amount of attention being paid to innovation, we have now entered a human-centered innovation society 5.0 (Carayannis et al., 2020). In this society, technology and production are integrated into the quality of life, social responsibility, and sustainability with several macro aspects. This had, in turn, led to the rise of Industry 5.0, which is not a single product or a single system. Therefore, the government’s active participation in the research and promotion of smart factories can have a macro effect on social responsibility and sustainable development and accelerate the people-oriented intelligent production and service, which is highly conducive to the development of Society 5.0 and Industry 5.0. In other words, for Industry 5.0, the government’s support and research are necessary; however, our study found that in the research of smart factories, only the proportion of enterprise-related research is high, whereas that of government research is not. Therefore, to promote the concept of the smart factory from Industry 4.0 to Industry 5.0 more quickly, the government must actively explore the research on Industry 5.0 and Society 5.0 and develop an integrated smart factory, intelligent manufacturing, and data-driven platform to adapt to the new model.

Future Research and Limitations

The smart factory in Industry 4.0 focuses primarily on the innovation and improvement of technology and production. Therefore, appropriate and meaningful results can be obtained from the triple helix structure of universities, industries, and governments. However, for conducting future research on Industry 5.0 and Society 5.0, which represents the macro of the entire society, the meso of industries, and the micro of individual customers and individual service audiences, a more complex helix structure is needed for the investigations (Carayannis et al., 2021). For example, the quadruple helix, quintuple helix, and N helix in the future research of smart factory, which not only include universities, the industry, and the government but also mass media, civil society groups, social media, and other multi-angle elements can be introduced to perform research based on a more complex helix model structure.
The limitations of this study are as follows. Although it used the scientific literature as the basis for the triple helix index analysis, patent cooperation and financial cooperation, such as non-state investment and invested relationship, were not considered. Further, although WoS provides relatively comprehensive and high-quality scientific literature data, it was not able to objectively cover all the scientific literature data.

**Conclusion**

The triple helix model is used in this study to analyze the knowledge structure of smart factories from three perspectives: university, government, and industry. The degree of helix of the research institutions was evaluated and discussed, and the characteristics of the smart factory’s knowledge production structure were identified. The study of smart factory organization cooperation has been added, and it provides useful suggestions and references for smart factory industry planning and government policy formulation. We find that China, Germany, and the USA receive a large proportion of state funding in the university sector, industry sector, and government sector, respectively. Research knowledge output also ranks relatively high. Research funding at the national level has led to knowledge spillovers in the smart factory field. The developments in the smart factory market and the concerns in various fields have paved the way for the formation of the triple helix structure.

Moreover, the overall knowledge structure of the smart factory evolved from the double helix to triple helix for the first time in 2015, forming a triple helix complex structure. The formulation of policies by governments around the world provides a guarantee for the comprehensive formation of the double helix and triple helix cooperation between universities, industries, and governments in the field of smart factory in 2015. Increasing national funding for the smart factory sector can effectively stimulate the development of the smart factory industry. In 2019 and 2020, the citation rate of the triple helix cooperative research of universities, industries, and government was relatively high; especially, the average citation rate per paper reached 71.38 in 2020. Triple helix cooperation research produces good benefits and has high impact. After 2015, the triple helix structure has maintained a certain amount of stability. In terms of research topics, universities conduct more extensive and deeper research on concepts and technologies, governments conduct more macro research, and industry research focuses more on Industry 5.0 and industrial processes. As the development model of the smart factory in the next stage, the government needs to conduct more research and develop new platforms to promote the formation of the triple helix structure or even the quadruple helix, quintuple helix, and N-tuple helix cooperative research and ensure the stability of the helix cooperation to promote the development of Industry 5.0.

**Author Contribution** Liu D. and Zhu Y. P. designed the study and wrote the manuscript. Zhu Y. P. is the principal investigator. Dong Liu: conceptualization, methodology, validation, investigation, writing—original draft, writing—review and editing, visualization, project administration. Yu Peng Zhu: conceptualization, methodology, software, validation, formal analysis, investigation, data curation, writing—original draft, writing—review and editing, visualization, supervision, project administration.
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