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Technological Convergence Assessment of the Smart Factory Using Patent Data and Network Analysis

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Abstract: The smart factory has evolved as a key and distinctive idea for Industry 4.0. These industries impart a significant influence on sustainable production because of their consistent industrial evolution/development. Recently, their technological advancements are deemed inevitable to survive in this competitive industry due to increasing market needs. Therefore, technological convergence analysis can provide deep insight into industrial progress and convergence. Consequently, contemporary research trends are centered on evaluating technological convergence. Although various studies are already available on the technological development of the smart factory concerning Industry 4.0, however far less significant work is available on the technological convergence assessment of the smart factory by employing data networks and patents. Therefore, this work is focused on the investigation of reliable data analysis of the smart factory's technologies and its technological convergence. This said methodology assisted in examining the network's hidden linkages using network analysis. A relevant case study of a smart factory is also discussed to evaluate its technological convergence. Thus, data-driven technologies have diverted focus from International Patent Classification (IPC) visual networks using convergence assessment tools. The findings of this study are intended to aid companies and government officials in forecasting future sustainable technological developments and decision making.

Keywords: smart factory; technological convergence; network analysis; IPC codes; centrality analysis; patent data analysis

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1. Introduction

Rapid advancements in information and communication technology (ICT), electronics, data storage, and manufacturing technologies have transformed the industry from simply digital to intelligent. A new age of cyber-physical systems (CPS) is on the horizon [1,2]. Various industrialized countries and economic sectors are attempting to adjust to the fourth industrial revolution age. Various nations have recently begun their plans to deal with this age, such as with Germany's Industry 4.0 [3], China's Made in China 2025 [4], and the United States' Smart Manufacturing [5]. With the fourth industrial revolution's rising speed of technological progress, many businesses are seeking new ways to compete, and many firms are seeking new convergent technologies to compete in an ever-increasingly competitive market [6]. The smart factory is a fundamental idea and component of Industry 4.0. Because of the participation of numerous unique technologies, the popularity of the smart factory is quickly rising. It is also known as the factory of the future, the real-time factory, and the factory of things [7–9]. Recently, traditional factories have been facing a considerable lag in both production and quality due to the lack of new technologies and the existence of complex manufacturing issues [2]. Therefore, advancement in technological structure and conversion to a smart factory with new technologies has become ample [10]. Thus, technologies are playing an important role in smart factory fame. Several studies on the smart factory were undertaken with the advent of the Industry 4.0 era. Radziwon et al. [11] defined the smart factory as the manufacturing solution that can provide flexible and adaptive production processes that can solve the complicated manufacturing problems of a production facility in an increasingly complex world. This flexible system can solve numerous issues associated with the manufacturing industry that are difficult to be handled by conventional technology. The smart factory is becoming more popular in countries across the globe due to its flexibility and problem-solving qualities. Among smart factory core technologies, industrial internet of things (IIoT), BIG data and analytics, augmented reality (AR), cloud computing, simulation, and artificial intelligence (AI) are included [1]. Smart factories can bring about a revolution in the manufacturing industry through their up-to-date technologies. The relevant terms alongwith their abbreviations throughout the manuscript have been reported as nomenclature in Table 1.

Table 1. Nomenclature.

Acronym	Terminology	Acronym	Terminology
IPC	International Patent Classification	ICT	Information and communication technology
CPS	Cyber-physical system	IIoT	Industrial internet of things
AI	Artificial intelligence	AR	Augmented reality
RFID	Radio frequency identification	SCADA	Supervisory control and data acquisition
SNA	Social network analysis	CE	Circular economy
USPTO	United States Patent and Trademark Office	WIPO	World Intellectual Property Organization

The technological advancements of the smart factory have been investigated in several studies. Chen et al. [2] studied smart factory key technologies concerning three different layers of smart factory architecture. Feng et al. [12] studied the RFID-based smart factory for data acquisition to improve quality and time-saving. Yang et al. [13] explored the current research trends of the smart factory using the topic modeling technique and highlighted some of the hot topics for the smart factory, which are quite famous among researchers. Similarly, Nagpal et al. [14] presented the smart factory's industrial internet of things (IIoT) perspective. The literature above indicates that, despite many researchers having investigated the smart factory from various perspectives, a study about the technological analysis of smart factories has had minimal research so far. On the other hand, technological analysis can provide deep insight into the relationships among various technologies in the smart factory. Moreover, it can help with short- and long-term technological planning. Besides, some significant technologies can be identified by analyzing the technological network of the smart factory. So, it becomes inevitable to investigate the technological convergence of the smart factory. Thus, there is a void in the research.

Thus, this research aims to evaluate and investigate the technological convergence of the smart factory utilizing the network analysis approach and patent data. Network analysis can uncover hidden connections between smart factory technologies. Furthermore, this study has employed patent data to discuss the case study since patents are easily accessible through commercial databases, allowing access to a huge amount of standardized information. Patent analysis may also be used to investigate the link between distinct technologies. Furthermore, patent data is a trustworthy source of technological information [15,16]. Technological convergence patterns can also be deduced from these patents. Because technological convergence can open up new avenues for technological potential, this could be a viable path forward [17].

The current work's subsequent architecture consists of the six main sections, followed by their sub-sections. Section 1 describes the rationale/importance of this study. In Section 2, the authors discuss the smart factory, network analysis, and centrality analysis, respectively. Data and methodology are explained in Section 3. Section 4 is comprised of the research results and discussion of the obtained data results. The concluding remarks and the recommendations for future research are explained in Section 5 A brief summary of overall work architecture is visually presented in Figure 1.

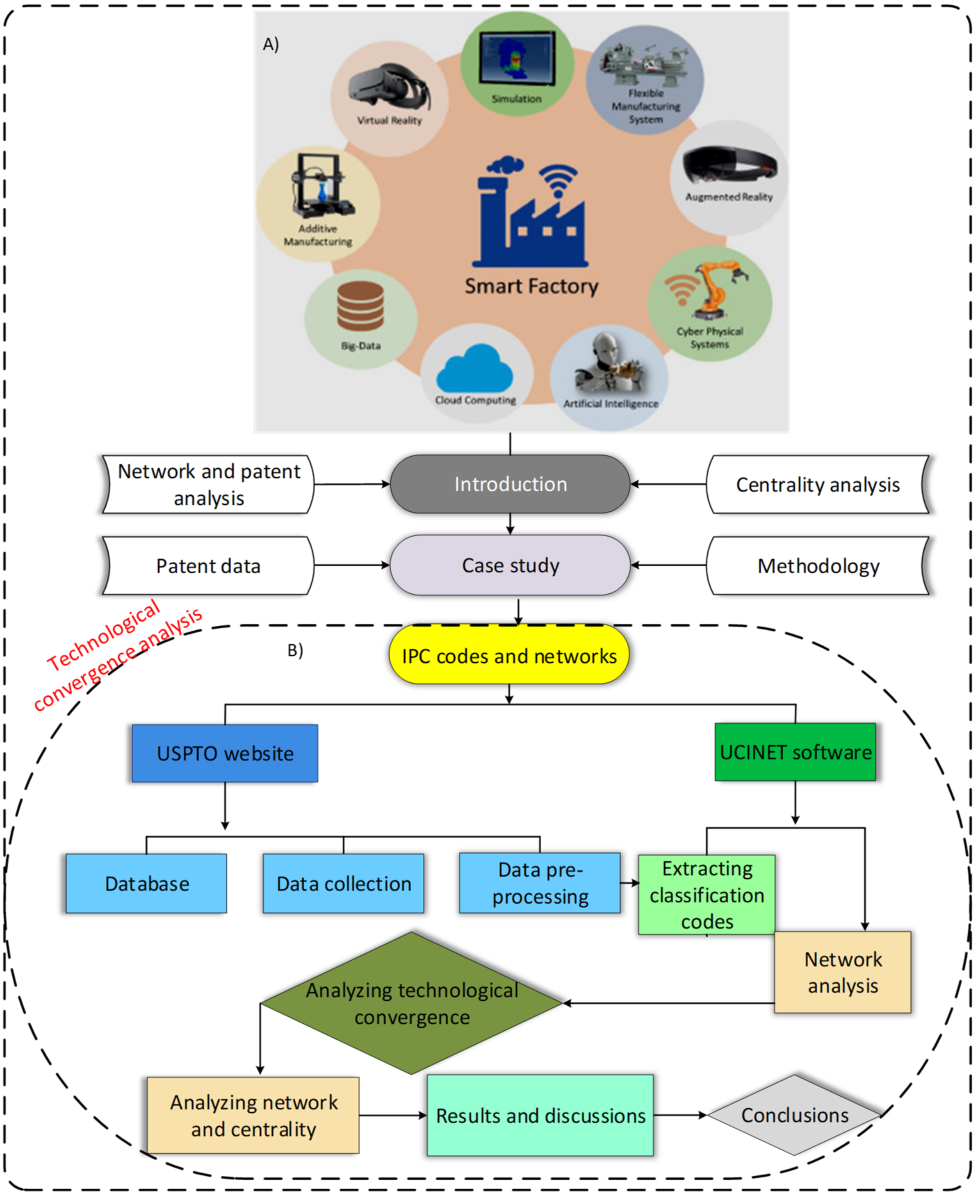


Figure 1. A detailed framework showing the architecture of the whole study. (**A**) Different application prospects of the smart factory [18]. (**B**) A practical demonstration of technological convergence assessment during patents and networks data analysis.

2. Literature Review

2.1. Smart Factory

With the rise of the fourth industrial revolution, the manufacturing sector is growing steadily and finding new ways to create opportunities for reducing cost, time and improving the overall operations. This goal can be achieved by using state-of-the-art technologies in production facilities [1,2,19,20]. This concept is famous as Industry 4.0 in Europe and smart manufacturing in the USA [3]. The smart factory has emerged as a unique concept of the fourth industrial revolution. Due to its unique qualities and advantages, the smart factory is famous among government policymakers, academic researchers, and industrial practitioners [2,19]. Many researchers have tried to define the smart factory in their ways. For example, Radziwon et al. and Wang et al. described the smart factory as a manufacturing unit that can increase the flexibility and efficiency of a production system by integrating autonomous devices and big data-based information systems [11,21]. In other words, it enhances the capacity of a production facility for small-lot and customized production. Before these technologies, manufacturing sectors could not solve complex problems and save resources such as time, money, and materials. Real-time data processing power and on-the-spot collaboration among the machines have been introduced. As a result, traditional digital manufacturing has been taken to the next level [22]. Moreover, various researchers have named it according to its different characteristics. Zuehlke defined the smart factory as the factory of things [9]. Lucke et al. call it the intelligent factory of the future because it is a step further from digital production in data processing and problem-solving capability [7]. As well, the smart factory is known as the "real-time factory" by [8].

Traditional factories are lagging in productivity due to their technological disadvantages, so a smart factory can be a suitable alternative. Further, the ability of a smart factory to solve complex problems is highlighted. Thus, upgrading existing technologies with new, up-to-date technologies in manufacturing units and building an intelligent factory to improve productivity and reduce cost and time is inevitable [10].

Plenty of modern technologies are being used in smart factory facilities. Among them, some of the famous are the industrial internet of things (IIoT), BIG data and analytics, augmented reality (AR), cloud computing, simulation, and artificial intelligence (AI) [1]. Many researchers have investigated the smart factory and its technologies. For example, Chen et al. proposed the hierarchical architecture of the smart factory, and then the key technologies were analyzed from the aspects of the physical resource layer, the network layer, and the data application layer [2]. In this study, the critical technologies of the physical, network, and data layers were discussed. As well, radio frequency identification (RFID) was thoroughly examined by [12]. Collection of data, extraction, and then its successful usage were discussed to meet industrial goals. In addition, the industrial internet of things (IIoT), which is considered an important technology and part of the smart factory, was investigated by [14]. In this research, the association of the smart factory and IIoT was studied. Forcina et al. presented a literature review about the enabling technology of the smart factory [23]. Lin et al. compared the centralized or decentralized structures of traditional supervisory control and data acquisition (SCADA) monitoring devices based on the framework of IoT smart factories. They outline the unique concept of smart factory cooperation and found it more beneficial than traditional methods [24]. Manufacturing technology transformation from the smart factory point of view has been analyzed by [25]. Profile et al. also found that technological transformation is beneficial in terms of cost-effectiveness, fewer resources, and high efficiency [25]. Not limited to these researchers, many others have studied various technologies, their performances, technological comparison, the evolution of technologies for smart factories, and enabling factors for smart factory technologies.

2.2. Network and Patent Analysis

Social network analysis (SNA) is a famous technique to check and understand various network characteristics [26–28]. Agbo et al. [29] defined network analysis as a powerful tool to present the systematic picture of network structure and its components. Moreover, it emphasizes the relationship of any node in a network. Understanding the network is essential because it reveals many under-considered details about the data. In this respect, many researchers had tried different local and global measures to understand and explore the possibilities within the network [26]. For example, at a global level, centrality measures were developed by [30] to illustrate the role of any candidate within a specific network. With the help of this measure, understanding of the central role of any network has been increased. Alongside this global measure to understand the network more deeply, various local measures have also been taken to ease the understanding of network characteristics [26].

Furthermore, patents are considered an essential source of intellectual property, and they protect the rights of organizations and innovators. Generally, patents are well known as authentic and updated sources of technological knowledge and innovative ideas [31–33]. Further, the forecasting trajectory of technology and its life cycle is possible through patent data. So, many researchers have used this source of technological knowledge to predict technological convergence and trends for various fields [33–37]. Park et al. have used patent data to select sustainable technology using the patent network analysis technique [35]. Moreover, Jun considered forecasting central technology using patent data [38]. As patent network analysis is among the famous applications of social network analysis, it has been considered in many studies. Data from patents have generally been assessed according to its need in patent network analysis, such as citation information, IPC codes, and patent numbers [39–41]. These patent networks help researchers to examine the relationships among nodes and predict the leading technological fields. Moreover, various firms use patents to document technology strategy, including merger and acquisition, technology transfer, and technological acquisition [32].

Following the network analysis applications, this research also follows the same technique to investigate the technological convergence of smart factories through IPC codes, including related technological fields.

2.3. Centrality Analysis

Centrality analysis looks for the most critical and highly influential node or character in a network [42]. It means that in a network, the most powerful node with a lot of connections and influence is considered a central node. These nodes control the knowledge flow and processing of any network. There are many indices to measure the centrality of any network, which depends upon the specific needs. However, some of the crucial indices include degree, closeness, and betweenness [42].

Degree centrality shows the number of nodes with which a node or character is connected. It is the easiest and most fundamental index to measure the centrality of a specific node in a network [43]. The degree of a character or node in a network is referred to as local centrality [44]. A node with a high number of direct connections to other nodes is considered a more central node, concerning the degree index of centrality. However, a central node does not need to be physically present in the center of a network [44]. The degree centrality of node n (i.e., p_n) is defined as seen below:

$$C_D(p_n) = \sum_{m=1}^{k} b(p_m, p_n) \quad (1)$$

where k is the total number of nodes in a network and $b(p_m, p_n) = 1$ if, and only if, nodes p_m and p_n are connected; otherwise, $b(p_m. p_n) = 0$.

Closeness centrality illustrates the closeness of a node to all other nodes which are either connected directly or indirectly. Thus, the more central the node is, the closer it is to all other nodes [42]. Due to its closeness to all other nodes in the network, it can obtain and transfer information more efficiently to all other network members. Moreover, transmission efficiency can also significantly impact its closeness to all networks [44,45]. The closeness centrality of node n (i.e., p_n) is defined as follows:

$$C_c(p_n) = \sum_{m=1}^{k} a(p_m, p_n)^{-1} \quad (2)$$

where k is the total number of nodes in a network, and where $a(p_m, p_n)$ is the closest path from actor m to actor n.

Furthermore, betweenness centrality measures the shortest path to other nodes from a specific node, i.e., a node that provides the fastest route to pass the information and provide a way to other nodes [42,46]. In a network, the nodes with a high betweenness centrality can play the broker's role (likely as a gatekeeper) in that network. Due to the role and influence of high betweenness nodes, they are considered vital actors to connect different subgroups and nodes within the given network [44,47]. More precisely, the betweenness of node n (i.e., p_n) is formulated as seen below:

$$C_B(p_n) = \sum_{m=1}^{k} \frac{g_{ms}(p_n)}{g_{ms}}; \qquad m \neq s \neq n \tag{3}$$

where g_{ms}, is the shortest path connecting nodes m and s. In comparison, $g_{ms}(p_n)$ is the shortest path linking nodes m and s, containing node n.

3. Data and Methodology

3.1. Data

A case study has been conducted to analyze the technological convergence of the smart factory. For this purpose, patent data was collected from the United States Patent Trade Organization (USPTO) website (www.uspto.gov, accessed on 30 March 2021), which is an open patent database in the United States [48]. This website provides a wide variety of useful information in the patent documents such as patent number, the application number, title, abstract, claims, assignee, inventors, and class (i.e., IPC, CPC, and USPC). It also contains vast information about some specific technologies. Moreover, patents are a reliable and valuable source of technological knowledge, so this study has used patents as input data. In this respect, patents were searched with some specific keywords associated with the smart factory. Finally, a total of 672 patents were collected from the database. Patent data was collected from the year 1976 to 2019. Table 2 shows the number of patents collected for each specific keyword for the smart factory.

Table 2. Number of collected patents for each keyword.

S. No.	Keywords	Quantity
1	smart factory	27
2	smart manufacturing	86
3	smart industry	14
4	cyber-physical system	140
5	Industry 4.0	52
6	connected factory	353
	Total	672

Moreover, Figure 2 shows how many patents were collected per year from 1976 to 2019. The graph also reveals how the number of patents increases suddenly during the last decade.

In this study, the International Patent Classification (IPC) codes were selected to analyze the case study because they contain the technological field information [34]. Our research focuses on the association of IPC codes with each other. The IPC codes have eight major sections from A (human necessities) to H (electricity). Detail about each category have been reported in Table 3.

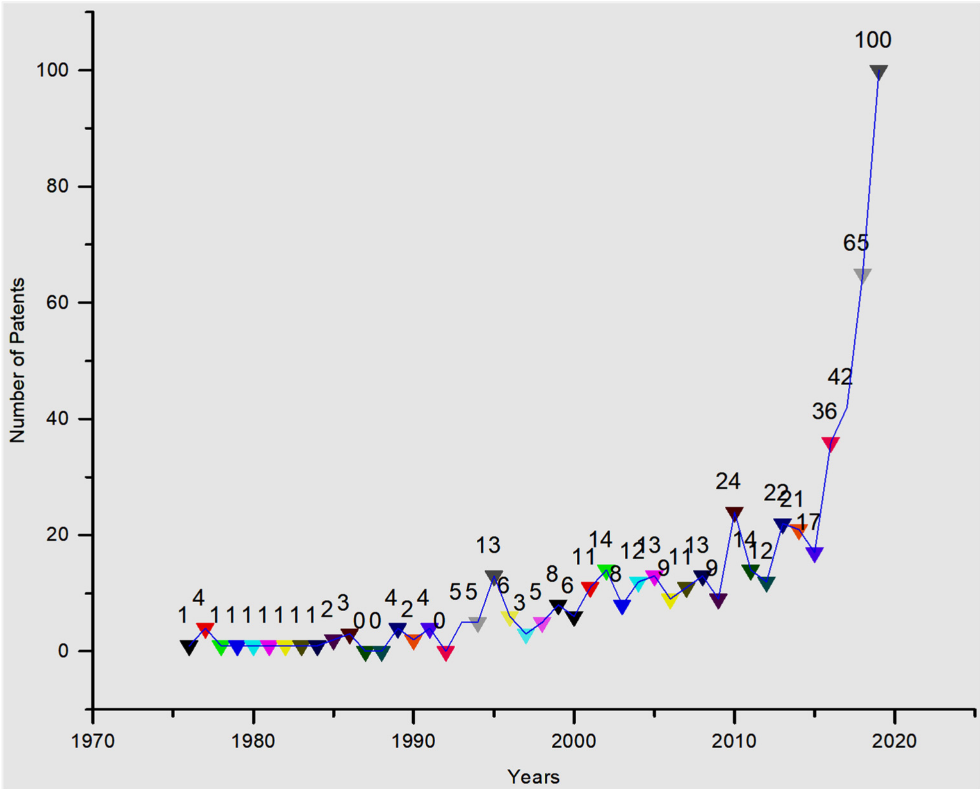


Figure 2. A detailed illustration to visualize the total number of patents collected per year (over the last couple of decades).

Table 3. An overview of major sections/classification areas of IPC network codes.

Sr. No.	IPC Code Alphabet	Major Classification
1	A	Human necessities
2	B	Performing operations; Transporting
3	C	Chemistry; Metallurgy
4	D	Textile; Paper
5	E	Fixed construction
6	F	Mechanical Engineering; Lighting; Heating; Weapons; Blasting
7	G	Physics
8	H	Electricity

In particular, the authors have used the subclass levels of IPC codes up to level 3 (four-digit IPC code) in this study. Previously, the four-digit IPC codes were used to find the sustainable technology and forecast central technology using social network analysis (SNA) [34,35,38]. This four-digit IPC code includes section, class, and subclass (for example, F02M). Here, F represents the main section, 02 represents the class, and M is for the subclass.

3.2. Methodology

First, the required patent data was collected from USPTO. A java-based web document collection program was used to collect the data. After collecting the smart factory patents, data were pre-processed to extract the IPC codes present in them. R program has been used to extract the IPC codes from patents. R program is an open source software used for statistical analysis. The IPC codes were pre-processed according to our needs. After that, these IPC codes were used to construct the adjacency matrix for each year's patents. Furthermore, from these adjacency matrices, the technology network for each year has been constructed using the network drawing software UCINET. Centrality analysis was also carried out using the network data. Figure 3 shows the research process of this study.

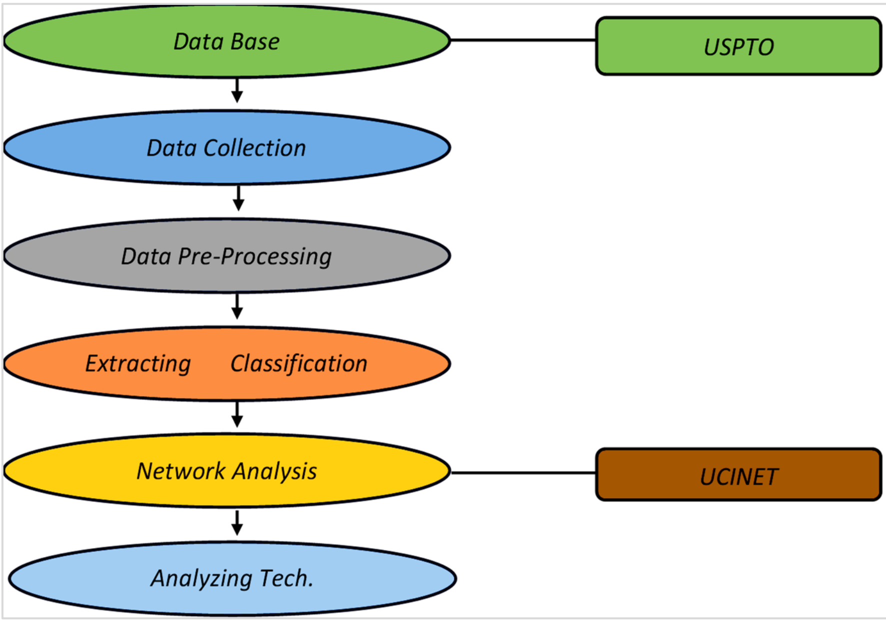


Figure 3. The overall research process of this study.

From the collected patent data, the authors extracted the IPC codes for the case study. Figure 4 shows the top ten IPC codes present in our corpus.

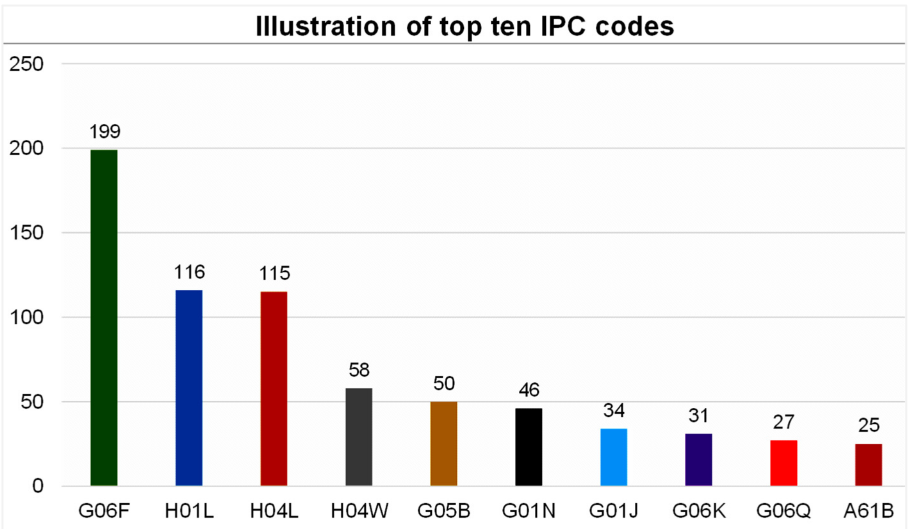


Figure 4. The top IPC codes present in our patent data.

The authors found that the most significant IPC codes in the patent data are G06F, H01L, and H04L. These codes represent the technologies of electrical digital data processing, semiconductor devices, and transmission of digital information. The World Intellectual Property Organization website (https://www.wipo.int/portal/en/index.html) accessed on 27 April 2021, has been used to define the technologies associated with these IPC codes. Moreover, the IPC codes and their respective technologies are shown in detail in Table 4 [49].

Table 4. An overview of the top IPC codes and their representative technologies.

Sr. No.	IPC Codes	Detailed Technological Applications Corresponding to IPC Codes
1	G06F	Electric digital data processing
2	H01L	Semiconductor Devices: Electric solid-state devices not otherwise provided for
3	H04L	Transmission of digital information, e.g. Telegraphic communication
4	H04W	Wireless Communication Networks
5	G05B	Control or regulating systems in general; Functional elements of such systems; Monitoring or testing arrangements for such systems or elements
6	G01N	Investigating or analyzing materials by determining their chemical or physical properties
7	G01J	Measurement of intensity, velocity, spectral content, polarization, phase or pulse characteristics of infra-red, visible or ultra-violet light; Colorimetry; Radiation pyrometry
8	G06K	Recognition of data; Presentation of data; Record carriers; Handling record carriers
9	G06Q	Data processing systems or methods, specially adapted for administrative, commercial, financial, managerial, supervisory or forecasting purposes
10	A61B	Diagnosis; Surgery; Identification

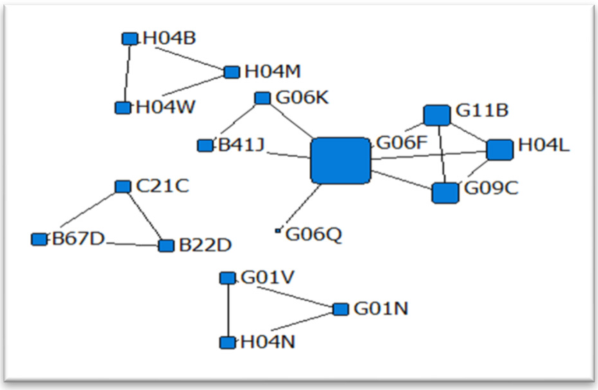
After that, these IPC codes were used to construct the adjacency matrix for each year's patents. The technology network for each year was constructed using the network analysis technique. For this purpose, we used the network drawing software UCINET.

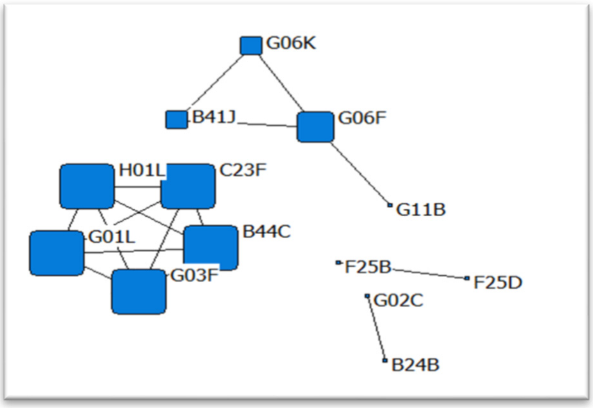
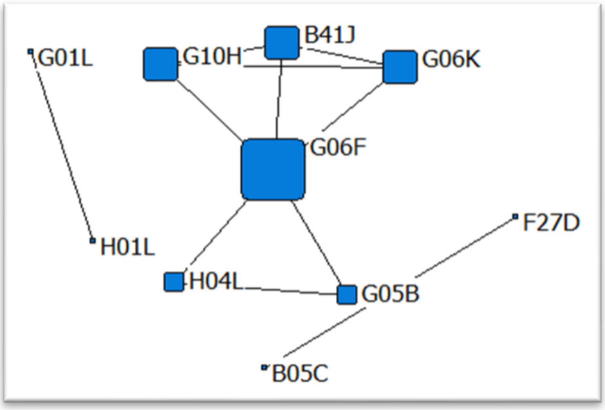
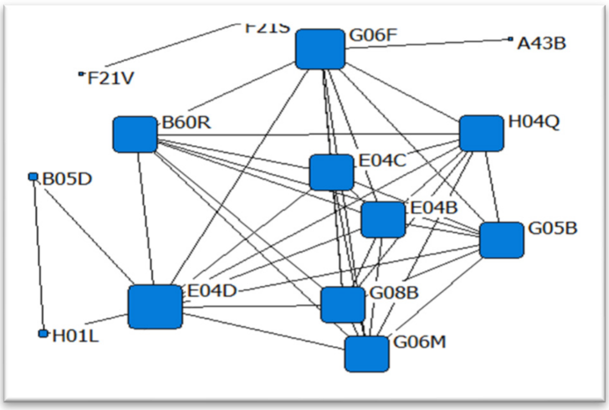
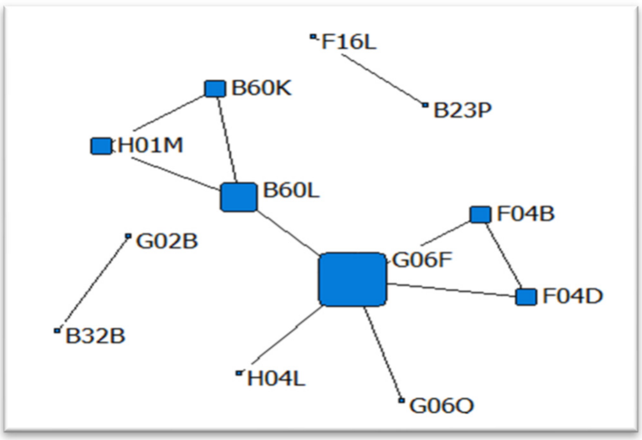
4. Results and Discussion

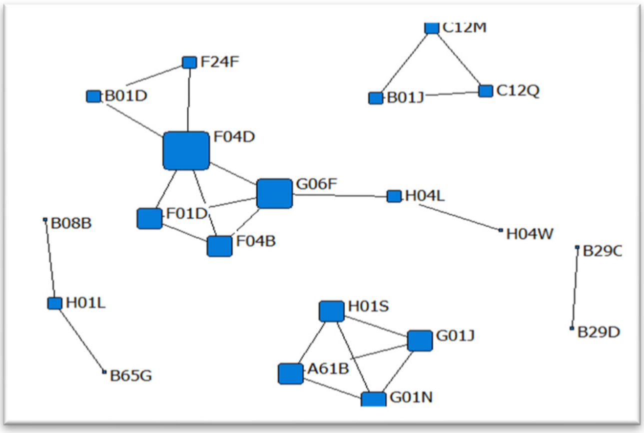
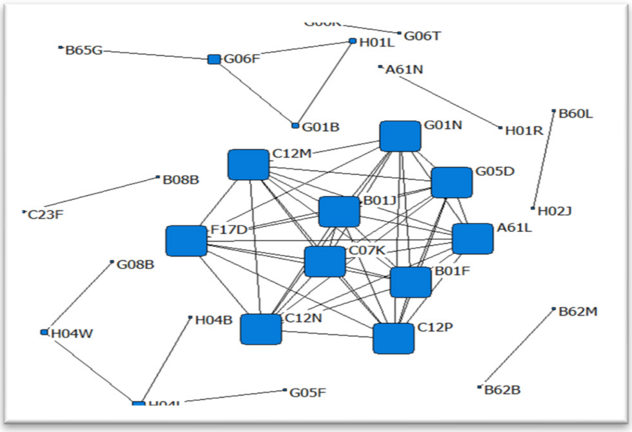
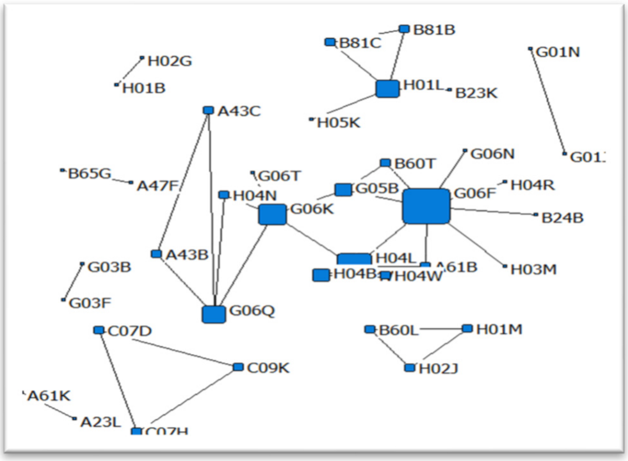
4.1. Results

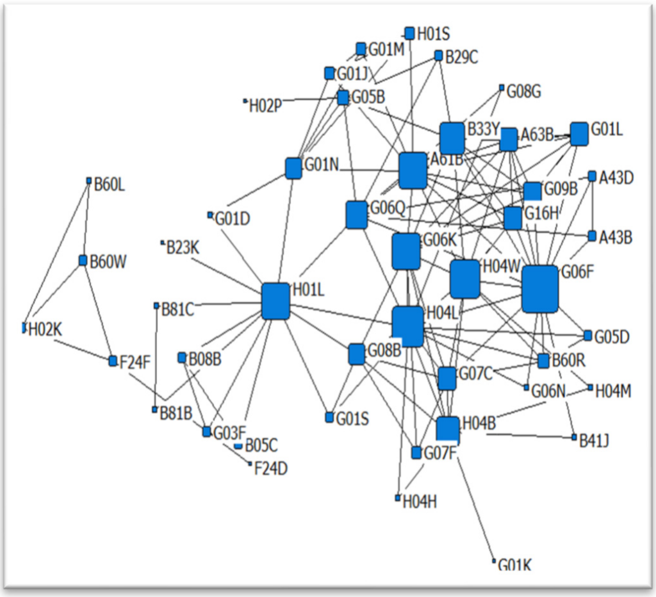
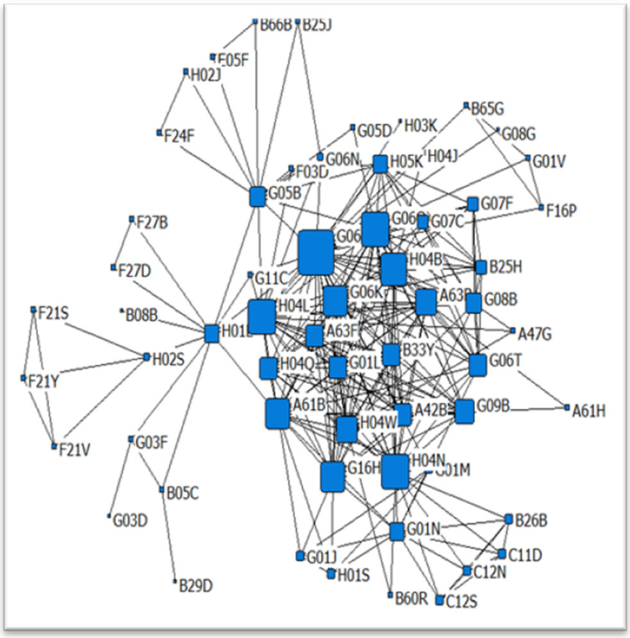
The network visualization of IPC codes per year is derived via UCINET. These networks show the relationship among various technologies in patent data for that particular year. It also highlights the major technologies which are playing a key role in networks. Technological convergence can also be seen and explored from the resulting networks. These networks can demonstrate the intersection of some specific areas of technologies over the years. The IPC codes associated with each year's patents were derived, and then the networks were created for each year. Some years have limited patents and IPC codes, so the authors derived networks from 1993 to 2019 in this study. In the results section, the authors presented networks for the last ten years because of space limitation. Here, the authors used these IPC code networks to analyze the technological convergence of the smart factory. Table 5 shows the IPC code networks for the respective years.

Table 5. IPC code networks and major technological convergence from 2008 to 2019.

Sr. No.	Year	IPC Code Networks	Remarks
1	2008		This network represents the technological convergence of digital data processing systems and related technologies.

<table>
<tr><td>2</td><td>2009</td><td>
</td><td>This network represents the technological convergence of photolithography for semiconductors.</td></tr>
<tr><td>3</td><td>2010</td><td>
</td><td>This network represents the technological convergence of data processing and data transfer control systems.</td></tr>
<tr><td>4</td><td>2013</td><td>
</td><td>This network represents the technological convergence of signal and call systems.</td></tr>
<tr><td>5</td><td>2014</td><td>
</td><td>This network represents the technological convergence of vehicle systems and data processing.</td></tr>
</table>

6	2015		This network represents the technological convergence of material diagnosis and communication systems.
7	2016		This network represents the technological convergence of wireless communication networks and investigating material properties.
8	2017		This network represents the technological convergence of recognition of data, electrical digital data processing, and communication networks.

9	2018		The IPC code network of the year 2018, containing technologies such as vehicle control systems, semiconductor applications, recognition and data processing, wireless communications, data transmission, and other technologies.
10	2019		While the IPC code network of the year 2019 contains the technological cluster of control systems in general, light and devices related to it, diagnosis and investigation technologies, furnace technology, digital data processing and transmission systems, and communication networks are also included.

The last two years, 2018 and 2019, contain the highest number of patents included in this case study. Therefore, their networks are complex too, as shown in Table 4. Both networks have clusters of many dominant technologies.

Moreover, centrality analysis has also been carried out for the extracted IPC codes from 1993 to 2019. Graphs of three different indexes of centrality are shown. First, the degree of centrality graph is shown in Figure 5. This graph shows how the degree centrality of some of the IPC codes increased rapidly during the last couple of years. Codes such as H01L, G06Q, and H04L are among the top IPC codes concerning degree increment. These IPC codes represent the technologies of semiconductor devices, data processing systems, and the transformation of data information.

As the actors with high degrees are considered central nodes in a network, major nodes are regarded as the most advantaged and most influential position in a network. So, the degree centrality graph illustrates that those codes with top degree centrality in recent years can highly influence the other technological nodes. Moreover, this graph shows that their linkages and relationships with other technologies have increased significantly in recent years. Figures 5–7 illustrate the need for and importance of technological convergence in a way that shows how technologies, associated with data orientation, have gained importance and have been continuously converged with other technologies for the smart factory.

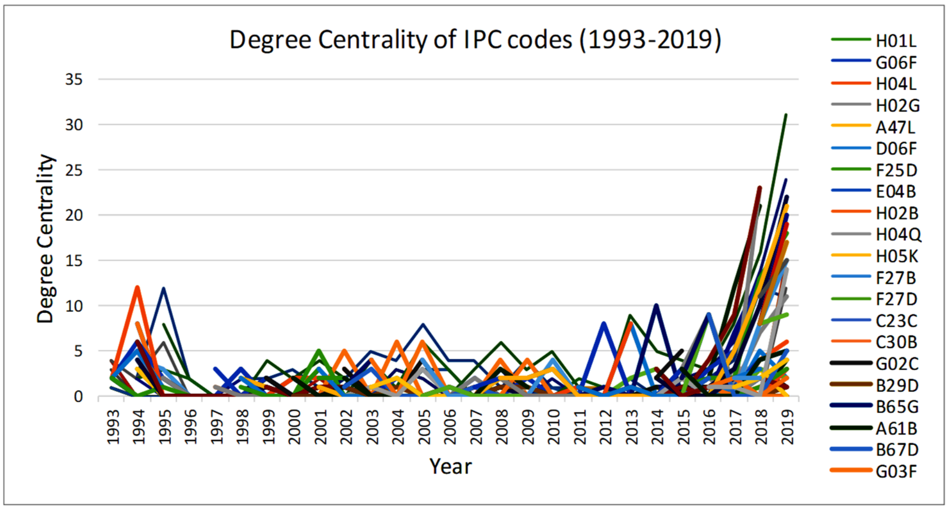


Figure 5. An illustration showing the degree centrality of all IPC codes in patent data from the years 1993 to 2019.

Figure 6 shows the closeness centrality of IPC codes from 1993 to 2019. IPC codes and their relevant closeness centrality are shown in the graph.

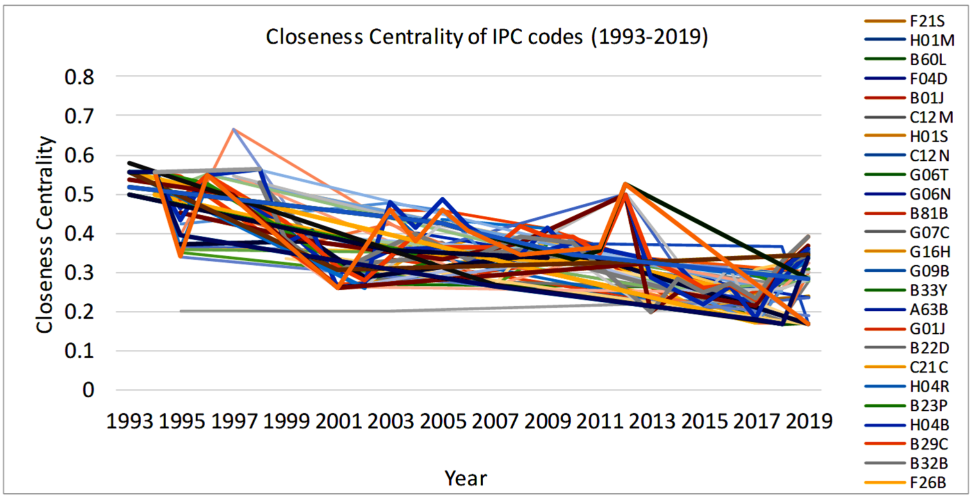


Figure 6. An illustration showing the closeness centrality of all IPC codes in patent data from the years 1993 to 2019.

Figure 7 shows the betweenness centrality of the IPC codes from 1993 to 2019. This graph illustrates that the betweenness of some top IPC codes has increased dramatically over the past few years. Mainly, the top IPC codes in this graph are G06F, H04N, and G06K. These IPC codes represent the technologies of electrical digital data processing, pictorial communication, and recognition of data.

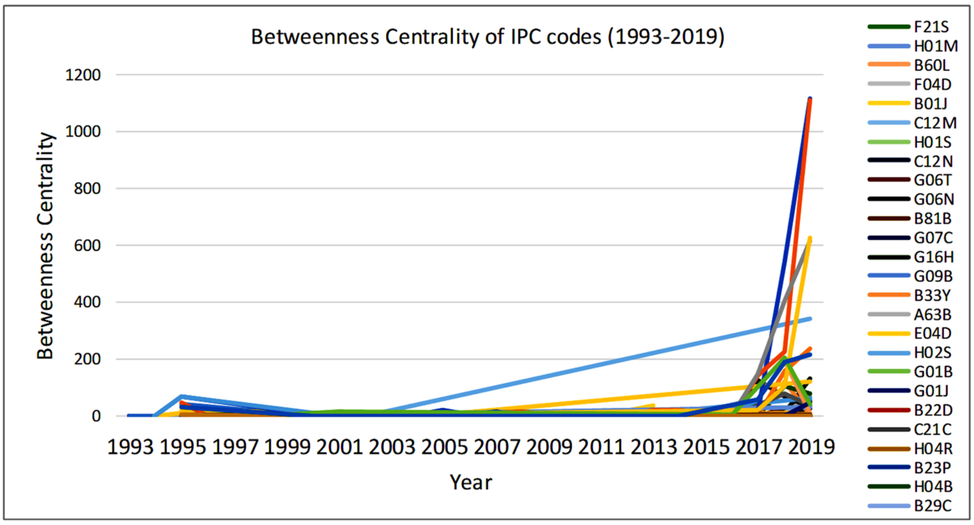


Figure 7. An illustration showing the betweenness centrality of all IPC codes in patent data from the years 1993 to 2019.

4.2. Discussion

This article addresses the technological convergence of the smart factory, which is a unique concept of Industry 4.0. So, a production facility such as a smart factory may lead to high efficiency, increased productivity, lower maintenance costs, customized production, etc. Hence, this article addresses issues related to the economic aspects of sustainable development. Further, it involves the evolution and investigation of technological convergence in the smart factory. It illustrates how the various technological convergence related to the smart factory has occurred during recent years. The technological evolution in recent decades can be easily understood with the help of technological convergence assessment.

The smart factory is a hot topic nowadays, and many researchers have studied it to investigate the implementation of various strategies and technologies in production systems. For example, Nascimento et al. explored smart factory technologies to implement the circular economy (CE) in a smart factory. And as a result, they found some positive effects of CE regarding waste reduction, reducing the negative environmental effects, and some positive social effects [1]. On the other hand, definitions, challenges, and hurdles in smart factory implementation and its enabling technologies have been discussed by [7]. In addition, RFID-enabled smart factories and IIoT-based smart factories have been investigated by [12,14]. Chen et al. discussed the key technologies and proposed the three-layer architecture for the smart factory, consisting of the physical layer, network, and data application layer. They conducted a case study and found some valuable findings regarding their proposed methodology for smart factory implementation [2]. Similarly, Won and Park explored the decision factors to introduce the smart factory concept in small and medium enterprises (SMEs) [50]. Resman et al. explained the procedure to implement the smart factory after reviewing the literature related to the smart factory [51].

So, from the previous findings, the authors had the idea that technological analysis of the smart factory has limited available literature. Therefore, a technological analysis was needed to provide valuable information about the technological convergence of the smart factory. In this study, the authors find that, with each passing year, the number of patents associated with smart factories increased. As a result, the technological networks have become more and more complex. Especially from 2016 onward, there is an increase in the number of related patents, showing the significance of smart factories in recent years. IPC code networks from the years 2016 to 2019 show the resulting complexity due to the higher number of nodes (codes) and more connections. Many innovations and technologies are being developed related to digital manufacturing. Our case study shows that, over time, technologies related to data analysis have gained significant importance. From the above networks, G06F, H04L, and H04W are the top three codes dominating the networks. G06F represents the technology of electrical digital data processing, according to the World Intellectual Property Organization (WIPO). H04L represents the transmission of data information technology, and H04W is related to wireless communication networks. We found that data-oriented technologies come as the major output. Many of the data-oriented technology convergence related to digital data transformation, data recognition, and data analysis technologies have appeared as appealing in smart factory scope. All of these codes are related to data analysis technology. Data has a vital role in smart factory development and operations. In the smart factory, machines are interconnected and share data. Indeed, the uniqueness of the smart factory lies in its ability to process real-time data and use it for decision-making processes. Better and on-time decisions are made based on data collected on the floor. Therefore, these technologies associated with data transmission, data processing, and communication networks truly represent the smart factory. Besides these technologies, there are some other technologies in the networks which also represent the technologies related to data processing and semiconductor devices. In short, the top IPC codes in the complex networks of recent years represent the technologies related to data processing and the transmission of information, which are the key aspects of the smart factory.

From the centrality analysis aspect, the authors obtained the top IPC codes related to the smart factory. These IPC codes also represent data-based technologies. After analyzing degree centrality, the authors identified G06F, H04L, H04W, and G06Q as the top IPC codes. These codes were obtained by analyzing their degrees in recent years. So, these codes have the highest degree in the last couple of years, showing their dominance in the degree centrality category. Table 6 reveals the top five degree centrality IPC codes of the last three years, from 2017 to 2019. It illustrates the dominance of some specific technological IPC codes, which are mostly related to data processing technologies.

Table 6. The top five degree centrality IPC codes and their representative technologies (2017–2019).

Year	2017	2018	2019
1st	G06F (Electric digital data processing)	G06F (Electric digital data processing)	G06F (Electric digital data processing)
2nd	H04L (Transmission of digital information)	H04L (Transmission of digital information)	H04L (Transmission of digital information)
3rd	G06K (Recognition of data)	H04W (Wireless communication networks)	G06Q (Data processing systems)
4th	H01L (Semiconductor devices)	H01L (Semiconductor devices)	H04N (Pictorial communication)
5th	G06Q (Data processing systems)	A61B (Diagnosis; Surgery; Identification)	H04B (Transmission)

Meanwhile, closeness centrality shows how close a node is to other nodes. In the case of the smart factory, the authors identified G06F, H04L, and G06K as the main codes for closeness centrality. These codes have the highest closeness centrality for the given networks in recent years. Further, betweenness centrality highlights the most influential nodes in a network between different clusters of the network. Here, the authors identified H04L, G06F, and H01L as the most important nodes for betweenness centrality.

Since the number of smart factory patents increased significantly from 2016 to 2019, the number of classification codes in each year increased. As a result, IPC code networks have become complex and more saturated as they include more nodes. Hence, the degree centrality of nodes increased in this manner. Due to an increment in the degree of centrality, some of the major nodes in the network gained more promising positions, which impacted their connections. They are playing a key role in the networks, and show that many technologies are dependent or connected with the more central node. In our case study, these nodes are mostly related to data-oriented technologies, which shows how these technologies have gained significant importance to the smart factory in recent years. Many nodes (technologies) are connected to these nodes (data-oriented technologies), showing the possible technological convergence of data-oriented technologies for the smart factory. The research results indicate how technological convergence evolution has taken place over the past few decades. The authors found some prominent technologies which gained significant importance over this time. The authors found that major IPC codes are associated with data processing and information transmission by analyzing both network and centrality aspects. So, it is clear from the above results that the future of production facilities and smart factories is based upon data-related technologies. The smart factory, where machines will be interconnected and share information, will rely on these data-oriented technologies.

5. Concluding Remarks and Recommendations for Future Work

This work was performed for a detailed investigation of the technological convergence assessment using network analysis. Firstly, the authors gathered patent data on the smart factory from the USPTO website. Subsequently, using patents, IPC codes were retrieved, which provided information about technology. In this investigation, four-digit IPC codes were used. Adjacency matrices were generated for each year, and then patent network analysis was performed using UCINET software. The network nodes reflect the smart factory's IPC codes. The networks depict the relationships between distinct codes. The authors discovered some of the most important smart factory technologies and the technological convergence of numerous technologies over the years through multiple networks. The findings of this study include the following:

- Results show that data-oriented technologies have gained a significant uprise over the last decade and they are going to play a vital role in the smart factory. The top related IPC network codes include G06f, H01L, and H04L.
- According to the World Intellectual Property Organization (WIPO), these IPC codes reflect digital data transformation and communication technologies. The technological convergence and connections between diverse technologies are investigated via these networks. The findings from WIPO patent data depict the major technologies in the smart factory's IPC code networks. Then, a centrality analysis of these networks demonstrates how some specific technologies have gained significance.
- The obtained results illustrate that major technologies in these networks are associated with digital data transmission, communication technologies, electrical digital data processing, and data recognition. Moreover, the authors witnessed the technological convergence and dominance of data-oriented technologies over the last couple of years.

Contributions of this research include:

- The technological convergence evolution of the smart factory over the past couple of decades.
- This work can provide a reference to assess the technological convergence of the smart factory field using patent data.
- This study offers assistance to industries in investing and flourishing in a predictable manner, rather than in an unpredictable manner.
- The results of this research offer help to policymakers and other relevant authorities in making decisions for future policy development.
- The smart factory technological assessment study can assist industry managers in identifying new technology investment possibilities, avoiding risks, and forecasting future technological trends in the transformation of industries.

- It will also assist government officials in developing policies based on future requirements. It can also be beneficial to science and technology research and development policies.

Despite having some contributions, this research also suffers from limitations. Moreover, there are some works that can be done in the future, such as:

- Firstly, the data employed in this study is restricted. In this study, only patent data from a small number of patents are evaluated. However, researchers will be able to use a large quantity of data from different sources in the future. Collecting more accurate and larger amounts of data can help to guarantee the legitimacy and breadth of the research.
- Secondly, IPC codes are occasionally altered or modified to meet other demands. In addition, other patent information, such as citation and patent number, can be utilized to evaluate the data, instead of only IPC codes.
- Future studies can also look at the new potential of the smart factory technological assessment using different techniques other than network analysis and patent analysis.

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