Asian Journal of Innovation and Policy (2021) 10.3:380-403
DOI: http//dx.doi.org/10.7545/ajip.2021.10.3.380

Analyzing Technological Trends of Smart Factory using Topic Modeling

Adnan Hussain*, Chulhyun Kim, Ganchimeg Battsengel***, Jeonghwan Jeon ******

Abstract Recently, smart factories have gained significant importance since the development of the fourth industrial revolution and the rise of global industrial competition. Therefore, the industries' survival to meet the global market trends requires accurate technological planning. Although, different works are available to investigate forecasting technologies and their influence on the smart factory. However, little significant work is available yet on the analysis of technological trends concerning the smart factory, which is the core focus herein. This work was performed to analyze the technological trends of the smart factory, followed by a detailed investigation of recent research hotspots/frontiers in the field. A well-known topic modeling technique, namely Latent Dirichlet Allocation (LDA), was employed for this study described above. The technological trends were further strengthened with the in-depth analysis of a smart factory-based case study. The findings produced the technological trends which possess significant potential in determining the technological strategies. Moreover, the results of this work may be helpful for researchers and enterprises in forecasting and planning future technological evolution.

Keywords Smart factory, Topic modeling, Latent Dirichlet Allocation(LDA), Patent analysis, Technological trends, Industry 4.0

Submitted on July 19, 2021; 1st Revised, August 29, 2021; Accepted, September 15, 2021
* Master student, Dept. of Industrial & Systems Engineering, Gyeongsang National University, Jinju, Republic of Korea, adi.husayn@gmail.com
** Professor, Dept. of Industrial Engineering, Induk University Seoul, Republic of Korea, stddevs@induk.ac.kr
*** Master student, Dept. of Industrial & Systems Engineering, Gyeongsang National University, Jinju, Republic of Korea, ganchimeg09@gmail.com
**** Corresponding, Professor, Dept. of Industrial & Systems Engineering, Gyeongsang National University, Jinju, Republic of Korea, jhjeon@gnu.ac.kr

I. Introduction

Boundaries among physical, digital, and biological space are blurring due to industry 4.0. As a result, competition between global firms is growing due to modern technologies used in industry 4.0. Industry 4.0 has many concepts that are currently in discussion regularly by researchers. Among these, the smart factory is a fundamental concept of industry 4.0. It is sometimes known as the factory of the future and smart industry (Lucke et al., 2008; Zuehlke, 2010). Several studies on smart factories have been undertaken with the advent of the industry 4.0 era. Radziwon et al. (2014) defined the smart factory as the manufacturing solution which 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 many issues associated with the manufacturing industry, which conventional technology cannot handle. For example, cloud computing and data analytics technologies will make it possible to use production data for system optimization. Similarly, the use of artificial intelligence in production systems will facilitate the decision-making process. Moreover, J. Lee et al. (2015) proposed five-step guidelines to implement the industry's cyber-physical systems (CPS). Lehmhus et al. (2016) considered the customized production in the smart factory using additive manufacturing techniques, such as 3D printing. Also, Tao & Zhang (2017) investigated the digital twin shop-floor (DTS) model for a smart manufacturing facility. Due to its flexibility and problem-solving quality, smart factory is becoming more popular in countries across the globe.

Many technologies are being used or expected to be used in the smart factory. Some of the core technologies are the Industrial Internet of Things (IIoT), Cyber-Physical System (CPS), Cyber Security, and Artificial Intelligence (AI) (Alcácer & Cruz-Machado, 2019). Smart factories can bring revolution in the manufacturing industry through its up-to-date technologies. However, the smart factory is still in its introductory stage, and authors can catch up on the technological trends. In this respect, enterprises and countries are looking to populate and implement the smart factory concept into their manufacturing industries and introduce new technologies. Such as B. Chen et al. (2017) have investigated the key technologies and the existing challenges to implementing these technologies. They successfully conducted a case study to implement and found that these technologies are helpful for the overall productivity of a smart factory. Similarly, Yang et al. (2018) explored the research trends of smart factory and found some of the hot topics for research in the existing literature. Smart manufacturing had many challenges in the past, so Kang et al. (2016) explained the past research, the present state of the art, and the future perspective of smart factory research. Besides some research on smart factory and its technologies by various researchers, the technological trend analysis of smart factory has limited research. Also, smart factory's quantitative technological trend analysis is key for survival in the ever-increasing competitive market.

To cope with smart factory technologies, accurate analysis and technological planning are needed to be undertaken. Therefore, this research aims to analyze the technological trend of the smart factory using the topic modeling technique. The authors further analyzed the hot and cold technological topics to see the future trend. For this purpose, topic modeling has been used in this study. It is a very famous data mining technique often used to monitor technological trends. Therefore, this method can make it possible to analyze the technological trends of the smart factory. Moreover, this analysis can help for long- and short-term technological planning.

The remaining of the paper is structured as follows. First, the authors presented a review of smart factory and topic modeling in section 2. Then the research procedure is given in Section 3. The case study is provided in Section 4. In Section 5, the authors discuss the results. Finally, in Section 6, the conclusion of this work is presented. Following Figure 1 shows the overall framework of this study.

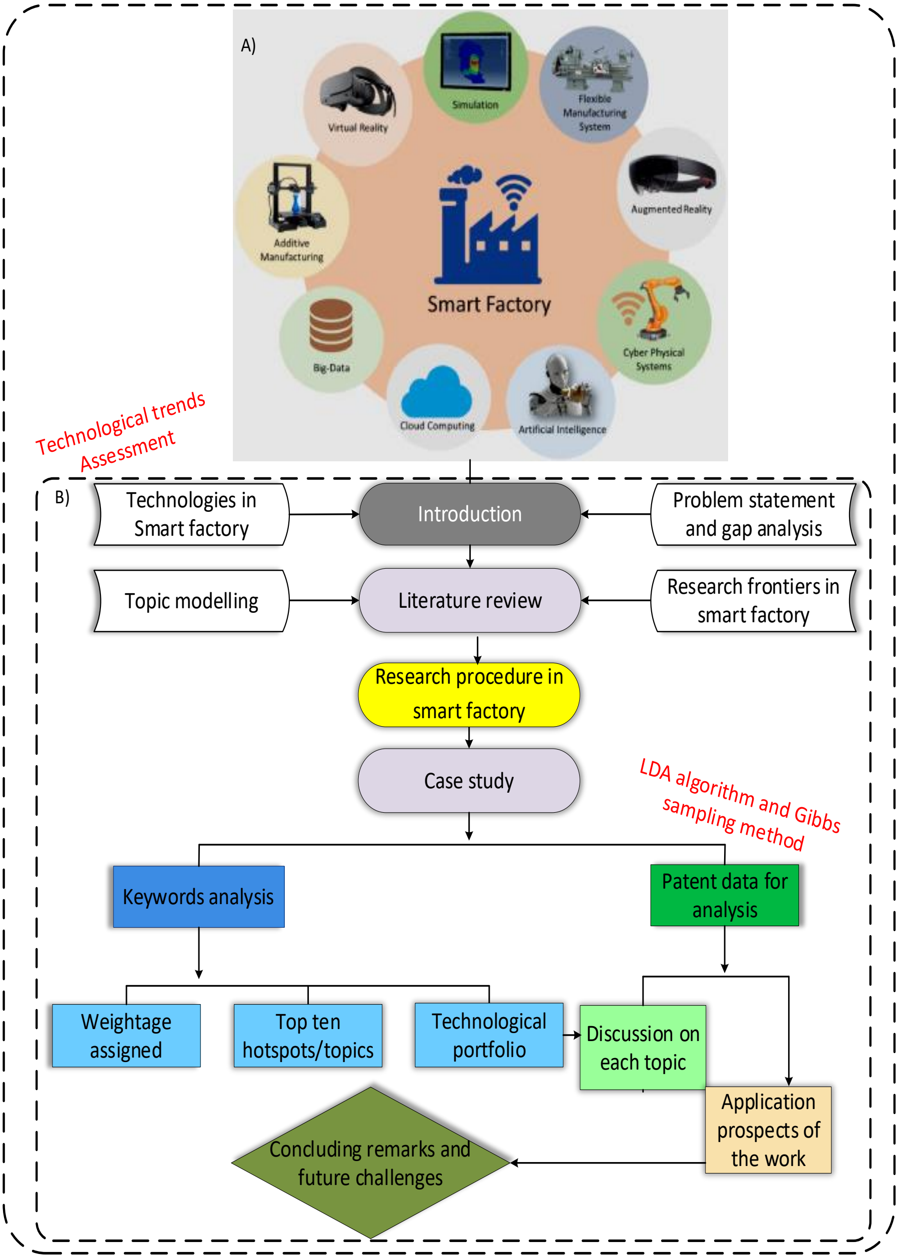

Figure 1 A detailed framework of the study,
(a) An illustration of different application prospects of smart factory (Phuyal et al., 2020)
(b) A practical demonstration of technological trends assessment using Topic modeling

II. Literature Review

1. Smart Factory

In the 4th industrial revolution paradigm, the manufacturing sector is growing steadily and finding new ways to reduce cost and time and improve overall operations. The concept of Industry 4.0 facilitates the paradigm-shifting from automated manufacturing to a fully integrated intelligent production system (Lucke et al., 2008; Thoben et al., 2017; Wiktorsson et al., 2018). A general view was developed to emphasize new ways to help smart decisions in a production facility. This concept is famous as industry 4.0 in Europe and smart manufacturing in the USA (Kang et al., 2016; Lasi et al., 2014; Mohamed et al., 2019). Many of its concepts are under discussion, and the smart factory is one of them. Industry 4.0 and its concepts, such as smart factory are equally famous among researchers and industrial practitioners. However, no agreed-upon definition is available for the smart factory (Lee et al., 2018). It can be defined as the manufacturing solution which can provide flexible and adaptive production processes that can solve the complicated manufacturing problems of a production facility in an increasingly complex world (Radziwon et al., 2014). Solution of challenges such as, Energy-saving, decentralization, and cyber security are a few examples of smart factory attributes which were not possible in the past. Technologies like the digital twin will help to stimulate the whole process in parallel to the actual process digitally. According to some researchers, the smart factory is limited to a plant level (a single entity) rather than extended to a broader scope of industry 4.0 (Lucke et al., 2008; Thoben et al., 2017). Moreover, it is also known by different names by various scholars, such as factory of things (Zuehlke, 2010), intelligent factory of future (Lucke et al., 2008), or real-time factory (Hameed et al., 2011). Yang et al. (2018) investigated the current research trends of the smart factory with the help of topic modeling technique and extracted some current research directions associated with smart factory. Moreover, an implementation guide for the smart factory has been carried out (Pagnon, 2017). He successfully experimented with implementing the smart factory concept and found it beneficial for the customers, workforce, and management (Pagnon, 2017).

It is a paradigm and practical example of the Cyber-Physical System (CPS), where machines are equipped with intelligent devices such as actuators and sensors (Cheng et al., 2018; Thoben et al., 2017). Industry 4.0 is associated with many technologies such as IoT, CPS, robotics, BIG data analysis, and cloud computing (Mittal et al., 2019) to witness the practical example of a data-driven production system (Thoben et al., 2017). In this respect, modern technologies such as IIoT, BIG Data, and Cyber Security are the key players which relate to paradigm-shifting (Thoben et al., 2017). For example, these technologies are capable of analyzing the production data and using it to optimize the system. Moreover, interconnectivity and data protection systems are also related to paradigm-shifting. Shi et al. (2020) investigated the key challenges, requirements, available technologies and provided guidelines to implement the smart factory in the context of the 4th industrial revolution. Similarly, Resman et al. (2020) also described the methodology, including eight crucial steps to implement the smart factory.

Competition among businesses is also increased due to the advanced technologies available in the present era. Furthermore, modern technologies being used in smart factories are expected to provide solutions for problems that conventional technologies cannot solve (Yang et al., 2018). Thus, upgrading the existing technologies with new up-to-date technologies in manufacturing units and building an intelligent factory to improve productivity and reduce cost and time (Zhu et al., 2018).

2. Topic Modeling

In this continuously growing complex world, electronic data is being generated every second. Unfortunately, the format of such a massive set of data is basically "unstructured," so it is difficult to find some crucial information from such comprehensive and unstructured data. Dealing with this large set of data and deriving some helpful information requires tools and techniques that can automatically organize, index, and search the extensive collection of calculations. Recent studies in machine learning and statistics develop new hierarchical probability models, finding the word pattern in a set of documents. These models are known as "Topic Models" (Alghamdi & Alfalqi, 2015; Blei & Lafferty, 2006).

Nevertheless, with the help of some text mining techniques and classification, the authors can attain some meaningful topics from the data. These topics consist of essential keywords in a large set of unstructured data (Anantharaman et al., 2019). These discovered word pattern often reflects the underlying topics which form a document. Figure 2 shows an example of topic modeling.

The figure shows that different topics can be derived from a set of documents through topic modeling techniques. The primary algorithm used in these techniques categorizes the keywords from documents into various topics. As a result, the words in topics are correlated and present an almost identical meaning.

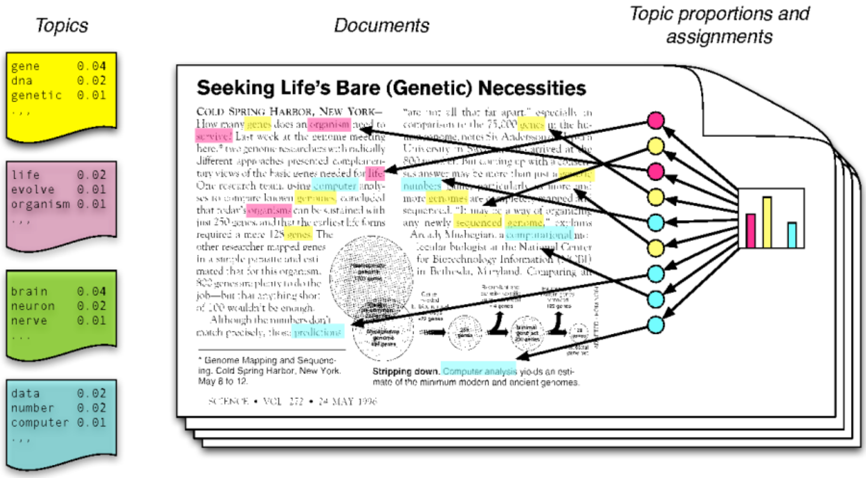

Figure 2 Example of Probabilistic topic modeling (Blei et al., 2010), an illustration of how this algorithm assigns words to topics

Following Figure 3 shows the primary topic modeling techniques.

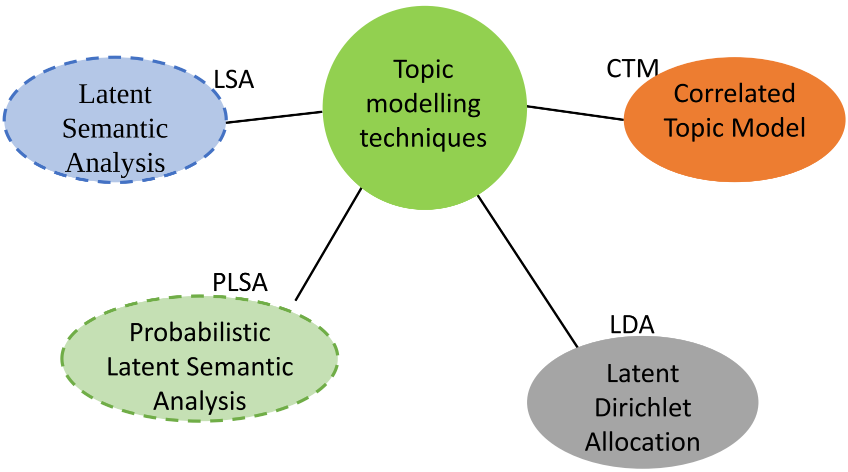

Figure 3 An illustration to show different primary classifications of Topic modeling techniques

Out of these topic model techniques, the authors selected LDA to be used in this study. LDA is the most famous among other methods (Porter, 2018). LDA maps the given document into a set of imaginary topics, and these imaginary topics capture the words present in the document. It is a technique or tool which facilitates the discovery of themes in a collection of documents. Another reason to choose LDA for our research it can estimate the mixture of existing topics in newly given documents without updating the current model. High volumes of documents can be handled in LDA because it has a fixed number of parameters regardless of the corpus size (Lee et al., 2018). Therefore, LDA is a very famous topic modeling technique. Many researchers used this technique to investigate or find trends in various fields. Such as, Erzurumlu & Pachamanova (2020) studied healthcare technological forecasting and used topic modeling to predict future technologies related to the healthcare system. Similarly, Chen et al. (2020) researched the detecting educational technologies over four decades using topic modeling techniques. They found crucial hotspots in the research trends of the computer and education field. Furthermore, Jeon & Suh (2017) used this technique to analyze the major issues of the 4th industrial revolution and extracted useful information.

Also, it is a probabilistic model in which it is assumed that a record is consists of topics (Blei & Lafferty, 2006; Campbell et al., 2015; Jeon & Suh, 2017). Hence, each topic has its unique probability distribution, defining how likely a word can be assigned to a topic (Anantharaman et al., 2019; D. Blei et al., 2010). Figure 4 illustrates the algorithm of the LDA model.

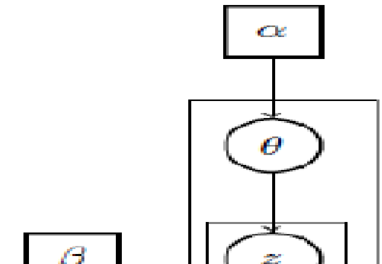

Figure 4 The Plate diagram of an LDA model

Here, "D" is the set of documents called the corpus, "W" represents the number of words in document "D", θ is the topic distribution for a document d, α represents the Dirichlet prior on the topic distributions in a document, β represents the Dirichlet prior parameter of the word distribution in a topic, z_{dn} refers to the topic for the nth word in document d, w_{dn} refers to the specific word and, ϕ refers to the word distribution for topic k.

III. Research Methodology

Figure 5 shows the research process for this study. First, data was collected from the United States Patent and Trademark Office (USPTO) related to the smart factory. USPTO (https://www.uspto.gov) is a well-known source for patent collection. The authors' search keywords were smart factory, smart manufacturing, connected factory, cyber-physical system, and industry 4.0. Next, patents associated with these keywords were collected using java code.

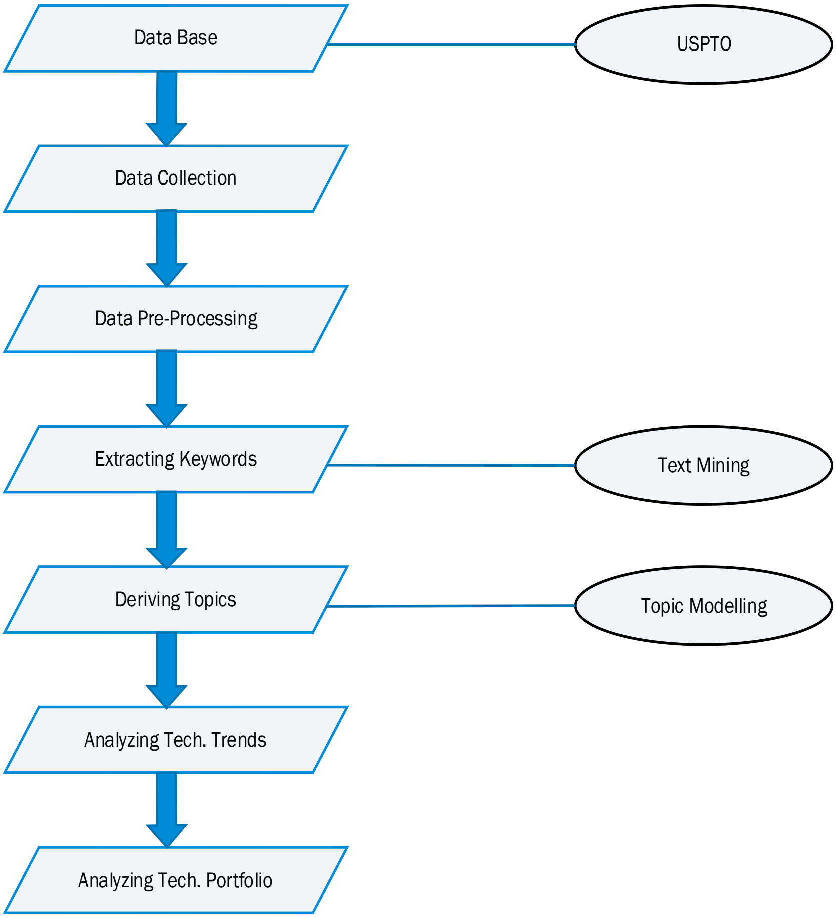

Figure 5 Resarch process of this study

Then data were pre-processed for extracting the keywords. In this context, a topic modeling package for R programs is used to extract the keywords. Next, topics were derived from these keywords. Each topic was named according to the correlated keywords it contains. Obtained topics were then analyzed to find the technological trends for the smart factory. A technological portfolio is then analyzed with the help of derived topics.

IV. Case Study

The authors conducted a case study to analyze the technological trends of smart factory. For this purpose, a total of 672 patents were collected from USPTO. The authors used some specific search keywords to search for the patent. Patent data was collected from the year 1976 to 2019. Table 1 shows how many patents were collected associated with each searching keyword.

Table 1 Patents for each keyword

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

The authors used six different keywords to search for patents associated with the smart factory in this study. These keywords were carefully decided after studying some literature related to smart factory and smart manufacturing. Figure 6 shows the number of patents collected for each year from 1976 to 2019.

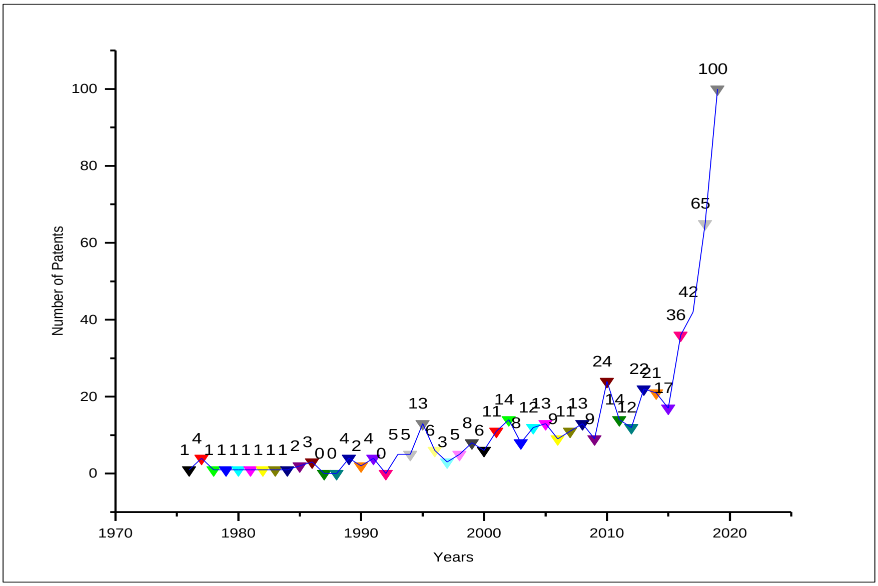

Figure 6 Patents collected per year(1976-2019)

The above graph indicates that how smart factory and smart manufacturing is gaining the attention of researchers. These terms achieved massive popularity after the German government initiated its Industry 4.0 program. Also, at almost the same time, the USA initiated its Smart Manufacturing program. Significantly, in the last decade, it gained a huge success. The authors collected the maximum number of patents from 2009 to 2019. Patents extracted in 2019 are 100, and maybe this number shall increase soon as the smart factory is becoming a hot topic nowadays. Collected patents were pre-processed (as collected data was unstructured) using text mining techniques to convert the data into structured data. In this process, the authors used R Programming to extract valid words and remove the abusive words. For this purpose, the R code was run multiple times to achieve good results and eliminate abusive words. Moreover, after removing abuse words, the authors got a dedicated and satisfactory result. Authors constructed a word cloud of these acceptable words. In this word cloud, words are related to the smart factory, manufacturing, sensors, devices, and other technologies being used in modern-day manufacturing. Based on the frequency, the most frequent words are highlighted in the word cloud, such as data, system, network, information. Figure 7 illustrates the word cloud of the top keywords as follows.

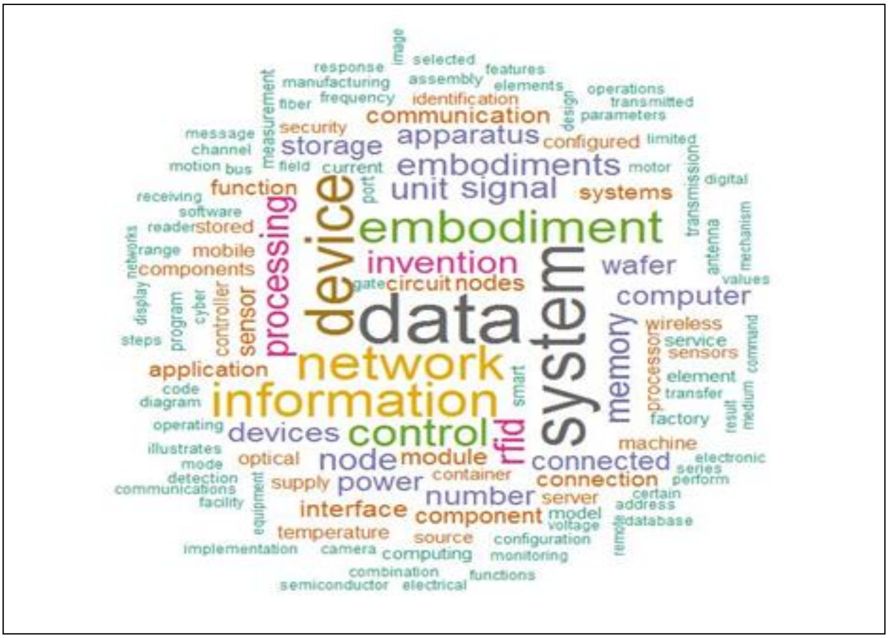

Figure 7 Word cloud obtain after pre-processing of data

Moreover, the authors extracted the valuable keywords from a large data set, so the authors had words and their relevant frequencies. The top 20 keywords regarding relevant frequency are shown in following Figure 8.

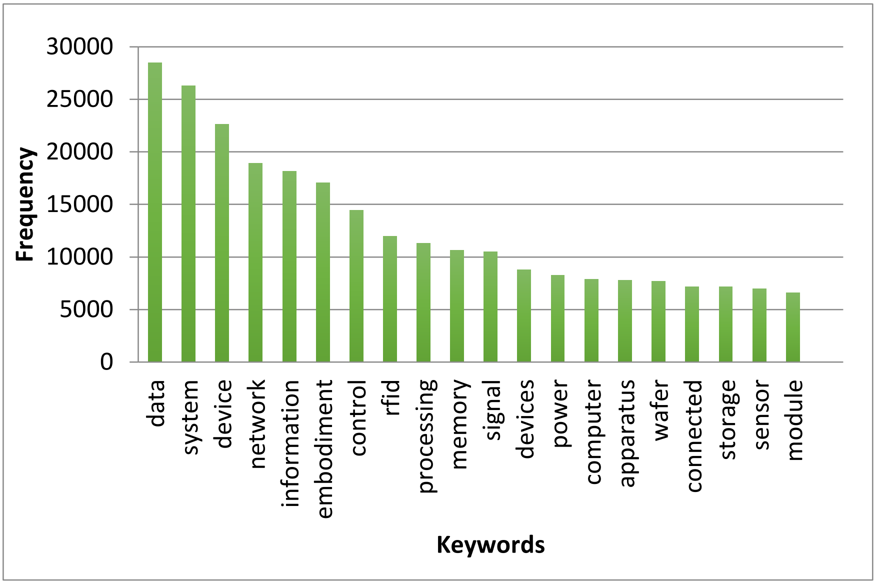

Figure 8 Top 20 keywords present in the smart factory patent data

To derive the topics, the authors used the LDA algorithm and Gibbs sampling method. Expressly, the authors set the necessary parameters and derived ten topics containing valuable keywords related to the different technologies used in the smart factory. Then according to the extracted words relevancy and relationship, authors named each topic. Table 2 shows the extracted topics using topic modeling.

Table 2 Topics derived from the data using topic modeling technique

T 1 **RFID**	T 2 **APIs**	T 3 **AI**	T 4 **Sensors**	T 5 **Cloud Computing**
information	security	wireless	invention	sensor
embodiment	frequency	values	data	controller
control	elements	measuring	signal	program
number	interface	address	network	model
processing	receiving	monitoring	embodiments	channel
rfid	port	features	power	database
using	sensors	wafers	apparatus	computing
computer	impedance	operating	connected	implemented
wafer	embodiment	automatically	module	pattern
component	generate	indicating	device	solution
T 6 **IT/OT Integration**	T 7 **Digital Twin**	T 8 **Mobile Interface**	T 9 **Cyber Security**	T 10 **IoT**
set	node	current	circuit	system
nodes	features	identification	supplied	data
diagram	data	application	password	device
via	cells	function	cyber	memory
limited	modules	range	resource	network
circuit	voltage	bus	security	devices
interface	graphical	steps	cables	storage
facility	bus	network	wireless	communication
software	embodiments	server	silicon	processing
connector	magnetic	mobile	programs	antenna

Topics titles are key technologies being used in the present era manufacturing system. Authors named topics like cybersecurity, IoT, AI, and RFID. Authors named them according to the keywords present in them and the relevance of keywords among each other. In this way, the authors analyzed the technological trends of the smart factory.

The authors extracted the weightage of each topic present in our corpus. The result of the above analysis is shown in Figure 9, which indicates that the most popular topics from the smart factory perspective are [T10] Internet of Things, [T1] Radio Frequency Identification (RFID), and [T4] Sensors. In contrast, other topics such as APIs and mobile interfaces are relatively low.

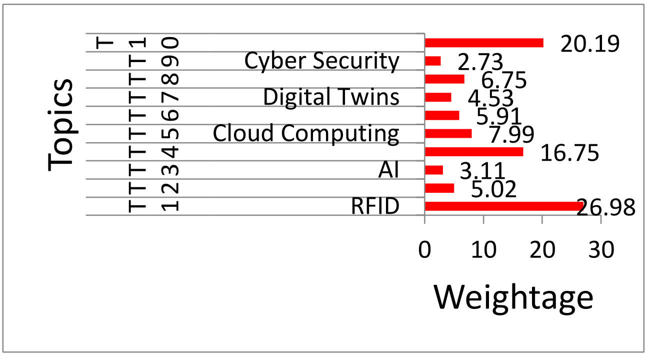

Figure 9 Topic weightage derived from the topic modeling technique (using R program)

After extracting the topics, the authors investigated rising and declining topics of the smart factory field over the last ten years. The yearly trend of topics over the previous ten years is classified as hot and cold topics. The purpose of the distinction between hot and cold topics in this study is to see which topics show an increase or decrease in the recent decade. So that authors can analyze its present status, whether this technology/topic reached its maturity or still has the potential to grow. For this purpose, regression coefficients of linear regression analysis were used as a criterion to judge the yearly trend of each topic as rising and falling. Time series analysis was performed, fixing year as an independent variable and yearly weighted average value of smart factory technology as a dependent variable to identify trends by year for each topic. In this case study, authors analyzed hot and cold topics for the last ten years, from 2010 to 2019. The authors chose only ten years because the number of patents increased significantly in the previous decade. The smart factory's hot and cold topics are shown in Figure 8, which shows that the hot topics are rising, such as T3, T5, T6, and T10. Hot topics indicate that these technologies are in discussion among the scientific community.

On the other hand, cold topics are T2, T1, T4, T7, T8, which shows their declining trend. T9 is in warm condition as its trend is continuously fluctuating over the last ten years. Figure 10 shows the hot and cold trends of topics.

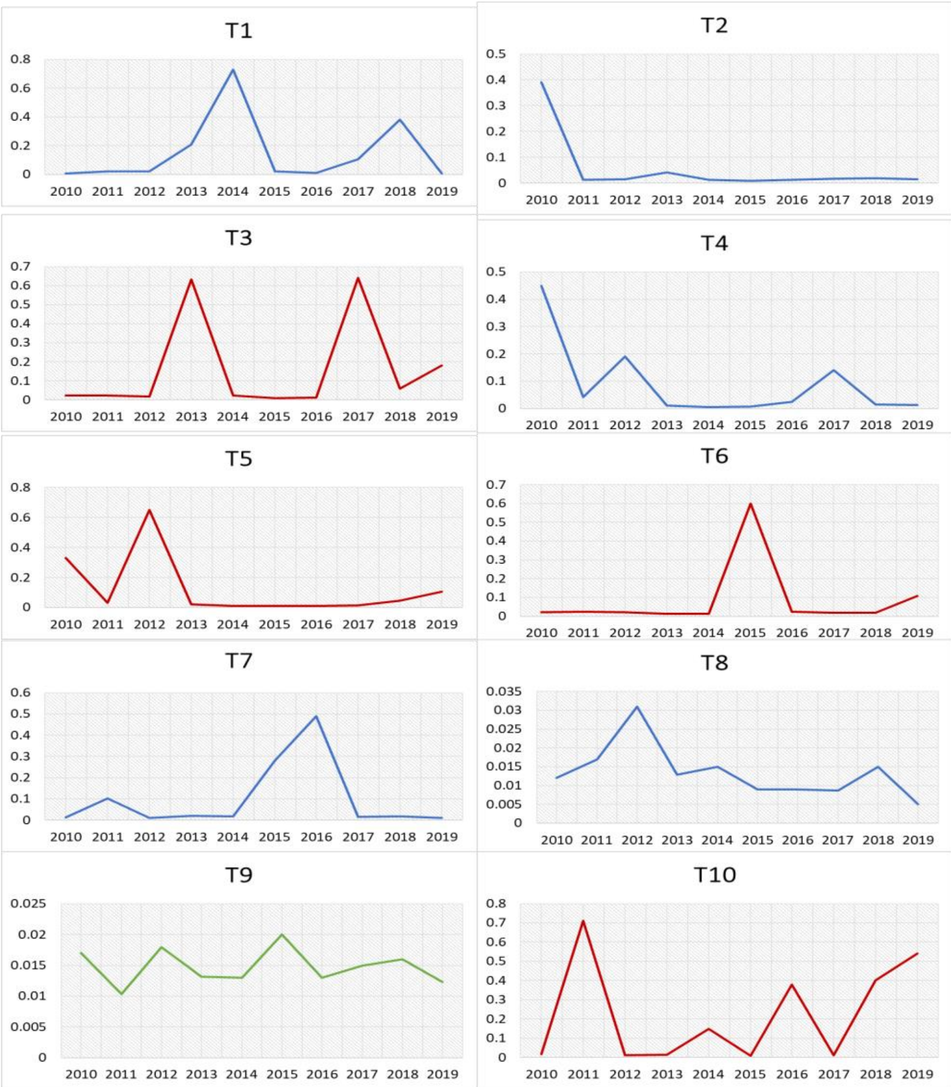

Figure 10 Hot and cold derived topics over the last 10 years

After assigning names to each topic and analyzing the technological trends, authors construct a technological portfolio for the derived topics.

The authors divided the smart factory into three subfields: Digitalization, Networked IIoT, and Manufacturing Technologies. The authors then assigned each topic to a specific subfield according to its relevance to that field. For example, [T7] Digital twins and [T2] APIs lie in the Digitalization field while

[T1] RFID and [T10] IoT lie in the Networked IIoT field. Following figure 11 shows the technological portfolio of the smart factory.

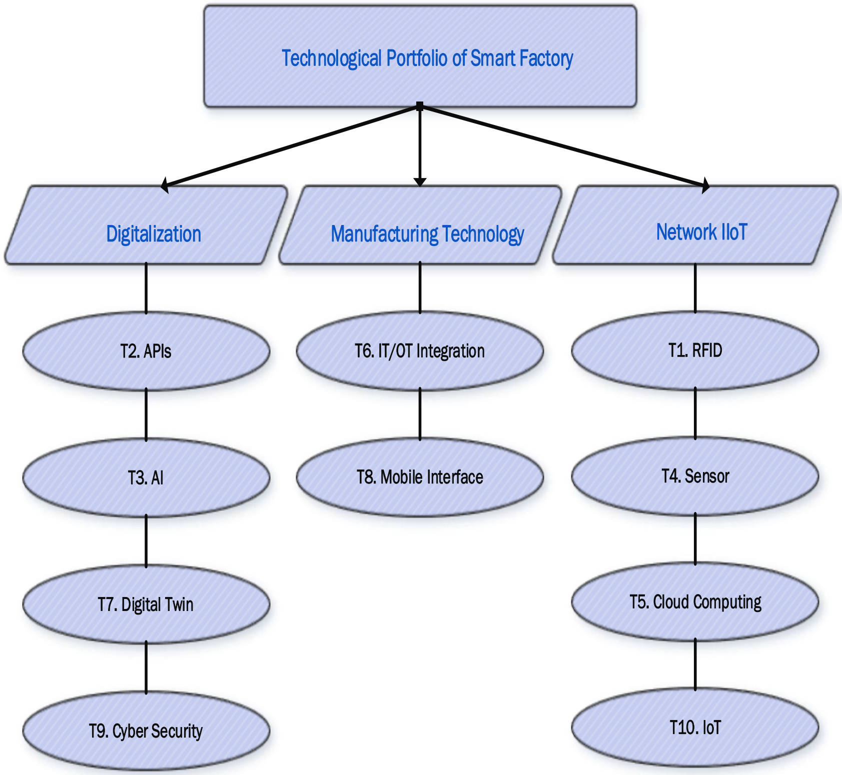

Figure 11 Technological portfolio of smart factory from patent analysis

V. Discussion

In this study, the authors analyzed the technological trends of the smart factory. By using the topic modeling technique, the authors extracted ten topics. These topics consist of keywords that are interconnected and relevant to each other. And then, according to the relevancy of the keywords, authors assigned the names of each topic. Thus, these topics reflect the technologies of the smart factory.

Topic 1, represented by RFID, information, and processing, reflects Radio Frequency Identification (RFID) technology or information processing. As RFID is an important means of information processing between the different entities, almost every industry uses this technology to process and collect information to provide data about the current status, location, and identification.

Topic 2, represented by the interface, receiving, sensor and port, reflect the Application Programming Interface (API). It is a set of functions that allows the application to access data and interact with an external data set. For example, in a smart factory, it is helpful to observe and management of operations remotely.

Topic 3 reflects monitoring, measuring, values and automatically reflects Artificial Intelligence (AI). As AI is a fundamental technology for modern-day manufacturing, it can help monitor and optimize the production process autonomously. It reduce4 human interaction in decision-making and helps to predict events.

Topic 4, represented by signal, network, apparatus, and device, reflects the sensor technology. As in a smart factory data is being collected through advanced devices and sensors. Therefore, sensor technology will play a crucial role in smart factory operations. In addition, these devices are often connected in networks for collected structured data.

Topic 5 reflects the database, computing, and program reflects the cloud computing technology. This technology deals with the massive data collected by the sensors and devices mounted on the machines in a smart factory. The data is then stored in the cloud and computed to extract useful information.

Topic 6, represented by nodes, circuit, interface, facility, connecter, and software, reflects IT/OT integration technology. Information technology and operation technology can be integrated to get better results in the manufacturing processes of the smart factory. Through this technology, the execution of processes along with data collection is smoothened.

Topic 7, represented by features, data, graphics, and embodiment, reflects the Digital Twin technology. The digital twin is used to replicate the processes to collect the data & predict how they shall perform in the future. This technology is critical in modern days to demonstrate the process before the actual operation.

Topic 8, represented by Mobile, function, network, current, identification, and application, reflects the Mobile Interface technology. It is a graphical and touch-sensitive display that allows users to interact with apps, functions and identify the current status of the process or machine.

Topic 9, represented by security, cyber, silicon, and programs, reflects Cyber Security. It is among the vital topics and technologies of the smart factory. A smart factory involves a massive amount of data to process and many digital devices in its processes, so it becomes ample to secure the data from any cyber-attack. Therefore, organizations are working to secure their facilities from any kind of such cyber-attacks.

Topic 10, represented by data, devices, communication, processing, and antenna, reflects the IoT technology. It is the most crucial technology of a smart factory as it involves connecting the machines and collecting data for further processing.

Also, the weightage of each topic is measured with R programming. Among ten topics of RFID(T1) is the highest in weightage, it received the most attention, which means that information processing technologies are very active. IoT(T10) is 2nd on the weightage list, and it is the important motivation for a data-oriented production facility. Then, sensor technologies(T4) are in third place for high weightage. Finally, cloud computing(T5) is also essential. In short top topics are related to data-oriented technologies. The rest of the topics, given their low rank, illustrates that they are still discussed relatively low in academic terms. After that, the authors analyzed the hot and cold trends of these topics for the last ten years. These trends illustrate, which technologies are being discussed widely in the previous ten years, and these topics are regarded as hot topics of the smart factory. Meanwhile, topics in the declining form are relatively less in the discussion by the scientific community.

Moreover, to further analyze these topics, authors grouped them according to their association with each other. First, the authors make the technological portfolio of the smart factory. Then, the authors divided it into three parts as manufacturing technology, digitalization, and network IIoT. In manufacturing technology, authors combined T6 and T8 as they involved the manufacturing technologies. Then for digitalization, authors combined APIs, Al, Digital Twin, and Cyber Security. And finally, the authors gathered topics of RFID, Sensors, IoT, and Cloud Computing as they reflect the relevancy to network IIoT.

This analysis can help to establish the long and short time technological planning. It also shows which essential technologies are being discussed more often by the research currently associated with smart factories. Such as the authors can see from the weightage graph that some topics have more weight than others.

VI. Conclusion

In this study, the authors analyzed the technological trends of smart factory technologies and thus provided an overview of the trending technologies of the smart factory. The rise of the 4^{th} industrial revolution and merging physical & digital space has raised many questions for the future manufacturing industry. Out of these Industry 4.0’s concepts, one is the "*smart factory"*. This study attempts to check these much-needed trends of technologies that can be helpful for researchers and policymakers. First of all, the authors collected the smart factory patent data from the database USPTO. For this purpose, the authors used specific keywords after careful examination of the literature review of the smart factory. Then pre-processed the data collected from USPTO, unification, and noun extraction have been done. After that, stopwords or unrelated words were removed. Then major topics under the smart factory were derived using topic modeling techniques. First, derived Topics have been assigned specific names according to the keywords it contains. After that, topics' weightage and their hot and cold trends were analyzed. Moreover, the smart factory portfolio had also been constructed.

The significance of this study is as follows.

- *Firstly, in the past, research on the quantitative and systematic derivation of technology trends associated with the smart factory field using text data was insufficient. So, in this way, this research work is a step forward to introduce this method into the smart factory field using patent data.*
- *Secondly, it analyzed the patents related to the smart factory instead of relying on some web articles or industrial reports. Patent data have the advantage of "timeliness" in that the main concern of the field is instantly textualized.*
- *In addition, patents are a reliable source of information. Regarding the implication of this study, this research can effectively be used for policy development & technological strategy of smart factory.*
- *This research highlighted the promising technological topic of smart factory, which are potentially helpful for other researchers to explore further.*
- *This analysis will help investors and companies understand trending technologies and select the appropriate technology for their business, as installing a specific technology has a considerable cost. So, it will give an idea about the possible target technology.*
- *Moreover, it will help regarding short and long-term technology planning too.*

However, this study has some limitations and future research aspects, such as.

- *Time-series analysis of each topic*
- *Analyzing the relationship between each topic*
- *Moreover, this study used a limited number of patents from a single source, but multiple sources and large data sets can be used to achieve more accurate results in the future*
- *Furthermore, this study used only the topic modeling technique (LDA) to analyze the technological trends of the smart factory. However, the researchers can use other modern methodologies such as citation analysis, patent classification codes, and network analysis in the future.*

Acknowledgment

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government(MSIT) (No.2019R1A2C1090655).

References

Alcácer, V., & Cruz-Machado, V. (2019). Scanning the Industry 4.0: A Literature Review on Technologies for Manufacturing Systems. *Engineering Science and Technology, an International Journal*, *22*(3), 899–919. https://doi.org/10.1016/j.jestch.2019.01.006

Alghamdi, R., & Alfalqi, K. (2015). A Survey of Topic Modeling in Text Mining. *International Journal of Advanced Computer Science and Applications*, *6*(1), 147–153. https://doi.org/10.14569/ijacsa.2015.060121

Anantharaman, A., Jadiya, A., Siri, C. T. S., Adikar Bharath, N. V. S., & Mohan, B. (2019). Performance evaluation of topic modeling algorithms for text classification. *Proceedings of the International Conference on Trends in Electronics and Informatics, ICOEI 2019*, *2019-April*(Icoei), 704–708. https://doi.org/10.1109/icoei.2019.8862599

Blei, D., Carin, L., & Dunson, D. (2010). Probabilistic topic models. *IEEE Signal Processing Magazine*, *27*(6), 55–65. https://doi.org/10.1109/MSP.2010.938079

Blei, D. M., & Lafferty, J. D. (2006). Dynamic topic models. *ACM International Conference Proceeding Series*, *148*, 113–120. https://doi.org/10.1145/1143844.1143859

Campbell, J. C., Hindle, A., & Stroulia, E. (2015). Latent Dirichlet Allocation: Extracting Topics from Software Engineering Data. *The Art and Science of Analyzing Software Data*, *3*, 139–159. https://doi.org/10.1016/B978-0-12-411519-4.00006-9

Chen, B., Wan, J., Shu, L., Li, P., Mukherjee, M., & Yin, B. (2017). Smart Factory of Industry 4.0: Key Technologies, Application Case, and Challenges. *IEEE Access*, *6*, 6505–6519. https://doi.org/10.1109/ACCESS.2017.2783682

Chen, X., Zou, D., Cheng, G., & Xie, H. (2020). Detecting latent topics and trends in educational technologies over four decades using structural topic modeling: A retrospective of all volumes of Computers & Education. *Computers and Education*, *151*(September 2019), 103855. https://doi.org/10.1016/j.compedu.2020.103855

Cheng, J., Chen, W., Tao, F., & Lin, C. L. (2018). Industrial IoT in 5G environment towards smart manufacturing. *Journal of Industrial Information Integration*, *10*. https://doi.org/10.1016/j.jii.2018.04.001

Erzurumlu, S. S., & Pachamanova, D. (2020). Topic modeling and technology forecasting for assessing the commercial viability of healthcare innovations. *Technological Forecasting and Social Change*, *156*(March), 120041. https://doi.org/10.1016/j.techfore.2020.120041

Hameed, B., Durr, F., & Rothermel, K. (2011). RFID based complex event processing in a smart real-time factory. *Expert Discussion: Distributed Systems in Smart Spaces*.

Jeon, J., & Suh, Y. (2017). Analyzing the Major Issues of the 4th Industrial Revolution. *Asian Journal of Innovation & Policy*, *6*(3), 262–273. http://web.b.ebscohost.com/ehost/detail/detail?vid=0&sid=32c5d468d8124fd68fb3b929e0e273ab%40sessiomgr102&bdata=JnNpdGU9ZWhvc3QtbGl2ZSZzY29wZT1zaXRl#AN=129379372&db=bsu

Kang, H. S., Lee, J. Y., Choi, S., Kim, H., Park, J. H., Son, J. Y., Kim, B. H., & Noh,

S. Do. (2016). Smart manufacturing: Past research, present findings, and future directions. *International Journal of Precision Engineering and Manufacturing - Green Technology*, *3*(1), 111–128. https://doi.org/10.1007/s40684-016-0015-5

Lasi, H., Fettke, P., Kemper, H. G., Feld, T., & Hoffmann, M. (2014). Industry 4.0. *Business and Information Systems Engineering*, *6*(4), 239–242. https://doi.org/10.1007/s12599-014-0334-4

Lee, H., Seo, H., & Geum, Y. (2018). Uncovering the topic landscape of product-service system research: From sustainability to value creation. *Sustainability (Switzerland)*, *10*(4). https://doi.org/10.3390/su10040911

Lee, J., Bagheri, B., & Kao, H. A. (2015). A Cyber-Physical Systems architecture for Industry 4.0-based manufacturing systems. *Manufacturing Letters*, *3*, 18–23. https://doi.org/10.1016/j.mfglet.2014.12.001

Lee, M. H., Yun, J. H. J., Pyka, A., Won, D. K., Kodama, F., Schiuma, G., Park, H. S., Jeon, J., Park, K. B., Jung, K. H., Yan, M. R., Lee, S. Y., & Zhao, X. (2018). How to respond to the Fourth Industrial Revolution, or the second information technology revolution? Dynamic new combinations between technology, market, and society through open innovation. *Journal of Open Innovation: Technology, Market, and Complexity*, *4*(3). https://doi.org/10.3390/joitmc4030021

Lehmhus, D., Aumund-Kopp, C., Petzoldt, F., Godlinski, D., Haberkorn, A., Zöllmer, V., & Busse, M. (2016). Customized Smartness: A Survey on Links between Additive Manufacturing and Sensor Integration. *Procedia Technology*, *26*, 284–301. https://doi.org/10.1016/j.protcy.2016.08.038

Lucke, D., Constantinescu, C., & Westkämper, E. (2008). Smart Factory - A Step towards the Next Generation of Manufacturing. *Manufacturing Systems and Technologies for the New Frontier*, *Sfb 627*, 115–118. https://doi.org/10.1007/978-1-84800-267-8_23

Mittal, S., Khan, M. A., Romero, D., & Wuest, T. (2019). Smart manufacturing: Characteristics, technologies and enabling factors. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, *233*(5). https://doi.org/10.1177/0954405417736547

Mohamed, N., Al-Jaroodi, J., & Lazarova-Molnar, S. (2019). Industry 4.0: Opportunities for enhancing energy efficiency in smart factories. *SysCon 2019 - 13th Annual IEEE International Systems Conference, Proceedings*. https://doi.org/10.1109/SYSCON.2019.8836751

Pagnon, W. (2017). The 4th Industrial Revolution – A Smart Factory Implementation Guide. *International Journal of Advanced Robotics and Automation*, *2*(2), 1–5. https://doi.org/10.15226/2473-3032/2/2/00123

Phuyal, S., Bista, D., & Bista, R. (2020). Challenges, Opportunities and Future Directions of Smart Manufacturing: A State of Art Review. *Sustainable Futures*, *2*(March), 100023. https://doi.org/10.1016/j.sftr.2020.100023

Porter, K. (2018). Analyzing the DarkNetMarkets subreddit for evolutions of tools and trends using LDA topic modeling. *Proceedings of the Digital Forensic Research Conference, DFRWS 2018 USA*, *26*, S87–S97. https://doi.org/10.1016/j.diin.2018.04.023

Radziwon, A., Bilberg, A., Bogers, M., & Madsen, E. S. (2014). The smart factory: Exploring adaptive and flexible manufacturing solutions. *Procedia Engineering*, *69*,

1184–1190. https://doi.org/10.1016/j.proeng.2014.03.108
Resman, M., Turk, M., & Herakovic, N. (2020). Methodology for planning smart factory. *Procedia CIRP*, *97*, 401–406. https://doi.org/10.1016/j.procir.2020.05.258
Shi, Z., Xie, Y., Xue, W., Chen, Y., Fu, L., & Xu, X. (2020). Smart factory in Industry 4.0. *Systems Research and Behavioral Science*, *37*(4), 607–617. https://doi.org/10.1002/sres.2704
Tao, F., & Zhang, M. (2017). Digital Twin Shop-Floor: A New Shop-Floor Paradigm Towards Smart Manufacturing. *IEEE Access*, *5*, 20418–20427. https://doi.org/10.1109/ACCESS.2017.2756069
Thoben, K. D., Wiesner, S. A., & Wuest, T. (2017). "Industrie 4.0" and smart manufacturing-a review of research issues and application examples. *International Journal of Automation Technology*, *11*(1), 4–16. https://doi.org/10.20965/ijat.2017.p0004
Wiktorsson, M., Noh, S. Do, Bellgran, M., & Hanson, L. (2018). Smart Factories: South Korean and Swedish examples on manufacturing settings. *Procedia Manufacturing*, *25*, 471–478. https://doi.org/10.1016/j.promfg.2018.06.128
Yang, H. L., Chang, T. W., & Choi, Y. (2018). Exploring the research trend of smart factory with topic modeling. *Sustainability (Switzerland)*, *10*(8). https://doi.org/10.3390/su10082779
Zhu, Q., Li, G., & Wu, W. (2018). Research on smart factory model of color TV industry based on Intelligent Manufacturing. *Proceedings of 2018 IEEE 4th Information Technology and Mechatronics Engineering Conference, ITOEC 2018*, *Itoec*, 1739–1742. https://doi.org/10.1109/ITOEC.2018.8740690
Zuehlke, D. (2010). SmartFactory-Towards a factory-of-things. *Annual Reviews in Control*, *34*(1), 129–138. https://doi.org/10.1016/j.arcontrol.2010.02.008