Application of Data Mining in Industry in the Transition Era to Industry 4.0: Review

Khaoula Sahraoui, Samia Aitouche, Karima Aksa,
Laboratory of Automatics and manufacturing
Industrial engineering department, University Batna 2, Batna, Algeria
e-mail: sahraouikhaoula12@gmail.com, s.aitouche@univ-batna2.dz, k.aksa@univ-batna2.dz

***Abstract*— The era of Industry 4.0 has already begun, however, several improvements should be achieved concerning this revolution. Data mining is one of the modest and efficient tools. Based on a specific query entered in Scopus, related to Industry 4.0, data mining (DM) and logistics, selected documents were studied and analyzed. A brief background of Industry 4.0 and DM are presented. A generic analysis showed that the attentiveness for the cited subject area by countries, universities, authors and especially companies and manufacturers increased through the years. Content analysis reveals that the improvement in quality of the technologies used in manufacturing was noticed, concluding that DM would give Industry 4.0 a leap forward, yet research is dealing with several challenges.**

Keywords-Industry 4.0; data mining; data mining techniques; data mining in Industry 4.0.

I. INTRODUCTION

Technological innovation and customer demands for sophisticated technology and services promote the emergence of new challenges, which make an increasingly changing industry [1]. Many companies have started to use Internet of Things (IoT) to have their devices interact with each other. They succeed in the usage of smart devices, RFID (Radio Frequency IDentification) technology, programmed robots and other technologies to automate many orders, make decisions and solve problems [2], with real-time interactions between people, products and devices during the production process. Hence, it was the beginning of the fourth revolution of industry. The concept of Industry 4.0 (I4.0) appeared first in an article published by the German government in November 2011 [2]. At this point, it is the intersection of different technologies at a different level. In addition to IoT, it includes the Cyber-Physical systems, cloud computing, smart factories, self-organization, smart product, etc. (Fig.1).

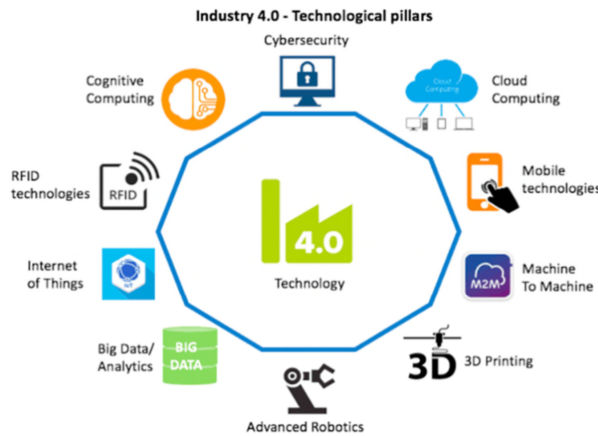

Figure 1. Industry 4.0 technologies pillars [3]

In today's competitive business environment, companies are facing challenges in dealing with big data issues of rapid decision-making for improved productivity. Many manufacturing systems are not ready to manage big data due to the lack of smart analytic tools [4]. Hence, the DM, with its methods and algorithms, was the best solution for the enormous volume of data. DM is the extraction of knowledge from a large volume of data, found its place in the research area, because of its importance in using the wasted data that could support decision-making, chosen from several directions and solve many problems. With the help of DM techniques, computers are no longer limited to passively store or collect data. They can also help the users to actively excerpt the key points from huge amounts of data, and make use of analysis or prediction [5]. This concept was used for the first time in the 1990s. It was developed across the years and many methods and algorithms were offered to science, prove their efficiency in many fields.

In industry, precisely logistics, the tremendous volume of data in the industrial environment has increased; therefore, the use of DM as an analytical tool [6] was necessary. The concept of big data and considerations of how to deal with such large datasets is an intrinsic challenge of any system operating in an I4.0 environment [6].

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In this paper, we aim to reveal the location of research and researchers in using DM for I4.0 in logistics and industry field generally. We start with a brief background of both industry and DM. A general statistical analysis was done, by using documents from Scopus database after entering a specific query; also a content analysis was discussed. After that, we present a discussion and challenges that this area is facing, finishing with a conclusion.

II. BACKGROUND

A. Industry 4.0

The industry began simple and easy, and it depended mostly on human work and simple machines. The first mechanical loom was in 1784, to witness the assembly lines; they used water, hydraulics and steam power. The second revolution came at the end of the 19th century with the introduction of electric powered mass production based of the division of labor. This development made the emerging automatic way of dealing with the processes possible. The improvement and the novelty of technologies, led the industry to a new era. The processes of the production were totally automated using electronic, IT systems and developed machines. The interaction of human in the production process arrived to its end, but it was limited to program the orders and deal with intelligent machines, leading to the third revolution in the early 1970s. The I4.0 or the fourth industrial revolution was a consequence of the introduction of high levels of technologies especially cyber-physical systems [7], where physical and software components interpenetrate on different spatial and temporal scales, having multiple and distinct behaviors and interacting in ways that change the context of the whole system. We can also cite: IoT, cloud computing and smart factory [8]-[9].

B. Data mining

The aim of DM is extracting the needed knowledge (knowledge discovery) supporting decision making. The terms knowledge discovery and DM first appeared in late eightieths and have been used ever since [10]. DM appeared basically from the development of statistic science where Bayes' theorem helped in understanding composite realities based on predictable probabilities. It was presented in 1763 in addition to regression analysis in 1805 [11] consisting in a learning function that maps a detail of data onto a real variable used for prediction. After that, Neural Networks, generic algorithms, databases and clustering, Knowledge Discovery in Databases (KDD) took place in 1989, and conducted to introduce the term data science in 2001. Today, DM is emerging by the novelty and high quality of technologies and the sophisticate demands of clients [12][13][14].

III. METHODOLOGY

Aiming at identifying the recent and relevant research on DM, I4.0 and logistics, a complex query was performed on 01/19/2020 in the scientific database Scopus. The query was too complex to improve the relevance and to limit the number of documents; it touched Industry 4.0, DM and logistics in titles and keywords. Twenty-eight documents were found, 75% were a conference paper (21), 17.9% were a journal article (5) and only 7.1% were a review (2). One conference paper was omitted because its content is duplicated in a journal paper, one was omitted because it is written in Russian. We processed then to descriptive (quantitative) analysis and content (qualitative) analysis.

IV. DESCRIPTIVE ANALYSIS

By observing the number of articles in this subject, it is noticed from Fig. 2 that in the beginning of Industry 4.0, the researchers interact DM with I4.0 and logistics systematically in analyzing big data by using one or more of its methods or algorithms. Then after, the volume of data had been increased, researchers began have more attention to apply DM's methods and algorithms in controlling and analyzing big data in some technologies of the Industry 4.0. In 2019, a considerable number of articles compared to the previous years, reveals the strong relationship of I4.0 and logistics with DM. Even though 2020 is at the beginning, two articles were published according to our request.

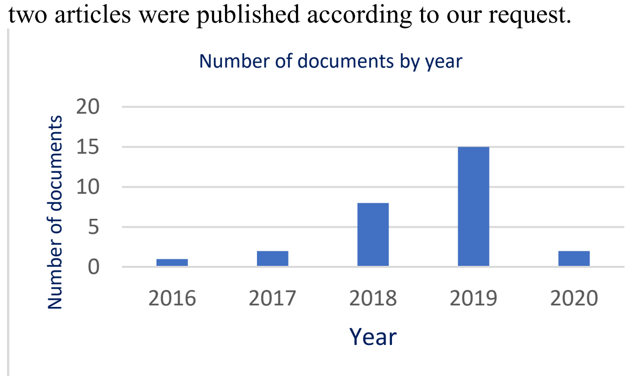

Figure 2. Histogram of the number of articles by year.

While Germany was the first to announce the era of Industry 4.0, it was the leader by 4 articles in this chosen group of articles. Russian Federation comes next with 3 articles. Two articles were the outcomes for each of Colombia, Finland, India, Italy, Netherlands, Spain and Turkey and 1 article for each of the rest of countries, as it is presented in Fig. 3.

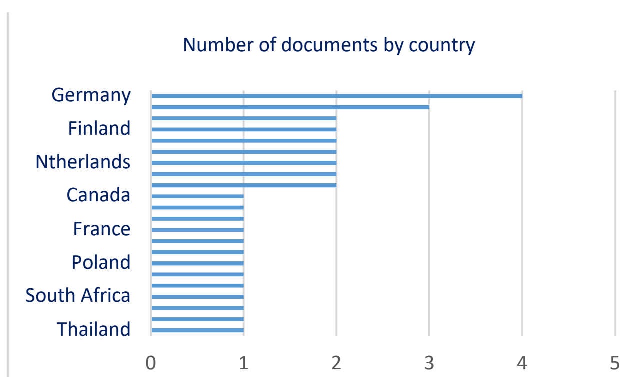

Figure 3. Histogram of the number of documents by country.

Fig. 4 shows that the controller of this group of documents in terms of the subject area was computer science with 30.6% since applying DM is totally dependent on programing languages and computers, while engineering was next with 22.6%, considering that we are in the field of industry. As mathematics is required in some problems along with the integration of DM methods, mathematic has 11.3%. The energy got 6.5% while each of business management and accounting, decision science, earth and planetary sciences, environmental science have 4.8%. Medicine, physics and astronomy each of them has 3.2%, materials science and social sciences have 1.6%. Those percentages prove the involvement of DM in variant fields.

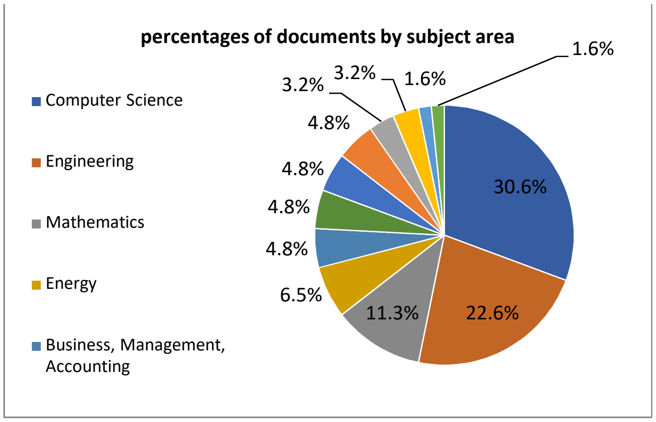

Figure 4. The subject areas of the selected documents.

Binder C., Schiemann R. and Kabugo J.C. each one wrote two documents in this subject area, while the other authors have one for each (Table1).

TABLE 1. NUMBER OF DOCUMENTS BY AUTHOR.

Author's name	Number of documents
Binder, C.	2
Kabugo, J.C.	2
Schiemann, R.	2
Other authors	1 to each author

Index keywords also have been analyzed. The most used keyword was I4.0 (Fig. 5) because it was specified in the title of papers, while DM was placed next, digital storage and learning systems were equal in term of usage as keywords. While many keywords of methods and concepts appeared, it was not expected to be relevant to this subject. Fig. 6 shows a sample of used keywords and their frequency in these documents.

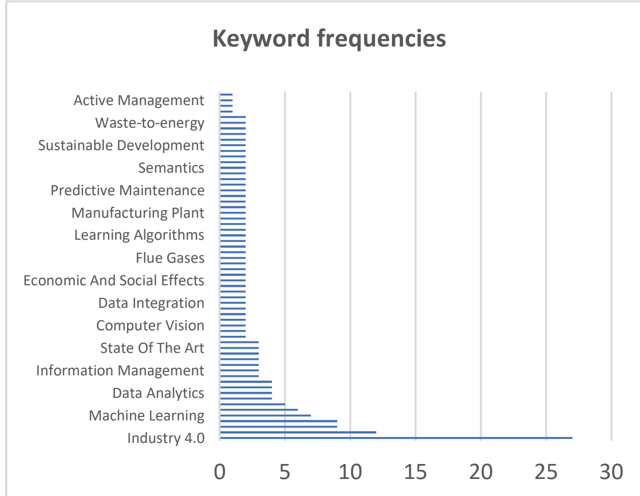

Figure 5. Keyword frequencies

The analysis of author's keywords showed a different frequency in comparison with the filtration by keywords of Scopus (Table 2), even though in three documents from the selected ones, the author's keywords weren't found.

TABLE 2. FREQUENCY OF SIMPLE OF AUTHOR'S KEYWORDS.

Keywords	Frequency	Keywords	frequency
Industry 4.0	19	Manufacturing	3
Enterprise	3	Supply chain	2
Manufacture	9	Industrial	4
Business	1	Data	14
Management	2	Machine learning	7
IoT or internet of things	4	Artificial intelligence	1
Data mining	5	Analytics + analysis	5

V. CONTENT ANALYSIS

A. *Content analysis in 2016*

The objective of this analysis is to identify the improvement that could hint to Industry 4.0 by using different technologies and methods particularly those ones dealing with data sets. K. Sakornsathien [15] develops a valuable framework for some organizations particularly the individuals who purpose to execute I4.0 or the individuals who previously incorporated it in their ventures. This connection of information mining with I4.0 advances assisted with improving the production network, to arrange the market and to fulfill the customers.

B. *Content analysis in 2017*

R. Frischer et al. [16] clarify the changes that must touch the metallurgical engineering to keep abreast of I4.0 and to be compatible with "other world" systems. They pointed out that, although the change already started along with putting into practice new approaches to human resource management, automation, data networks interconnections, data storage, DM and much more in the context of Industry 4.0, the implementations and human stance to new ideas will take decades.

M. Gokalp et al. [17] propose a framework handling collection of data from IoT and Web based data sources, implementation of big data analytics applications containing machine learning and DM components, translation of visually designed programs to platform specific ones, management of jobs among processing units, and delivery of results to people and services. It facilitates the integration of big data analytics with business processes encouraging by that the adoption of big data techniques as part of I4.0 vision in future enterprises.

C. Content analysis in 2018

The validation is necessary to data management, measurement, retrieving, storage, organization, data processing and their presentation. G. DeMilia et al. [18] present a practical case study related to a sensor-based condition monitoring application for validation techniques at the post-processing stage of the data management flow to realize a better feature extraction for the classification algorithm. It is applied in a complex mechanical system of an automatic production with a set of sensors of displacement.

K. Villalobos et al. [19] present a system called I4TSRS1, available as a Web Application, that efficiently guides a data engineer in the task of obtaining industrial time-series data reduced representations that preserve their main characteristics to reduce data storage and transmission costs, without limiting the future exploitation of the data in different processes. I4TSRS recommends the best techniques to achieve a reduced representation of time-series captured in industrial settings.

Several works focus on application of DM and I4.0 in logistics. E. Sternberg and M. Atzmueller [20] apply knowledge-based data analysis in logistics to model background knowledge in the form of knowledge graphs to discover subgroup for identifying exceptional patterns. Overall, the process and the results are well accepted by the domain experts. In the same context, J.I.R. Molano et al. [21] study the relation between I4.0 and supply chain in Colombia and, propose a strategy based on I4.0 for small and medium-sized companies to diagnose their needs and solve them. The work of K. Chaudhary et al. [22] presents a machine learning based adaptive framework for logistics planning and digital supply chain growing, acclimate and expand as its knowledge grows to provide a generalized solution to all kinds of logistics and supply chain activities

J.I. Rodríguez-Molano et al. [23] analyze the man-things-software communication and propose a metamodel of integration (IoT, social networks, cloud and Industry 4.0) for generation of applications for the Industry 4.0, and the manufacturing monitoring prototype implemented with the Raspberry Pi microcomputer, a cloud storage server and a mobile device for controlling an online production.

D. Content analysis in 2019

The year 2019 was rich in this topic because of its improvement and its quick spread in the mining field transportation with the use of belt conveyors allows cost reductions and increased range. It also allows fully automatic operation as well as remote monitoring and control from the centralized control room. L. Jurdziak et al. [24] introduce diagnostic systems and integrate data from a number of sources in order to include the idea of conveyor belt 4.0 into the digitally controlled conveyors 4.0. It is reliant on several technologies, for example, it is depending on a lot of information given by an expanding number of sensors and identified with the activity of machines and devices.

M. Kebisek et al. [25] focus on the utilization of neural networks for paint errors classification in the area of automotive industry, utilizing hypothesis, that outdoor weather has significant impact on the number of paint errors, as a basis for comparison of neural network algorithms. Deep learning was from the used methods. They concluded that neural networks algorithms are suitable for this kind of analyses and data sets. While D. Penumuru et al. [26], with the use of machine vision and machine learning techniques, develop a novel generalized methodology based on Support Vector Machine (SVM) to accurately identify and classify flat materials being machined in a typical manufacturing environment. They saw that the proposed methodology will be applied to machine tools and robots commissioned in smart manufacturing set up and that these results will be made available in future communications. M.D. Anuşlu et al. [27] used DM differently; they cluster countries using cluster analysis and group them within the scope of significant impact areas of I4.0 using global innovation index. They observed that the most important supporting elements of I4.0 are creativity and innovation. C.C. Osman et al. [28] introduced the difficulties that meet up with I4.0 and proposed process mining procedures as another methodology for business process examination to help organizations to quickly adjust to advertise changes by offering modified answers for clients. The study affirms that the digitization is a key factor in I4.0 changing business forms.

The study of J. Stentoft et al. [29] was based on 270 valid answers to a questionnaire-survey distributed among Danish manufacturers. The study identifying potential drivers and barriers for I4.0 and how to deal with respecting different technologies such as data processing and big data. L.A. Rodríguez et al. [30] propose a new architecture for a web platform for management and inference of information based on machine learning. The experimental part was obtained from simulator of a hydrogen production biorefinery. The designed platform uses methods and algorithms of automatic learning and DM to receive process and analyze large amounts of data that generates a biorefinery which produces hydrogen from wastewater. The authors mentioned that improving the platform's architecture is worthwhile to use it in other complex systems to support decision making and for the good reception and storage of data in addition to displaying the results. A. Edirisuriya et al. [31] identify gaps in the field of logistics in applying lean and green concepts in the context of I4.0. They develop a conceptual framework enhancing operational performance of logistics operations by applying lean and green concepts with special reference to I4.0 technologies mentioning that realizing I4.0is becoming critical for almost all the manufacturing industries existing in the world.

A. Mayr et al. [32] compare different generic approaches for identifying, selecting and implementing I4.0 use cases. They present also a methodical approach in order to tap the numerous I4.0 potentials within the electric motor production although that they see that the application of I4.0 technologies in this domain has hardly been examined yet. They presented the DM and machine learning from the fundamental relevant I4.0 technologies, as tools for intelligent data analyses. S. Cho et al. [33] propose semantic-driven architecture to facilitate the real-time update/control of incoming data together with the runtime module and distribution of computers resources without direct active management by users. The proposed approach provides a novel method to open an efficient way to manage/integrate data in I4.0 applications through the semantic technology.

J. Para et al. [34] suggest a new methodology ASPPID for efficiently selecting sensing equipment in industrial processes and machinery essentially capitalizing on a predominant role of the data scientist along the entire decision workflow, not only within the stages where the captured data are exploited. All decisions through the proposed methodology are made towards minimizing the costs and fulfilling the target benefit of the overall project. F. Galati et al. [35] use text mining methodologies, to discuss technological solutions at the core of I4.0. ′Work and skills′ stream of literature attempts to under the human element lurking behind the scene of I4.0 regarding opportunities and implications. J. Piest et al. [36] discussed the problem of limited usage of real time data originating from I4.0 technologies by Small Medium Enterprises (SMEs) in the logistics industry. SMEs benefit from such data and help them streamline their operational processes and overall performance, by developing an intelligence amplification framework in the context of SMEs in logistics and overall performance of supply chain. The used methods (KDD, SEMMAn CRISP-DM) could be limited therefore a technical knowledge and extensiveness of the methods are required.

K. Bertayeva et al. [37] studied the I4.0 concept in the field of mining and suggested that research and development should be carried out to constantly support projects such as “Virtual Mine of the Future”, “Virtual Section of the Future”, aimed at optimizing the combination of promising technologies, organizational, economic and other solutions. In their opinion, implementation of the I4.0 project involves the creation of a smart industry that has evolved evolution from the use of integrated information and communication control systems to cyber physical systems. Moreover, to achieve the positive effects of the formation of innovative systems in the long term, it is necessary to strategically plan the system of government regulation measures, develop a set of measures combining elements of industrial and innovation policies that stimulate the innovative development of not only the mining industry, but also related sectors and industries.

E. Content analysis in 2020

During the current year (2020), J. P. UsugaCadavid et al. [38] contributed to the definition of a methodology to implement machine learning for production planning and control and proposed a mapping to classify the scientific literature in order to identify further research perspectives. In their opinion, classical methods like simulation and Enterprise Resource Planning (ERP) perform poorly at the operative level therefore the implementation of smart manufacturing is required. J. C. Kabugo et al. [39] developed a concept of a process monitoring platform aiming at highlighting the use of the state-of-the-art machine learning methods coupled with big-data processing tools and cloud computing technologies in process data analytics. They applicate the developed platform on a waste-to-energy plant as a study case to better predict of both syngas heating value and flue gas temperature in this process.

VI. Discussion and Challenges

It appeared after analyzing the selected documents that a remarkable attentiveness head towards using DM techniques aiming to implement, develop and improve I4.0 in the industrial field generally or even know barriers and the constraints in front of this objective, and it is increasing from year to another. Logistics and supply chain have also benefited from DM and its technologies. The research reveals also that relying I4.0 with DM makes it featuring more technological systems and smart methods.

I4.0 faces different challenges and difficulties involving many aspects, including scientific, technological, and economic challenges, in addition to social problems and political issues [2]. The increase of using DM in the context of I4.0 is a main challenge that can eliminate or even reduce the previous challenges in different levels. Even though, due to the complexity of I4.0 with various types, volumes and uncertainty of data [8], it is well known that the simple use of DM algorithms will not produce good results; very complicated and efficient algorithms and methods need to be used in order to catch the desired results using a high quality and strong potency machines that would be expensive. Furthermore, it is difficult to generalize the integrated DM in all the technologies of Industry 4.0; each technology requires a specific algorithm or method.

VII. Conclusion

The aim of this paper was to define where research is in the field of applying DM in I4.0 and logistics. A quick review about the background of I4.0 and DM was presented. A complicated query was entered in Scopus database to do a generic analysis on the resulting documents; furthermore, the contents had to be analyzed to distinguish what was the novelty given by each one. Through this research, different challenges were observed and have been presented.

The analysis of the documents shows the interest in this subject area increased through the years, and as it was

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expected, Germany was the leader in the number of the selected documents. The variant branches articulating this subject confirms that the application of DM is touching numerous fields and has the attention of many researchers. The content of those documents showed the rapidly spread of using DM in Industry 4.0, improving by that the supply chain management and logistics industry. From the two analyses, the improvement quality of the technologies that are used in logistics and industry was noticed, concluding that DM would give logistics and I4.0 a leap forward.

This group of documents was chosen according to the query that was written to limit the search to our domain of research; however, many other articles have discussed this subject which could be analyzed and treat. Future research may focus on dealing with the faced challenges; also other challenges could appear by consulting other articles in this field.

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