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Business Analytics in Industry 4.0: A Systematic Review

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Summary

Recently, the term "Industry 4.0" has emerged to characterize several Information Technology and Communication (ICT) adoptions in production processes (e.g., Internet-of-Things, implementation of digital production support information technologies). Business Analytics is often used within the Industry 4.0, thus incorporating its data intelligence (e.g., statistical analysis, predictive modeling, optimization) expert system component. In this paper, we perform a Systematic Literature Review (SLR) on this Business Analytics usage, covering a selection of 169 papers obtained from six major scientific publication sources from 2010 to March 2020. The selected papers were first classified in three major types, namely, Practical Application, Reviews and Framework Proposal. Then, we analyzed with more detail the practical application studies which were further divided into three main categories of the Gartner analytical maturity model, Descriptive Analytics, Predictive Analytics and Prescriptive Analytics. In particular, we characterized the distinct analytics studies in terms of the industry application and data context used, impact (in terms of their Technology Readiness Level) and selected data modeling method. Our SLR analysis provides a mapping of how data-based Industry 4.0 expert systems are currently used, disclosing also research gaps and future research opportunities.

KEYWORDS:
Artificial Intelligence, Industry 4.0, Machine Learning, Optimization, Predictive and Prescriptive Analytics

1 | INTRODUCTION

In the recent years, several industry sectors are being changed through the adoption of Information and Communication Technologies (ICT). More digital and connected sensors are being added to production systems, generating big data that can be processed using analytical systems, allowing to produce new insights and knowledge about the productive processes. Born in Germany in 2011 (BMBF 2011), the term "Industry 4.0" is widely used to identify this fourth industrial revolution. Indeed, the German Federal Ministry of Education and Research defines the Industry 4.0 concept as *"the flexibility that exists in value-creating networks is increased by the application of cyber physical production systems. This enables machines and plants to adapt their behavior to changing orders and operating conditions through self-optimization and reconfiguration. ... The main focus is on the ability of the systems to perceive information, to derive findings from it and to change their behavior accordingly, and to store knowledge gained from experience. Intelligent production systems and processes as well as suitable engineering methods and tools will be a key factor to successfully implement distributed and interconnected production facilities in future Smart Factories"* (Shrouf, Ordieres, & Miragliotta 2014).

Business Analytics is a major ICT tool for the Industry 4.0. It focuses in the analysis of historical raw data in order to achieve useful and focused insights and a better understanding of the business performance areas (Krishnamoorthi & Mathew 2018). Business Analytics is an expert systems subarea that results from the combination of Business Intelligence techniques with Optimization, Forecasting, Predictive Modeling and

Statistical Analysis (Arnott & Pervan 2014). Business Analytics systems are being increasingly applied in the Industry sector, thus behaving as the data intelligence component of the Industry 4.0. Indeed, Business Analytics can bring new advantages to the organizations such as product and process digitization, the creation of new products, services and solutions, the offering of Big Data Analytics as a service, the breadth of product customization and the mass production of custom products. There are also other potential advantages for industries, such as obtaining larger profit margins and increasing the market share of key business products by gaining valuable insights from customers using Data Analytics (Geissbauer, Vedso, & Schrauf 2016). Industries can gain efficiencies and lower costs by using real-time production line controls via Big Data Analytics. In addition, the Industry 4.0 offers production concepts that are modular, flexible and customer-tailored. Real-time visualization of the production process and variance of the product, as well as the use of data analytics for optimization and augmented reality, have emerged with the context of Industry 4.0. Predictive maintenance is another advantage that arises in this context because it uses forecasting algorithms to optimize the maintenance and repair processes. An increased vertical integration can be obtained by using sensors through the manufacturing execution system, allowing a real-time production planning with the objective of obtaining greater efficiency in terms of machine occupation times. Horizontal integration is another efficiency gain that allows track-and-trace products for better inventory management and improved operating speeds. Other efficiency gains include the digitization and automation of processes for a more efficient use of human resources (Geissbauer et al. 2016).

Given the emergence of this topic, this paper performs a Systematic Literature Review (SLR) on the usage of Business Analytics within the Industry 4.0 concept, which a particular focus on practical applications and three main types of analytics (Descriptive, Predictive and Prescriptive). The specific Research Question (RQ) addressed by this SLR is: ***How and in what areas of the industry are Business Analytics techniques being used in an Industry 4.0 context?*** To answer the RQ, a total of 168 papers, from 2010 to March 2020, were selected for the review. Then, the practical studies were further analyzed, allowing to identify the specific industrial context where analytics were used (e.g., business goal, data used), the selected modeling method (e.g., analysis of variance, artificial neural networks) and the obtained impact. Thus, the performed SLR characterization summarizes how Industry 4.0 expert systems are being used, also disclosing current research gaps that can be addressed in future research works.

This article is structured as follows. Section 1 presents an introduction and conceptualization of the two main topics analysed in this SLR: Industry 4.0 and Business Analytics. Section 2 describes similar research literature surveys, contrasting them with this SLR. The SLR method is presented in Section 3. Then, the executed SLR is detailed in Section 4 and discussed in Section 5. Finally, Section 6 presents the main conclusions and research implications of this literature review.

1.1 | Business Analytics

The Business Analytics topic assumes the Big Data age in an extensive manner. It also includes useful data processing decision support methods, namely Optimization, Forecasting, Predictive Modeling, and Statistical Analysis. The goal is to extract useful, often actionable knowledge from historical data based on advanced Artificial Intelligence (AI) analytics (Arnott & Pervan 2014; G. Cao, Duan, & Li 2015; H. Chen, Ling Li, & Chen 2020; Koch 2015; Lu 2019). In 2013, the the famous Gartner Group defined four main types of analytics: Descriptive, Diagnostic, Predictive and Prescriptive. The Descriptive analysis attempts to answer the question "what happened?". Business Intelligence (BI) and Big Data systems (e.g., Data Warehousing) can be used to access the historical data and provide summarization reports, visualizations and dashboards (e.g., pie charts, bar charts, table or generated views). Next, the Diagnostic analysis aims to understand "why did it happen?", using mostly exploratory data analysis techniques via a interaction with the data analyst which is looking for insights. For example, by visualizing drill down/up operations of an online analytical processing tool of a Data Warehousing. Then, the Predictive analysis aims to answer the question "what will happen?". This can be achieved by using Statistical Analysis and Machine Learning (e.g., Classification, Regression, Time-Series Forecasting). Predictive Analytics are being used in diverse application domain areas, such as Marketing (Chi-Hsien & Nagasawa 2019) and Finance (Swamy & B. Sarojamma 2020). The last and most difficult analytic type is termed Prescriptive Analysis and it is related with the question "how can make it happen?". This type of analytics can be achieved by using diverse techniques, including Simulation, What-if scenarios, Machine Learning, Heuristics and Optimization. We note that Diagnostic analytics are often difficult to distinguish from Descriptive ones, since both are assumed to analyze historical data and are often performed simultaneously by the same analysts. Thus, in this paper, we adopt the same strategy used by Chong and Hui Shi (2015) and Khatri and Samuel (2019), which group all historical analyses (Descriptive or Diagnostic) into a single Descriptive analytics category.

1.2 | Industry 4.0

The Industry 4.0 is defined as the global transformation of the manufacturing industry through the introduction of digitalization and the Internet. The transformations applied imply enormous advances in the design and the manufacturing processes, operations and services of manufacturing products and systems. The term Industry 4.0 was coined in Germany in 2011 and it shares similarities with developments produced in many European countries and that have been labelled differently, as Smart Factories, Smart Industry, Advanced Manufacturing of Internet of Things (IoT) (BMBF 2011; Tjahjono, Esplugues, Ares, & Pelaez 2017). The term Industry 4.0 was born in Germany because the German engineers realized that manufacturing had been developed into a new paradigm shift, where products tend to control their own manufacturing process (Lasi, Fettke, Kemper, Feld, & Hoffmann 2014). The Industry 4.0 is considered the fourth industrial revolution, which contains a extreme potential impact in the future (Kagermann, Helbig, Hellinger, & Wahlster 2013). Smart Factories use new technologies, such as advanced robotics and AI, cloud computing, IoT, Data Analytics, Software-as-a-Service and platforms that use algorithms to direct motor vehicles, delivery and ride services, and the embedding of all these elements, and many more, in an interoperable global value chain, shared by many companies from different countries (Geissbauer et al. 2016).

Until recently, the term Industry 4.0 has not yet been conclusively defined, neither are its features. Nevertheless, there are four main features that typically categorizes the term (Tjahjono et al. 2017): vertical networking of smart production systems; horizontal integration via a new generation of global value chain networks; through-life engineering support across the entire value chain; and acceleration through exponential technologies. This perspective of the analysis is believed to be relevant since there is no complete or concise knowledge of how to implement Industry 4.0 correctly or predict future problems to be prevented in advance. The use of IoT and Cyber-Physical Systems (CPS) on Industry 4.0 made possible the connection between materials, sensors, machines, products, supply chain, and customers, which means these necessary objects are going to exchange information and control actions with each other independently and autonomously. The technologies that support the Industry 4.0 concept are the IoT, CPS, Cloud Computing and Big Data Analytics (Lasinkas 2017). These concepts are described in the next subsections.

1.2.1 | IoT

The concept of IoT describes an inter-networking world where various objects inside of that world are embedded with sensors, and other digital devices, so they can be networked in order to be possible to collect and exchange data from them (Xia, Yang, Wang, & Vinel 2012). IoT-enabled manufacturing features real-time data collection and sharing among various manufacturing resources such as machines, workers, materials, and jobs. Usually, the IoT can provide advanced connectivity of various objects, systems and services, and enable data sharing. IoT is particularly useful for industries (Zhong, Xu, Klotz, & Newman 2017). In the future, it is expected to occur a convergence of IoT-related technologies, such as ubiquitous wireless standards, Data Analytics and Machine Learning (L. D. Xu, He, & Li 2014; Zhong et al. 2017). IoT is being applied in other sectors besides Industry, such as in the Healthcare area where IoT is being combined with Machine Learning techniques to predict lung cancer in patients (Pradhan & Chawla 2020).

The Radio-Frequency Identification (RFID) is an example of a technology that is used in IoT. The manufacturing industry will be affected by this change because RFID is used for identifying various objects in warehouses, distribution centers, production shop floors, logistic companies and disposal/recycle stages (Y.-M. Wang, Wang, & Yang 2010). The identifiers have smart sensing abilities, and they can connect and interact with other objects, which may create a huge amount of data from their movements and behaviors. These objects are given specific applications or logics, so that they can be followed after being equipped with the RFID readers and tags (Guo, Ngai, Yang, & Liang 2015). RFID can also capture data related to the daily operations so that production management is achieved on a real-time basis (Zhong et al. 2017).

1.2.2 | Cyber-Physical Systems

A CPS involves a various number of methodologies such as cybernetics theory, mechanical engineering and mechatronics, design and process science, manufacturing systems, and computer science. The ability to have highly coordinated and combined relationships between physical objects and their computational elements or services is one of the key elements of a CPS (Tan, Goddard, & Pérez 2008). Unlike a traditional embedded system, the CPS contains networked interactions that are developed and designed with inputs and outputs, along with their cyberwined services, such as computational capacities and control algorithms. A large number of sensors have crucial roles in a CPS. For example, multiple sensory devices can be used in a large number of purposes such touch screens, light sensors, and force sensors (Zhong et al. 2017).

One example of a real-world project with CPS is the Festo Motion Terminal, which aims to create a standardized platform that makes full use of an intelligent fusion of mechanics, electronics, embedded sensors and control (Zhong et al. 2017). However, the typical CPS applications have been reported for using sensor-based communication-enabled autonomous systems, and a various number of wireless sensor networks can supervise aspects such as environmental so that information can be centrally controlled and managed for decision-making (Ali et al. 2015).

1.2.3 | Cloud Computing

The general term that describes computational services through visual and scalable resources over the Internet is cloud computing (Armbrust et al. 2010; X. Xu 2012). Cloud computing is interesting for business owners because the advantage of scalability allows organizations to start small and invest in more resources if the service demand goes up (Q. Zhang, Cheng, & Boutaba 2010).

An ideal cloud service must have these five characteristics (Mell & Grance 2011): on-demand self-service, broad network access, resource pooling, rapid elasticity, and measured service. The ideal cloud service model is composed of four deployment models (public, private, community, and hybrid) and three delivery models (Software-as-a-Service, Platform-as-a-Service, and Infrastructure-as-a-Service). Cloud computing services are being implemented by all kind of organizations to increase their capacity with a minimum budget investment, as cloud computing does not require investments in new software, incorporate new infrastructures or train new personal (Saxena & Pushkar 2016).

Despite the benefits of cloud computing, this technology also has challenges, in particular related with privacy and security concerns. Other challenges, such as data management and resource allocation, scalability and communication between clouds, reduce the reliability and efficiency of cloud-based systems (Zhong et al. 2017). Because of its relative innovation and increasing development in recent years, a great body of research has been conducted on cloud computing (H. Yang & Tate 2009).

1.2.4 | Big Data Analytics

The Big Data trend was mostly motivated by the use of Internet and IoT technologies, which generate vast amounts of data in various industries (Manyika et al. 2011). Big Data stems from various channels such as sensors, devices, networks, transitional applications and social media feeds (Rich 2012). The Big Data environment has gradually taken shape in the manufacturing sector. Besides the advance of the IoT and the collection of data, there are questions to be resolved, such as how to collect and store the Big Data obtained from real-time sensors which can be processed properly in order to provide the right information for the right question at the right time (J. Lee, Lapira, Bagheri, & Kao 2013). Y. Chen et al. (2016) defined Big Data Analytics as the fusion of Big Data and IoT technologies that created opportunities for the development of services for smart environments like smart cities. Nowadays, there are a set of Big Data technologies available to process the large data obtained from the IoT devices which have emerged as a need to process the data collected from different sources in the smart environment.

The Big Data datasets are much larger than the normal datasets, thus they can be too complex for conventional data analytics software (Barton & Court 2012). As such, it is essential for organizations and manufacturers with vast operational shop-floor data to have advanced analytics techniques for uncovering hidden patterns and unknown correlations between the data, or other things such as market trends, customer preferences and other information useful for the business (Zhong et al. 2017). The particular concept of Big Data Warehouse (BDW) emerged due to the studies made about the applications of BDW in Big Data (Krishnan 2013; Mohanty, Jagadeesh, & Srivatsa 2013). Actually, the state-of-the-art refers that the design of BDW should focus on the physical layer and logical layer using two strategies. The first strategy, "lift and shift", is the use of Big Data technologies to solve specific cases and augment the capabilities of traditional and relational Data Warehouses. However, the use of a case driven approach instead of a data modeling approach can lead to possible uncoordinated data silos (Clegg 2015; Russom 2014). The second strategy, "rip and replace", is where occurs a replace of the Data Warehouse in favor of Big Data Technologies (Russom 2014 2016). In this field, a number of literature reviews were performed; however, they did not focused on the application of Big Data Analytics in Industry 4.0. Duan and Ye Xiong (2015) performed a literature review about the use of Big Data Analytics and Business Analytics, and they concluded that the Big Data concept implies the investment in equipment to capture and store data combined with a Business Analytics approach linked to each business strategy and organizational process, and being aware with the evolving of the state-of-the-art techniques in Big Data. Chong and Hui Shi (2015) studied the use of Big Data Analytics and concluded that these techniques can help the decision-making process, increase the business model understanding, and reveal hidden information to attain competitive advantage.

2 | RELATED WORK

There are several reviews about the implementation of analytical techniques in the Industry 4.0 context. O'Donovan, Leahy, Bruton, and O'Sullivan (2015) made a mapping study about the use of Big Data in the manufacturing sector. The research method was performed manually. Chiang, Lu, and Castillo (2017) reviewed the recent advances of Big Data in data-driven approaches in five industries inside the manufacturing sector. Similarly to O'Donovan et al. (2015), the study only focused on the use of Descriptive and Diagnostic Analytics techniques. Nikolic, Ignjatic, Suzic, Stevanov, and Rikalovic (2017) made a review about Predictive Analytics in the Industry 4.0 context. The authors searched and reviewed different types of Predictive Maintenance systems. They provided an overview of the various challenges, existing solutions, and benefits of Predictive Manufacturing systems in Industry 4.0. Qi and Tao (2018) reviewed the state of Big Data and digital twins in the manufacturing sector. This review also included the applications in product design, production planning, manufacturing, and predictive maintenance. On this basis, the similarities and differences between Big Data and digital twins were compared from the general and data perspectives. Uhlmann, Hohwieler, and Geisert (2017) made a literature review about the historical development of intelligent production systems in the context of adding value to business models. They focused on techniques such as the use of barcodes, RFID, and wireless sensor nodes to make condition monitoring and Predictive Maintenance in the availability oriented business model. They also studied, based on practical examples, the organizational prerequisites for an implementation of these techniques in the industry. X. Xu and Hua (2017) summarized and analyzed the current research status for industrial Big Data Analysis in smart factories (both domestic and abroad). Also, they proposed research strategies for Industrial Big Data Analysis, including acquisition schemes, ontology modeling, predictive diagnostic methods based on Deep Neural Networks (DNN) and three-dimensional self-organized reconfiguration mechanism. In the area of Augmented Reality solutions, J. Yang, Chen, Huang, and Li (2017) presented a comprehensive survey of AI in 3D painting

TABLE 1 Literature surveys about the topic of Business Analytics in Industry 4.0

Reference	Industry Sector	Search Method [a]	Descriptive Analytics	Predictive Analytics	Prescriptive Analytics
O'Donovan et al. (2015)	Manufacturing	SLR	X		
Chiang et al. (2017)	Manufacturing	Manual	X		
Nikolic et al. (2017)	Manufacturing	AA		X	
Uhlmann et al. (2017)	Manufacturing	Manual		X	
X. Xu and Hua (2017)	Manufacturing	AA	X	X	
J. Yang et al. (2017)	Manufacturing	AA		X	
Bordeleau et al. (2018)	All Industry	SLR	X		
Sharp et al. (2018)	Manufacturing	AA		X	X
Diez-Olivan et al. (2018)	Manufacturing	Manual	X	X	X
Qi and Tao (2018)	Manufacturing	Manual	X		
Muhuri et al. (2019)	All Industry	AA	X	X	
Bakar et al. (2019)	Manufacturing	Manual			X
This Review	**All Industry**	**SLR**	**X**	**X**	**X**

[a]Automatic Analysis (AA), Systematic Literature Review (SLR)

to detect defective products in the Industry 4.0 context. The survey only analyzed Predictive Analytics techniques. Bordeleau, Mosconi, and Santa-Eulalia (2018) also performed a literature review of Business Intelligence in the context of Industry 4.0. The goal was to understand how Business Intelligence and data analysis generate value creation in manufacturing companies. This review only studied Descriptive Analytics. Sharp, Ak, and Hedberg (2018) presented another literature review about the use and development of Machine Learning in smart manufacturing. We note that this review studied practical cases that used Machine Learning in contexts different to the Industry 4.0 context. They reviewed the articles published between 2007 until 2017, while the Industry 4.0 concept was introduced in the 2010s. Moreover, the authors only analyzed the Diagnostic and Predictive Analytics. More recently, Diez-Olivan, Del Ser, Galar, and Sierra (2018) presented a survey of the recent developments in data fusion and Machine Learning for industrial prognosis during the Industry 4.0 context. In the same year, Muhuri, Shukla, and Abraham (2019) performed a literature review about the growth of the Industry 4.0 in the last years. Bakar, Ramli, Sin, and Masran (2019) presented a survey regarding the use of Metaheuristics techniques and Robotic Assembly Line Balancing in the Manufacturing industry. This SLR review is more focused on the whole Industry 4.0 concept, and thus it does not detail much the Business Analytics methods.

A summary of the related work is presented in Table 1. None of the reviews analyzed addressed all main Gartner's Analytical levels. In contrast, this SLR contains a stronger focus on the Descriptive, Predictive and Prescriptive analytics, when applied to the context of the Industry 4.0. Moreover, we particularly detail the practical applications, allowing to characterize the main business goals, data usage, modeling methods and obtained impacts. It should also be noted that most surveys consider only the Manufacturing sector, which is where the Industry 4.0 concept is producing a higher impact. Indeed, while this SLR considers all industry sectors, the selected practical research works in this SLR are highly related with the Manufacturing sector (as shown in Section 4.1.2).

3 | LITERATURE REVIEW METHOD

3.1 | Paper Collection

We performed a manual SLR review, similar to what was proposed by Kitchenham et al. (2009). For this literature review, we used several scientific search engines, in order to search for the relevant documents: Google Scholar (`https://scholar.google.com/`), Google Books (`https://books.google.com/`), ScienceDirect (`https://www.sciencedirect.com/`), SpringerLink (`https://link.springer.com/`), Scopus (`https://www.scopus.com/home.uri`) and IEEE Xplore (`https://ieeexplore.ieee.org/Xplore/home.jsp`). The term "Industry 4.0" was coined in 2010. As shown in Figure 1, the Web interest in the term starts from 2010, although the popularity only increases substantially after 2014. Thus, we have retrieved articles that were published since 2010 until March 2020 (when this SLR was executed). Using the listed search engines, we performed several queries, using the combinations of the following keywords: "Industry 4.0", "Decision Support Systems", "Business Analytics", "Predictive Analytics", "Machine Learning", "Data Mining", "Text Mining", "Process Mining", "Forecasting", and "Metaheuristic". Table 2 presents the literature search protocol used during this SLR.

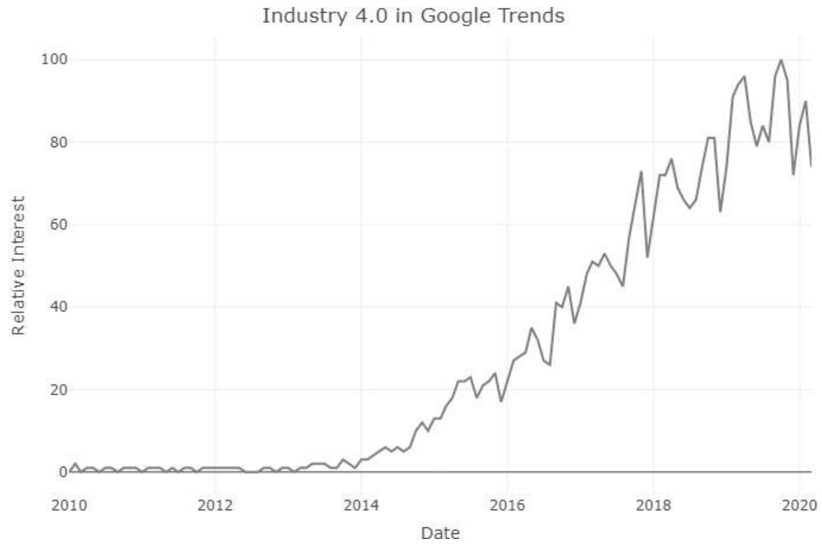

FIGURE 1 Evolution of the interest in the term "Industry 4.0" in Google Trends

TABLE 2 Summary of the literature search protocol

Subject	Business Analytics in Industry 4.0
Time period	January 2010 to March 2020
Search Engines	Scopus, ScienceDirect, SpringerLink, IEEE Xplore, Google Scholar, Google Books
Search Criteria	English; Title, abstract and keywords OR All (except full text)
Search Query	"Industry 4.0 + Decision Support Systems", "Industry 4.0 + Business Analytics", "Industry 4.0 + Predictive Analytics", "Industry 4.0 + Machine Learning", "Industry 4.0 + Data Mining", "Industry 4.0 + Text Mining", "Industry 4.0 + Process Mining", "Industry 4.0 + Forecasting", "Industry 4.0 + Metaheuristic"

3.1.1 | Paper Selection

Table 3 presents the distribution numbers of the collected scientific publications for the different search engines used. The paper search queries resulted in a total of 285 articles. All retrieved documents were manually inspected to check their relevance. First, the title and abstract was read. When the abstract was not conclusive, a more in-depth reading of the article was performed, in order to verify if the document fits the SLR goal. The manual inspection filtered 116 papers that were considered irrelevant for the survey, thus resulting in a total of 169 articles that were selected.

4 | LITERATURE REVIEW ANALYSIS

4.1 | Quantitative Analysis

As stated earlier, 169 papers were selected for this literature review. To make a general overview about the papers selected, a quantitative analysis was performed, in which the papers are characterized according to the year of publication and the paper type.

4.1.1 | Paper type

The papers collected were manually inspected and divided into the three different categories proposed in Öchsner (2013):

- *Practical Application* - These papers describe and discuss real implementation results of a framework, methodology, method or information technology in one or more application domain areas;

TABLE 3 Distribution of papers obtained by each database

Database	Quantity
Scopus	202
ScienceDirect	75
SpringerLink	35
IEEE Xplore	60
Google Scholar	35
Google Books	5
Total with duplicates	390
Total without duplicates	285

- *Reviews* - Articles of literature review (such as this paper), with the main objective of performing a survey of the state-of-the-art on a certain scientific research topic area, possibly identifying research gaps; and
- *Framework Proposal* - The aim is to document the proposal of a new framework developed by the authors. However, these articles do not have a specific application target, thus the authors do not validate the framework in a real-world environment.

Table 4 shows the respective distribution of the selected 169 papers in terms of the three main paper categories. The majority of the selected

TABLE 4 Distribution of the three main paper types

Paper Type	Quantity
Practical Application	139
Reviews	12
Framework Proposal	18
Total	169

papers are Practical Application ones (139 papers). There are 11 papers that were categorized as Reviews and 18 publications categorized as Framework Proposal. Given that this survey is more focused on practical usage of Business Analytics, we will only further detail and analyze the 139 Practical Application studies. The quantitative analysis includes the industry sector, the Gartner Analytic type and year, and finally the paper keyword frequencies.

4.1.2 | Industry sectors of the Practical Applications

To describe the Industry sections we adopted the Standard Industrial Classification Bureau (2017), which includes five main categories listed in Table 5. The Manufacturing sector is by a large margin the sector with most Industry 4.0 practical applications of Business Analytics, with 130 papers. This happens because the manufacturing sector is a vast sector that includes a relevant number of production processes, widely used by several industries. The manufacturing sector has also high Business Analytics needs. For instance, the shop floor usually has different kinds of machines, which should work efficiently and produce quality products. Thus, Predictive Maintenance and automatic quality inspection/prediction methods, based on data-driven models, can be used to enhance the manufacturing process.

The other industry sectors have much less practical application works. Within the Transportation and Warehousing and Utilities sector, the surveyed papers relate with three practical applications. In the Eolic Energy area, Canizo, Onieva, Conde, Charramendieta, and Trujillo (2017) presented a data-driven solution deployed in a cloud that used Random Forest (RF) for predicting failures on wind turbines. In the transformation energy field, Bagheri, Zollanvari, and Nezhivenko (2018) analyzed the analytical approach to the transformer vibration modeling, using Machine Learning techniques such as Linear Regression (LR), Model Trees, Support Vector Regression with Gaussian Kernel and Multilayer Perceptron, and also signal techniques to develop prognosis models of transformer operating condition based on vibration signals. Masoudinejad et al. (2018) proposed a set of Support Vector Machine (SVM) algorithms, addressing indoor localization within a warehouse. The Construction sector has two

TABLE 5 Distribution of the Practical Applications per industry sector

Industry Sector	Quantity
Manufacturing	130
Transportation and Warehousing and Utilities	3
Construction	2
Educational Services, and Health Care and Social Assistance	1
Agriculture, Forestry, Fishing, and Hunting, and Mining	2
Finance and Insurance, and Real Estate, and Rental and Leasing	1
Total	139

TABLE 6 Distribution of the Practical Applications for the three Analytics types and year of publication

Year	Descriptive Analytics	Predictive Analytics	Prescriptive Analytics	Total
2015	2	0	0	2
2016	2	8	2	12
2017	8	17	2	27
2018	9	21	5	35
2019	2	25	10	37
2020	0	9	8	17
Total	23	80	27	130

practical applications. J. Lee, Kao, and Yang (2014) made a review about the trend of the manufacturing service transformation in Big Data and proposed a framework for sustainable innovative service. The data used to make the case study came from sensors installed in a bulldozer. They used a Bayesian Belief Network to classify if the engine had some problem or malfunction and used a Fuzzy-Logic based algorithm to predict the remaining useful life of the engine. R. Costa, Figueiras, Jardim-Gonçalves, Ramos-Filho, and Lima (2017) proposed a system with the aim to create knowledge representations from unstructured data sources used in a construction environment, based on enriched semantic vectors. Regarding the Educational Services, and Health Care and Social Assistance sector, Bordel and Alcarria (2017) presented a solution to automatically assess the human motivation in Industry 4.0 scenarios with the use of an ambient intelligence infrastructure. Turning to the Agriculture, Forestry, Fishing, and Hunting, and Mining sector, Teschemacher and Reinhart (2017) used Ant-Colony Optimization (ACO) algorithms to enable dynamic milk-run logistics. Also, Dutta, Mueller, and Liang (2018) implemented a Machine Learning based interactive architecture for industrial scale prediction for dynamic distribution of water resources across the continent and, at the same time, keeping four corners of Industry 4.0 in place. The algorithms tested were LR, Bayesian Ridge Regression, Logistic Regression, Linear Discriminant Analysis, Adaptive Neuro-Fuzzy Inference System, Multi-Layer Perceptron (MLP), and Radial Basis Function Network. Finally, within the Finance and Insurance, and Real Estate, and Rental and Leasing sector, Ma and Li (2018) used a Grey Model (GM) to predict eight indexes of the tertiary industry.

4.2 | Analytics Type

Table 6 shows the distribution of the selected Practical Application papers in terms of publication year and analytics type. The most common type is the Predictive Analytics level, with 80 applications, followed by the Prescriptive Analytics, with 27 applications, while the Descriptive Analytics were only addressed in 23 applications. The smaller number associated with the Prescriptive and Descriptive Analytics denote an important research gap. The lack of further Prescriptive studies is probably due to two main reasons. Firstly, the Industry 4.0 concept implementation is very recent (just a few years). Most of its initial implementation effort is devoted to setting the right infrastructure to generate and collect data, and Business Analytics can only be applied after collecting enough historical data. Secondly, Prescriptive Analytics are more complex than other types of data analyses (Koch 2015). As more mature Industry 4.0 applications are implemented, we expect this gap to be reduced. It is also interesting to note that there are more Predictive Application studies than Descriptive ones. This behaviour might be explained by the current Machine Learning hype. Also, building a stable and valuable Data Warehousing system, which results in better Descriptive analysis, requires several Extract, Transform, Load (ETL)

	Term	Frequency
1	industry	74
2	data	63
3	learning	46
4	manufacturing	42
5	maintenance	35
6	machine	34
7	predictive	34
8	big	31
9	smart	23
10	analytics	21

FIGURE 2 Word cloud of the keywords (left) and top 10 term frequency values (right)

processes that are often costly, requiring manual effort and time, but that do not tend to translate into novel methodologies or interesting application usages that justify a research publication. Overall, the yearly numbers from Table 6 show a substantial growth in the number of publications starting from 2017: 25 papers in 2017; 34 works in 2018; and 31 research publications in 2019 (the 8 papers from the year of 2020 report only until the month of March).

4.2.1 | Keywords frequencies

The last quantitative analysis is obtained by applying a word cloud technique to the 112 application paper keywords. We have selected keywords because these help to index and classify papers, facilitating research queries. The word cloud analysis was performed using R tool with the package `wordcloud`. The word cloud is presented in Figure 2, which also details the top term frequency numeric values. The most frequent term is "Industry", followed by "data", "learning" and "manufacturing". Other terms such as "maintenance", "machine" and "predictive" are also popular, which aligns with Table 6, since most practical applications use Predictive Analytics.

4.3 | Qualitative Analysis

The qualitative analysis was executed by a manual inspection of the selected practical papers. The description of practical cases are divided by the analytics type (Descriptive, Predictive and Prescriptive), using a chronological order. Each practical application is briefly described, including the:

- **Function** – Industry 4.0 function area, which is categorized by the four main functions of the Industry 4.0 architecture presented by Qin, Liu, and Grosvenor (2016): Hardware Connection (HC), focuses on hardware development (e.g., sensor network); Information Discovery (ID), where the raw data is transformed into useful knowledge; Predictive Maintenance (PdM), aiming to anticipate maintenance issues; and Intelligent Production (IP), automating or adapting the production process.
- **Data** – type of industry data used (e.g., generated by a production machine, captured image).
- **Sector** – addressed industry sector (e.g., aerospacial, automotive).
- **Goal** – brief description of the application goal.
- **Impact** – measured using the Technology Readiness Level (TRL) scale, from 1 to 9 (Table 7) (ESRTC 2009).
- **Modeling** – Business Analytics method used to analyse the data.

4.3.1 | Descriptive Analytics

Table 8 presents an overview of the practical applications that used Descriptive Analytics techniques. As shown in the table, there is a diversity of Descriptive applications and adopted types of historical analyses. For instance, some studies perform a simple statistical analysis (Birglen &

TABLE 7 Description of the Technology Readiness Levels (TRL)

Phase	Level	Definition
Research	TRL 1	Basic research
	TRL 2	Technology formulation
	TRL 3	Concept validation
Development	TRL 4	Prototype in laboratory environment
	TRL 5	Prototype in relevant environment
	TRL 6	Prototype system tested in relevant environment
Deployment	TRL 7	Demonstration system in operational pre-commercial environment
	TRL 8	First commercial system, ready for operational environment
	TRL 9	Full commercial system with general availability

Schlicht 2018; Lenz, Wuest, & Westkämper 2018; Mozgova, Yanchevskyi, Gerasymenko, & Lachmayer 2018; Niño, Blanco, & Illarramendi 2015; Sanz, Matey, Blesa, & Puig 2017; Stürmlinger, Haar, Pandtle, & Niemeyer 2018; Tang et al. 2016; Ventura et al. 2019), while others use more sophisticated outlier detection (Y.-M. Lee, Lin, Li, Xiangqian, & Li 2016; Trunzer et al. 2017) and clustering methods (Y. Wang et al. 2017). Some studies use data warehousing databases and dashboards (Kirchen, Schütz, Folmer, & Vogel-Heuser 2017; Neuböck & Schrefl 2015; Vathoopan, Johny, Zoitl, & Knoll 2018; Zheng & Wu 2017), and other studies used Neural Networks (Kaupp, Beez, Hülsmann, & Humm 2019; C.-J. Kuo, Ting, Chen, Yang, & Chen 2017; Qin, Liu, & Grosvenor 2017; Subakti & Jiang 2018; Tieng et al. 2018).

TABLE 8 Overview of the Practical Articles that used Descriptive Analytics Techniques

Reference	Func.[1]	Data[2]	Sector[3]	Goal	Impact	Modeling[4]
Neuböck and Schrefl (2015)	ID	Pr	ND	New analysis graphs are proposed for building production insights (e.g., show urgent missing materials).	7	DW, AG
Niño et al. (2015)	IF	MF	CE	Big Data Analytics for pursuing a servitization strategy.	2	DA
Y.-M. Lee et al. (2016)	ID	S	A	Real-time analysis to explore the reasons for abnormality of load rate data of main shaft machine.	5	BPANN, TSC
Tang et al. (2016)	HC	MF	ND	Intelligent architecture for the smart shop floor.	5	NEIMS
Durakbasa, Bauer, and Poszvek (2017)	ID	S	ND	Improve the quality of the manufacturing process.	2	FL
Kirchen et al. (2017)	ID	S	CI	Explore signal data quality.	4	DA
C.-J. Kuo et al. (2017)	IP	S	SM	Explore inexpensive add-on triaxial sensors for the monitoring of machinery.	5	NN
Qin et al. (2017)	ID	MC	AM	Facilitate a better understanding of the energy consumption of digital production processes.	5	LinR, DT, BPNN

[1] Hardware Connection (HC), Information Discovery (ID), Intelligent Production (IP), Predictive Maintenance (PdM)
[2] Car Specification (CS), Grippers (G), Historical (H), Machine (MC), Manufacturing (MF), Production (Pr), Sensor (S), Sparse Data (SD), Temporal Logs (TL)
[3] Additive Manufacturing (AM), Aerospace (As), Automotive (A), Capital Equipment (CE), Chemical Industry (CI), Glass Industry (GI), Not Disclosed (ND), Semiconductor (SC), Spring Manufacturing (SM)
[4] Analysis Graph (AG), Artificial Neural Networks (ANN), Augmented Reality (AR), Back-Propagation Artificial Neural Networks (BPANN), Back-Propagation Neural Networks (BPNN), Browns Double Exponential Smoothing (BDES), Classification Trees (CT), Clustering (Cl), Cross-Departmental Data Analytics (CDDA), Data Analysis (DA), Data Warehouse (DW), Decision Trees (DT), Deep Learning (DL), Descriptor Silhouette (DS), Digital Twin (DigT), Failure Mode Metrics (FMM), Fuzzy Logic (FL), Genetic Algorithm (GA), Interpolation Fitting (IF), K-Mean Clustering (KMC), Linear Regression (LinR), Monkey Algorithm (MA), Neural Networks (NN), NeuroEndocrine-Inspired Manufacturing System (NEIMS), Partial Least Square (PLS), Residual Prediction Calculator (RPC), Self Organizing Map (SOM), Simulation (Sim), Standard Silhouette (SS), Two-Stage Clustering (TSC)

Sanz et al. (2017)	ID	S	A	Advanced monitoring of an industrial process that integrates several data sources.	3	BDES
Trunzer et al. (2017)	ID	S	ND	Classify failures in control valves.	4	FMM, GA
Y. Wang et al. (2017)	ID	SD	ND	Methodology to enrich sparse data by fast and frugal reduced models.	3	CI, CT
Zheng and Wu (2017)	ID	Pr	SC	Smart spare parts inventory management system for semiconductors.	5	DA, Sim
Birglen and Schlicht (2018)	ID	G	A	Review the characteristics of pneumatic, parallel, two-finger and industrial grippers.	3	DA
Lenz et al. (2018)	ID	S	ND	Holistic approach for machine data analytics.	2	CDDA
C. Lin and Yang (2018)	HC	S	ND	Intelligent Computing System to connect the different facilities in a logistic center.	6	MA, GA
Mozgova et al. (2018)	ID	S	A	Monitor actual stress state of a structural component and estimate its residual fatigue life.	6	RPC
Ploennigs, Ba, and Barry (2018)	ID, HC	S	ND	Cognitive IoT architecture with scalability and self-learning capabilities.	5	AR
Stürmlinger et al. (2018)	HC	S	ND	Development of a new generation of a manufacturing system.	5	DA
Subakti and Jiang (2018)	ID	MC	ND	Augmented reality system to visualize and interact with machines in smart factories.	7	DL
Tieng et al. (2018)	ID	S	As	Virtual metrology system for sampling.	4	BPNN, PLS, GA, IF
Vathoopan et al. (2018)	HC	H	ND	Corrective maintenance using the digital twin of an automation model.	3	DigT
Kaupp et al. (2019)	IP	TL	GI	Outlier identification to measure the glass quality.	5	NN
Ventura et al. (2019)	ID	S, P	ND	Automatic industrial equipment maintenance system.	6	DS, SS, KMC

4.3.2 | Predictive Analytics

The practical applications that used Predictive Analytics techniques are shown in Table 9. Predictive Analytics involve a set of data-driven models that are typically obtained by applying supervised Machine Learning algorithms. Predictive Analytics are the most used techniques in the practical applications obtained for this SLR. For instance, some studies perform classification techniques (Q. Cao, Zanni-Merk, Samet, De Bertrand de Beuvron, & Reich 2020; Kiangala & Wang 2018; S. C. Li, Huang, Tai, & Lin 2017; Miškuf & Zolotová 2016; Sellami, Miranda, Samet, Bach Tobji, & de Beuvron 2019), while other used regression techniques (Calabrese et al. 2020; Charest, Finn, & Dubay 2018; Peralta et al. 2017; Rousopoulou et al. 2019). Simple neural networks are used in several research works such as (Cisotto & Herzallah 2018; Kabugo, Jämsä-Jounela, Schiemann, & Binder 2020; Miškuf & Zolotová 2016; Soto, Tavakolizadeh, & Gyulai 2019; Spendla, Kebisek, Tanuska, & Hrcka 2017). Other studies used more advanced Deep Learning Neural Networks (Choi, Kim, Kim, & Kim 2017; Essien & Giannetti 2020; H. Kuo & Faricha 2016; W. J. Lee et al. 2019; Maggipinto, Terzi, Masiero, Beghi, & Susto 2018). Furthermore, some of the surveyed Preditive Analytics used optimization techniques (e.g., Genetic Algorithm, Paticle Swarm Optimization) (Rosli, Ain Burhani, & Ibrahim 2019; Saldivar, Goh, Li, Chen, & Yu 2016; Saldivar, Goh, Li, Yu, & Chen 2016), while other works focused on outliers detection and statistical analysis (Albers et al. 2017; Stein et al. 2016).

TABLE 9 Overview of the Practical Articles that used Predictive Analytics Techniques

Reference	Func.[5]	Data[6]	Sector[7]	Goal	Impact	Modeling[8]
Kohlert and König (2016)	ID, PdM	S	Pl	Human-machine-based process monitoring and control for yield optimization in polymer film industry.	6	NN, SVM, KNN, NOVCLASS
H. Kuo and Faricha (2016)	IP	S	SC	Improve the accuracy of grating displacement offset prediction.	4	ANN
T. Lin, Chen, Yang, and Chen (2016)	PdM	S	Sp	Triaxial sensors to aid in machine monitoring to facilitate the transition of data.	5	NN, SVM, KNN, NFM
Miškuf and Zolotová (2016)	ID	T	ND	Multi-Class Classifiers and Deep Learning in the Industry 4.0 Context.	4	NN, DF, DJ, LogR, SVM, h2oDL
Saldivar, Goh, Chen, and Li (2016)	ID	CS	A	Developed a Predictive Analytics framework to add mass customization.	3	SOM
Saldivar, Goh, Li, Yu, and Chen (2016)	IP	CM	A	Predict the decision-making and customize the intelligent product design.	4	FL, GA
Saldivar, Goh, Li, Chen, and Yu (2016)	ID	CS	A	Predictive Analytics framework for the automotive area.	4	GA, KM
Stein et al. (2016)	IP	Pr	A	On-line process monitoring and predictive modeling to optimize the car production process.	2	GLOSS
Albers et al. (2017)	ID	Ac	ND	Evaluate the product quality and tool defects by using an acoustic emission sensor.	6	ANOVA
Borgi, Hidri, Neef, and Mohamed Saber (2017)	PdM	Rb	ND	Predictive maintenance of industrial robots using movements power condition-monitoring.	6	MSD, Sk, K
Choi et al. (2017)	ID	RM	ND	Deep Learning to analyze and evaluate the performance of the Deep Learning method.	3	DL

[5] Hardware Connection (HC), Information Discovery (ID), Intelligent Production (IP), Predictive Maintenance (PdM)

[6] Acoustic (Ac), Car Manufacturing (CM), Car Specification (CS), Chemical (Ch), Chemical Laboratory (ChL), Gas Turbine (GT), Gesture Images (GI), Image (I), Machine (Mc), Machine Center (McC), Material (Ma), Network (N), Pellets Images (PI), Production (Pr), Reference Metadata (RM), Robotic (Rb), Sensor (S), Sheet Material (SM), Simulated Sensor (SimS), Solar Panel (SolP), Steel (St), Text (T), Time Series (TS), Welding Images (WI)

[7] Aerospacial (Ae), Automotive (A), Coil (C), Electronic (El), Energy (En), Food (Fo), Footwear (F), Furniture (Fu), Healthcare (Hc), Naval (Na), Not Disclosed (ND), Oil (O) Petrochemical (Pc), Polymer (Pl), Robotic (Rb), Semiconductor (SC), Spring (Sp), Steel Plate (SP), Transportation (Tr),

[8] Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Analysis of Variances (ANOVA), Artificial Neural Networks (ANN), Association Rules (AsR), Backtracking Search Optimization Algorithm (BSOA) Bagged Decision Trees (BDT), Bagged Trees (BagT), Bagging (Bag), Bayesian Filter (BF) Boosting Trees (BosT), Complex Fuzzy (CF), Conference Trees (CT), Convolutional Neural Networks (CNN), Decision Forest (DF), Decision Jungle (DJ), Decision Trees (DT), Deep Learning (DL), Density-Based Spatial Clustering of Applications with Noise (DBSCAN), Discriminant Analysis (DA), Extreme Gradient Boosting (EGB), Extreme Learning Machine Boundary (ELMB), Extremely Randomized Trees (ERT), Fast Nearest Neighbors (FaNN), Feed Forward Neural Network (FeNN), Fog Computing (FC), Fuzzy-Logic (FL), Gaussian Model (GM), Gaussian Noise (GN), Genetic Algorithm (GA), Genetic Programming Based Symbolic Regression (GPBSR), Global Local Outliers in Sub Spaces (GLOSS), Gradient Boosted Regression Trees (GBRT), Gradient Boosted Tree Classifier (GBTC), Gradient Boosting (GB), Gradient Boosting Decision Trees (GBDT), Gradient Boosting Machine (GBM), H20 Deep Learning (h2oDL), Hidden Gama Process-Particle Filter (HGP-PF), Hidden Markov (HM), In Situ Classification System (ISCS), Isolation Forest (IF), Kalman Filter (KF), Kurtosis (K), K-Means (KM), K-Nearest Neighbor (KNN), Linear and Polynomial Fit (LPF), Linear Regression (LinR), Local Outlier Factor (LOF), Logistic Regression (LogR), Map Reduce (MR), Matlab Model Predictive Toolbox (MMPT), Mean and Standard Deviation (MSD), Mean Shift (MS), Microsoft Azure Machine Learning (MAML), Micro-Cluster Continuous Outlier Detection (MCCOD), Model Predictive Controller (MPC), Multiple Regression (MR), Multivariate Adaptive Regression Splines (MARS), Multi-Entity Bayesian Networks Regression (MEBNR), Multi-Layer Regression (MLR), Naive Bayes (NB), Neural Networks (NN), Neuro-Fuzzy Networks (NFN), Noise Impulse Integration (NII), Novelty Classifier (NOVCLASS), Out-of-Bag Error (OBE), Partial Least Squares (PLS), Particle Swarm Optimization (PSO), Principal Component Analysis (PCA), Pure Quadratic Regression (PQR), Quadratic Discriminant Analysis (QDA), Random Forest (RF), Random Support Vector Machine (RSVM) Recursive Partitioning (RP), Regression Trees (RT), Ridge Regression (RR), Rule-Based (RB), Skewness (Sk), Spectral and Agglomerative Clustering (SAC), SRT Model (SRTM), Stochastic Model Predictive Controller (SMPC), Support Vector Machines (SVM) Survival Analysis (SA), Time Series Forecasting (TSF), ZeroR (ZR),

Cicconi et al. (2017)	IP	Mc	F	Modeling and simulation of an induction heating process for aluminum-steel mold.	4	MMPT
Gomes et al. (2017)	IP	S	ND	Ambient Intelligent decision support system for creation of standard work procedures.	2	ANN
Haffner, Kucera, Š. Kozák, and Stark (2017)	IP	WI	A	Automatic welding recognition on cloud computing and single-board computer.	4	MAML
He and He (2017)	PdM	Ac	ND	Deep Learning for bearing fault diagnosis.	4	DL, CNN
Z. Li, Wang, and Wang (2017)	ID, PdM	McC	ND	Fault diagnosis and prognosis using data mining to formulate a systematic approach.	4	ANN
S. C. Li et al. (2017)	HC	N	ND	Data mining to detect network intrusions in a Industry 4.0 context.	4	DT, NN, ZR
Park, Laskey, Salim, and Lee (2017)	IP	Pr	SP	Predictive Manufacturing situation awareness system for enhancing competitiveness in manufacturing.	6	MEBNR
Peralta et al. (2017)	IP	N	ND	Fog computing-based IoT scheme to predict future data measurements.	4	MLR, RT, BDT, ANN, FC
Spendla et al. (2017)	PdM	Mc	A	Hadoop based knowledge discovery platform focused on predictive maintenance for production systems.	4	NN
Sun and Chen (2017)	PdM	S	ND	Low-cost customized wireless data transmission module to predict the remaining useful life of the machines.	6	LPF
Vazan, Janikova, Tanuska, Kebisek, and Cervenanska (2017)	PdM	Pr	ND	Data Mining to obtain knowledge of the future behavior in manufacturing systems.	4	CT, DT, BagT, RF, MARS, SVM, KNN, MR, NN
Wan et al. (2017)	PdM	Mc, Ma	S, ND	Big Data solution for active Preventive Maintenance in manufacturing environments.	7	NN
J. Yan, Meng, Lu, and Li (2017)	PdM	Pr	ND	Predict remaining life of a key component of a machining equipment.	5	ANN
Zhou and Yu (2017)	ID	S	ND	FNN and KNN to resolve the incorrect or biased analysis of sensor data.	4	FNN, KNN
Apiletti et al. (2018)	PdM	Mc	ND	Integrated Self-Tuning Engine for Predictive Maintenance, based on big data.	4	RF, LinR, SVM, GBM
Charest et al. (2018)	IP	S	PI	Artificial Intelligence to improve the injection molding process performance.	5	DT, BosT, RF, NB, KNN, FaNN, ANN
Y.-J. Chen and Chien (2018)	IP	Pr	SC	Diffusion model and adjustment mechanism to incorporate domain insights.	2	SRTM
Cisotto and Herzallah (2018)	PdM	GT	Na	Used NNs in a system that support the maintenance function in the decision-making process.	4	NN
Dwaraka and Arunachalam (2018)	ID	Ac	ND	Acoustic emission signals to characterize the spark activity in the Electrical Discharge Machining process.	5	MLR
C. Lin et al. (2018)	PdM	SimS	ND	Learning method with multiple classifier types and diversity for condition-based maintenance in manufacturing industries.	4	MR

Maggipinto et al. (2018)	IP	S	SC	Deep Learning using Computer Vision to model data that have both spacial and time evolution.	4	CNN
Mulrennan et al. (2018)	IP	S	PI	Hybrid Principal Component Analysis RF (PCA-RF) soft sensor model for the inline prediction of tensile properties of polylactide (PLA).	5	DT, Bag, OBE, PCA, RF
Nuzzi, Pasinetti, Lancini, Docchio, and Sansoni (2018)	IP	GI	Rb	Smart hand gesture recognition for collaborative robots with R-CNN object detector to find the hands position.	4	DL
Kiangala and Wang (2018)	PdM	S	PI	Predictive and scheduling maintenance based on the data gathered by the sensors in the conveyors.	5	RB
Kumar, Chinnam, and Tseng (2018)	PdM	S	ND	Health state estimation to facilitate autonomous diagnostics and prognostics models.	5	LinR, PQR
Rendall et al. (2018)	IP	PI	Ch	DNNs in images to predict the pellet shape.	4	ISCS, PLS, DA, RF, DL
Alberto Sala, Jalalvand, Van Yperen-De Deyne, and Mannens (2018)	IP	S	St	Predict the endpoint temperature and chemical concentration of phosphorus, manganese, sulfur and carbon at the basic oxygen furnace.	5	RR, RF, GBRT
Sezer, Romero, Guedea, Macchi, and Emmanouilidis (2018)	IP	S	ND	CCPS to predict the parts rejection based on a quality threshold.	6	RP, RT
Straus, Schmitz, Wostmann, and Deuse (2018)	HC, PdM	S	A	Low-Cost Sensors to enable predictive maintenance in old production machines.	6	IF, LOF, KM, MS, SAC, DBSCAN, DT, RF, SVM, LinR, KNN, NB, QDA, NN
Subramaniyan, Skoogh, Salomonsson, Bangalore, and Bokrantz (2018)	IP	Pr	A	Predict throughput bottlenecks in the production line for the future production run.	5	TSF
Susto, Schirru, Pampuri, Beghi, and DeNicolao (2018)	PdM	Mc	SC	Adaptive parameter identification to verify the best trade-off between promptness and low noise sensitivity.	4	SVM, HGP-PF
Tiwari, Shaik, and N (2018)	IP	Mc	ND	Explored the opportunities in the area of tool wear prediction.	5	KF
Tsai and Chang (2018)	IP	SM	C	Deep Learning application based for coil leveling system.	6	DL
Wu, Zheng, Chen, Wang, and Cao (2018)	ID, PdM	TS	Pc	Visual analytics system to reach automated analytical approaches, and generating results for real-world applications.	4	GM

H. Yan et al. (2018)	PdM	S	ND	Device electrocardiogram and an deep denoising auto-encoder algorithm to predict the remaining useful life of the equipment.	5	DL
Antomarioni et al. (2019)	PdM	Pr	O	Predict component breakages and determine the optimal set of components to repair.	5	AsR
Akhtari, Pickhardt, Pau, Di Pietro, and Tomarchio (2019)	IP	S	Tr	DNN to detect and classify the load on a power-train.	5	DL
Aydemir and Paynabar (2019)	PdM	I	ND	Deep Learning methods for estimating time-to-failure of and industrial system using its degradation image.	5	DL
Bousdekis et al. (2019)	PdM	S	St	Predictive Maintenance architecture according to RAMI 4.0.	2	NN, DL, HM
Bose, Kar, Roy, Gopalakrishnan, and Basu (2019)	PdM	Mc	Ae	Anomaly Detection based Power Saving (ADEPOS) scheme using Extreme Learning Machine Boundary through the lifetime of the machine.	4	ELMB
Bruneo and De Vita (2019)	PdM	Mc	Ae	Deep Learning to analyze the history of a system to predict the Remaining Useful Life.	4	DL
Candanedo, González, De la Prieta, and Arrieta (2019)	PdM	S	Tr	Predict failures in Air Pressure System in trucks.	4	KNN, NB
Hesser and Markert (2019)	IP	S	ND	ANN to monitor the tool wear in retrofitted CNC milling machines.	5	ANN
W. J. Lee et al. (2019)	PdM	Pr	ND	Predictive Maintenance to monitor two machine tool system elements, the cutting tool, and the spindle motor.	5	SVM, DL
Liulys (2019)	PdM	S	El	Open-source software to develop predictive maintenance applications with basic programming knowledge.	3	GBM, NN
Massaro, Manfredonia, Galiano, and Xhahysa (2019)	IP	Pr	Fu	ANN to predict the product defects in a kitchen manufacturing Industry.	5	ANN
Massaro, Manfredonia, Galiano, Pellicani, and Birardi (2019)	IP	S	Fo	Predict the humidity during the pasta production.	5	ANN
Martinek and Krammer (2019)	IP	I	El	Machine Learning based prediction methods to optimize the process parameters of pin-in-paste.	5	ANN, ANFIS, GBDT
Packianather, Munizaga, Zouwail, and Saunders (2019)	PdM	ChL	Hc	Three phase methodology to automate quality control in healthcare clinical laboratory.	5	KNN
Pinto and Cerquitelli (2019)	PdM	S	Rb	Predict the fault detection and remaining life estimation of robots.	5	SA, ERT, KNN, CNN
Plehiers et al. (2019)	IP	S	Ch	Framework for chemical production in process-steam cracking to optimize the process control.	4	ANN

Proto et al. (2019)	IP	S	Ch	PREdictive Maintenance service for Industrial procesSES (PREMISES) to predict alarms in slowly-degrading multi-cycle industrial process.	6	GBTC, RF
Rogier and Mohamudally (2019)	IP	SolP	En	NN to predict the conversion of solar energy by a photovoltaic unit.	5	NN
Rosli et al. (2019)	PdM	S	SC	Preventive maintenance for air booster compressor motor failure.	4	ANN, PSO
Rousopoulou et al. (2019)	PdM	Pr	Hc	Predictive analytics for industrial ovens in the healthcare industry.	5	SVM
Sellami et al. (2019)	PdM	Mc	SC	Predict machine failures and presented an algorithm for frequent chronicles extraction.	4	Clasp-CPM
Soto et al. (2019)	PdM	S	ND	IoT Machine Learning and orchestration to failure detection of surface mount devices during production.	4	NN, RF, GB
Naskos, Gounaris, Metaxa, and Köchling (2019)	PdM	Mc	O	Predictive Maintenance with applied unsupervised Machine Learning techniques to detect early oil leaks.	5	MCCOD
Zenisek, Wolfartsberger, Sievi, and Affenzeller (2019)	PdM	S	ND	Machine Learning algorithms to detect changing behavior to enhance the maintenance on a microscopic level.	3	RF, SVM, GPBSR
T. Zhang, Feng, and Hao (2019)	IP	Pr	El	Random-SVM (R-SVM) to predict the quality of the TFT-LCD liquid.	4	RSVM
Alasali, Haben, Foudeh, and Holderbaum (2020)	IP	Mc	Tr	Predict the stochastic loads to improve the performance of a low voltage network.	6	MPC, SMPC
Calabrese et al. (2020)	PdM	Mc	Fu	Machine Learning to predict the health status of a woodworking industrial machine.	6	GB, RF, EGB
Q. Cao et al. (2020)	PdM	Pr	ND	Rule-based refinement approach for detect and predict anomalies.	4	RB
Essien and Giannetti (2020)	IP	Mc	ND	Deep Learning model for univariate, multi-step machine speed forecasting in a manufacturing process.	4	DL
Kabugo et al. (2020)	IP	Pr	En	Predict syngast heating value and hot flue gas temperature from data obtained from soft sensors.	5	NN
Karakose and Yaman (2020)	PdM	S	Tr	Fuzzy system-based approach for Predictive Maintenance on electric railways.	4	CF
Kim, Lee, Adhi Tama, and Lee (2020)	IP	Pr	ND	Predict the state of an unseen camera lens module using semi-supervised regression.	5	DL
Ruiz-Sarmiento et al. (2020)	PdM	Pr	SP	Estimate and predict the gradual degradation of production machines.	5	BF
de Sá, Casimiro, Machado, and Carmo (2020)	HC	Pr	ND	Metaheuristics to identify data injection attacks by man-in-the-middle.	4	BSOA, GN, NII

4.3.3 | Prescriptive Analytics

The last table of this SLR (Table 10) presents the practical cases that used Prescriptive Analytics. These types of analytics aims to describe what courses of action may be taken in the future to optimize business processes in order to achieve business objectives. Typically, this is achieved by associating decision alternatives (or choices) with estimated business outcomes. A diverse set of modeling tools can be used to obtain such analytics, namely optimization and simulation, design experimentation and scenario scheduling (Banerjee, Bandyopadhyay, & Acharya 2013; Jugulum 2016).

The majority of the surveyed studies used optimization techniques. In particular, the most explored method was the Genetic Algorithm (Khayyam et al. 2019; Silva, Jesus, Villaverde, & Adina 2020). Other authors (Ansari, Glawar, & Nemeth 2019; Brik, Bettayeb, Sahnoun, & Duval 2019; Fu, Ding, Wang, & Wang 2018; H. Li 2016; Qu, Wang, Govil, & Leckie 2016; Tsourma, Zikos, Drosou, & Tzovaras 2018; Uriarte, Ng, & Moris 2018), employed other optimization techniques, such as (Tsourma et al. 2018) that proposed a Task Distribution Engine to automate and optimize the task scheduling and resources assignment procedure in industrial environments. We also found studies that performed Prescriptive Analytics by using predictive models to directly perform actions: Deep Learning (Richter, Streitferdt, & Rozova 2017); Regression Trees and Nearest Neighbors (Romeo, Paolanti, Bocchini, Loncarski, & Frontoni 2018); and SVM combined with Q-Learning (Qu et al. 2016).

5 | DISCUSSION

Figure 3 presents the Literature Map resulted from this SLR. This Literature Map contains three different levels of interactions, where the first level is the Analytics Level and the second level contains the components of the different Analytics application levels (Data Visualization, Detect Production Anomalies, Improve Product Quality, Detect Costumers Needs, Predictive Maintenance and Resources Optimization). The last level presents the different techniques used for each component, as well as some studies that use these techniques. To simplify the visualization, the map only details business analytics techniques that were used in two or more practical cases.

It is clear in Figure 3 that Supervised Learning techniques (Classification and Regression algorithms) are a popular approach of Business Analytics in Industry 4.0, being adopted in all the application types identified in this SLR. Statistical Data Analysis is a technique used mainly for Data Visualization, but it was also used for Predictive Maintenance (Mozgova et al. 2018), to Detect Anomalies in Production (Zheng & Wu 2017) and to Improve Product Quality (Kirchen et al. 2017). Clustering is a more advanced technique compared to Statistical Data analysis, and is used to find Production Anomalities (Y. Wang et al. 2017), to improve the products quality (T. Lin et al. 2016), to detect costumers needs (Saldivar, Goh, Li, Yu, & Chen 2016), and for predictive maintenance (Candanedo et al. 2019). Reinforcement Learning was used mostly for Resources Optimization (Pane, Nageshrao, Kober, & Babuska 2019; Qu et al. 2016), while Optimization techniques were used for Resources Optimization (Uriarte et al. 2018), to Detect Production Anomalies (Trunzer et al. 2017) and to Improve Product Quality (Khayyam et al. 2019).

Regarding the Supervised Learning techniques, based on Classification and Regression algorithms, it is important to mention the popularity of Neural Networks (in their ANN, DL, or CNN forms), in the different Industry 4.0 areas. In effect, the use of Neural Networks reaches every area of application studied in this SLR with a total of 38 practical applications retrieved in this study. Moreover, the use of Neural Networks is growing over the time, with 4 applications in 2016, 10 in 2017, 7 in 2018, 14 in 2019, and 3 applications in the first months of 2020.

The Literature Map from Figure 3 provides a general overview of the different application areas of Business Analytics in Industry 4.0, where it is clear that the areas of Improve Product Quality, Anomalies Detection and Predictive Maintenance are the most popular. While Business Analytics techniques can also be employed to optimize resources in the Industry or to Detect Costumers Needs, a small number of research application studies have addressed these topics, with 9 applications focused on Resources Optimization and 4 applications in Detect Costumer Needs.

6 | CONCLUSIONS AND RESEARCH IMPLICATIONS

This paper presents the results of a Systematic Literature Review (SLR) to analyze the evolution and the application of Business Analytics techniques in the Industry 4.0 context. As stated in Section 1, the Research Question targeted by this SLR research is: ***How and in what areas of the industry are Business Analytics techniques being used in an Industry 4.0 context?*** The papers were surveyed by performing an initial keywords query on scientific search engines. Then, the retrieved papers were manually inspected by performing a careful analysis, to assure that the most relevant studies for this SLR were selected. Next, we have analyzed the selected papers in terms of both quantitative and qualitative elements. The quantitative analysis showed that the most published type of paper is the Practical Application. As for the quantitative analysis, it consisted in a characterization of the Descriptive, Predictive and Prescriptive analytics in terms of what types of applications are implemented in the Industry, what are the techniques used in the practical applications and the impact of the results achieved. Considering the presented SLR we highlight that:

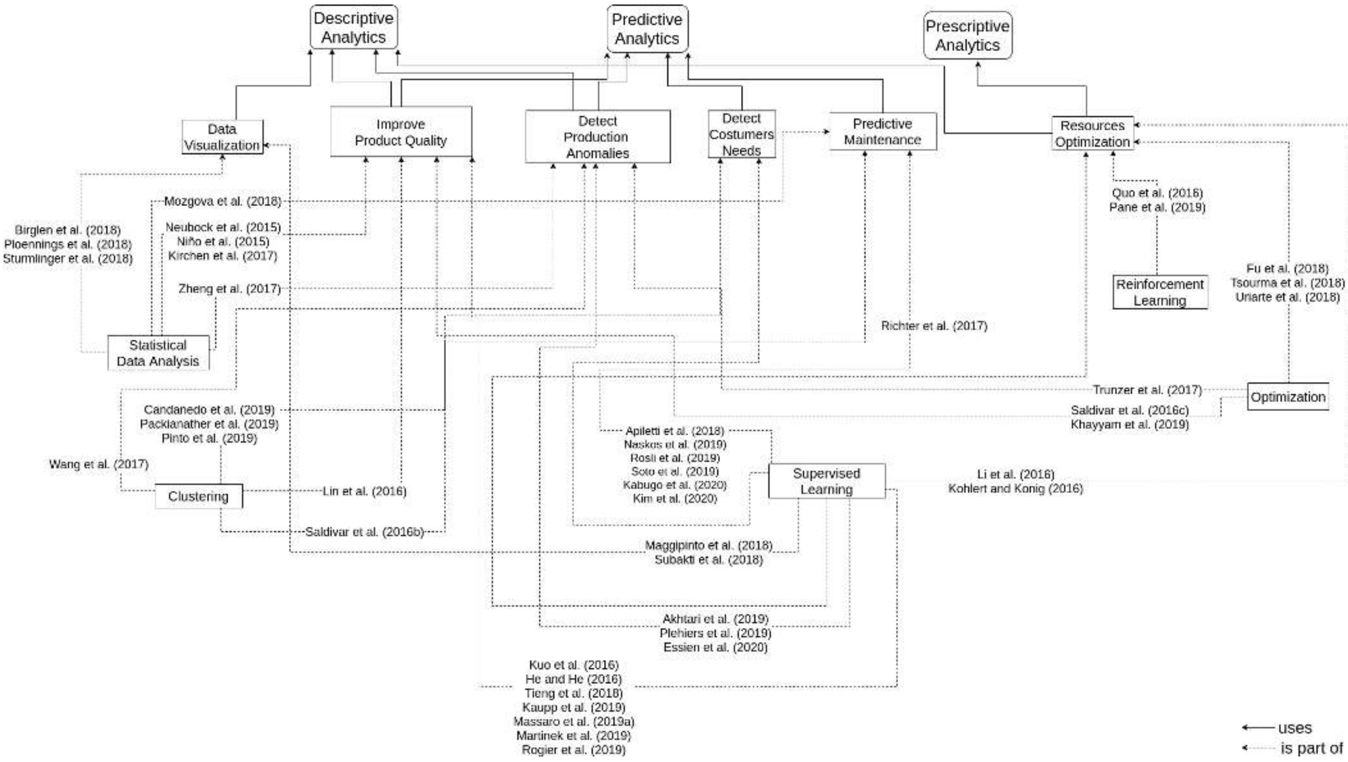

FIGURE 3 Literature Map

TABLE 10 Overview of the Practical Articles that used Prescriptive Analytics Techniques

Reference	Func.[9]	Data[10]	Sector[11]	Goal	Impact	Modeling[12]
H. Li (2016)	IP	Co	ND	Classification algorithm and Q-learning algorithm to reduce the electricity consumption in an automation system.	4	SVM, QL
Qu et al. (2016)	IP	Pr	ND	Synchronized, station-based flow shop with multi-skill workforce and multiple types of machines.	3	RL, MARL, Op
Klement and Silva (2017)	IP	Pr	Pl	Hybrid approach with List Algorithm and Metaheuristic to optimize planning, assignment, scheduling and lot sizing.	3	LA, SA
Richter et al. (2017)	IP	Mc	El	Optimization techniques for the manufacturers and users of AOI machines.	2	DL
Bányai, Illés, and Bányai (2018)	HC	Ge	Tr	Black Hole Optimization for first mile and last mile supply.	6	BHO
Fu et al. (2018)	IP	In	ND	Two-objective stochastic flow-shop deteriorating and learning scheduling problem for advanced intelligent machines.	4	MOO, FA

[9] Hardware Connection (HC), Information Discovery (ID), Intelligent Production (IP), Predictive Maintenance (PdM)
[10] Conveyor (Co), Geospatial (Ge), Industrial (In), Machine (Mc), Network (N), Production (Pr), Sensor (S)
[11] Automotive (A), Chemical (Ch), Electronic (El), Lean (Le), Mechanical (MC), Not Disclosed (ND), Polymer (Pl), Transportation (Tr)
[12] Artificial Neural Networks (ANN), Black Hole Optimization (BHO), Constrained Optimization (CO), Coyote Optimization Algorithm (COA), Crow Search Algorithm (CSA), Decision Trees (DT), Deep Learning (DL), Fireworks Algorithm (FA), Fog Computing (FC), Genetic Algorithm (GA), Global Cheapest Arc (GCA), Grey Wolf Optimizer (GWO), Guided Local Search (GLS), Iterative Local Search (ILS), K-Nearest Neighbor (KNN), List Algorithm (LA), Memetic Algorithm (MmA), Mixed Integer Linear Programming Model (MILPM), Multi-Agent Reinforcement Learning (MARL), Multiple-layer perceptron neural network (MLPNN), Multi-Objective Optimization (MOO), Neighborhood Component Feature Selection (NCFS), Optimization (Op), Particle Swarm Optimization (PSO), Path Cheapest Arc Savings (PCAS), Prescriptive Maintenance Model (PriMa), Q-Learning (QL), Random Forest (RF), Regression Trees (RT), Reinforcement Learning (RL), Self Organizing Migrating Algorithm (SOMA), Simplified Swarn Optimization (SSO), Simulated Annealing (SA), Simulated Annealing Tabu Search (SATS), Simulation-based Multi-Objective Optimization (SBMOO), Support Vector Machines (SVM), Tabu Search (TbS), Variable Neighborhood Descent Based (VNDB), Variable Neighborhood Search (VNS), Whale Optimization Algorithm (WOA)

Romeo et al. (2018)	IP	Mc	El	Design Support System (DesSS) for the prediction and estimation of machine specification data.	4	DT, RT, KNN, NCFS
Tsourma et al. (2018)	IP	In	ND	Task Distribution Engine to automate and optimize the task scheduling and resources assignment procedure in industrial environments.	5	CO
Uriarte et al. (2018)	IP	Le	ND	Simulation and optimization to improve the lean efficiency, speeding up system improvements and reconfiguration.	2	SBMOO
Ansari et al. (2019)	IP	Mc	MD	Prescriptive Maintenance model for production CPS.	6	PriMa
Brik et al. (2019)	IP	In	ND	Fog computing architecture to deal with system disruption monitoring.	4	FC
Khayyam et al. (2019)	IP	Pr	Pl	Genetic Algorithm to predict the stabilization process of a Plyacrylonitrile fiber structure.	5	GA
Leite, Pinto, and Alves (2019)	IP	Pr	Pl	Optimize the integrated planning and scheduling using Metaheuristic approach.	4	VNDB
Liang, Kuo, and Lin (2019)	PdM	S	ND	Memetic Algorithm and Variable Neighborhood Search to improve Predictive Maintenance.	4	MmA, VNS
Negri et al. (2019)	IP	S	ND	Metaheuristics with Digital Twin for scheduling optimizations based on the equipment health predictions.	6	GA
Pane et al. (2019)	IP	Mc	MC	Two reinforcement learning based compensation methods for robot manipulators.	5	RL
Pierezan, Maidl, Massashi Yamao, dos Santos Coelho, and Cocco Mariani (2019)	IP	S	En	Coyote Optimization Algorithm to optimize a heavy duty gas turbine used in power generation.	6	COA
Senkerik, Kadavy, Viktorin, and Pluhacek (2019)	IP	S	Ch	Ensemble of strategies and Metaheuristic for optimization of waste processing batch reactor geometry and control	4	SOMA
Yeh and Tsai (2019)	IP	N	ND	Optimization techniques to find the cost minimization deployment of a smart factory.	4	SSO
Abdelmaguid (2020)	IP	Pr	ND	Algorithm to obtain optimal solutions for Dynamic Open Shop Scheduling Problem.	4	MILPM
Abdirad, Krishnan, and Gupta (2020)	HC	Ge	A	Two-stage metaheuristic to solve dynamic vehicle routing problem.	4	PCAS, GCA, GLS, SATS
Abdous, Delorme, and Battini (2020)	IP	S	A	Design semi-automated assembly lines using Machine Learning and Optimization techniques.	4	ILS
Kharwar, Verma, Mandal, and Mondal (2020)	IP	S	Pl	Particle Swarn Optimization to optimize milling parameters (weight, spindle speed, feed rate and depth of cut).	4	PSO
Y. Li et al. (2020)	IP	Pr	Pl	Hybrid model using Optimization and Machine Learning for production rescheduling.	4	GA, TbS, RF, SVM, MLPNN

Milošević, Durdev, Lukić, Antić, and Ungureanu (2020)	IP	Pr	ND	Compared three optimization algorithms for intelligent process planning optimization.	4	GWO, WOA, CSA
Rahman, Janardhanan, and Nielsen (2020)	IP	Pr	ND	PSO for line balancing and automated guided vehicles scheduling for smart assembly systems.	4	PSO
Silva et al. (2020)	IP	Pr	ND	Hybrid ANN model and use GA for the multi-objective strength optimization of concrete with fiber.	5	ANN, GA

- The application of Business Analytics techniques within the Industry 4.0 concept has grown in recent years and its popularity is still rising (as shown in Figure 1 and Table 6). Thus, there is a research opportunity for publishing more papers regarding Business Analytics applied to the Industry 4.0.

- Manufacturing is the industry sector with the most practical applications (Table 5). One contributing factor for this phenomenon is that there has been a financial support for the adoption of innovative manufacturing techniques (European Commission 2013). Nevertheless, there is a research opportunity set in terms of addressing other industry sectors, such as Transportation or Construction.

- Within the manufacturing sector, most of the practical applications focused on problems existing in production lines, with different goals, such as detecting faults in production components, defective products, until monitoring the production process and optimization of productive components such as energy consumption and resources allocation.

- Regarding the type of analytics, Descriptive Analytics involved a total of 23 practical applications, Predictive Analytics with 80 application studies and Prescriptive Analytics included 24 research works. The popularity of Predictive Analytics is being linked with the growing interest in the fields of Machine Learning and Data Science in the decade of 2010 (C. Costa & Santos 2017).

- Regarding the modeling techniques used, Supervised Learning was the most used approach, with Neural Networks being used in 39 applications, Random Forest in 10 applications, Support Vector Machine in 6 applications, Decision Tree in 5 applications and Rule-Based in 2 applications. Classical Statistical Data Analysis was used in 11 applications, Clustering was addressed in 6 applications, the same number as Optimization techniques, and Reinforcement Learning was employed in 2 applications. Given the current success of the Deep Learning field (Goodfellow, Bengio, Courville, & Bengio 2016), it is expected that the number of Industry 4.0 research works that use Neural Networks will further increase in the future.

- Practical applications that use Descriptive Analytics are focused on analyzing the data obtained in order to find answers for diverse problems, such as verifying the tool wear through the time or what is the most common cause that leads to the equipment failure.

- The practical applications that used Predictive Analytics were more focused in Predictive Maintenance, such as predict when the equipment will fail, or verify if the equipment is not corresponding in terms of its typical performance.

- Practical applications that use Prescriptive Analytics target more on resources optimization, such as optimize the energy consumption or optimize the resources scheduling. However, the SLR results reveal that there is still a scarce number of research studies that use Prescriptive Analytics techniques within the Industry 4.0. Therefore, there is a huge potential for future research on more Prescriptive Analytics studies since there is a large number of industrial needs that are related with resource optimization and scheduling. Moreover, as pointed out by Davenport (2013), these are the analytics "that tell you what to do" and thus hold a higher business value by providing an actionable knowledge for the industry. Thus, in future works, we believe there will be an increase of Prescriptive Analytics applications for the Industry 4.0.

This SLR reviewed research papers published in the last decade (from 2010 to 2020). In the next decade, it is expected that Business Analytics will be more prevalent in the Industry, due to further advances in Artificial Intelligence (AI) and Machine Learning. In particular, as the European Commission plans a future investment of 7.5 Billion EUR in the areas of Advanced Computing and Artificial Intelligence (Commission 2020), several of these funds will be devoted to Industry applications, which surely will be reflected in an increased number of research papers.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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