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Industry 4.0 technologies: Implementation patterns in manufacturing companies

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ABSTRACT

Industry 4.0 has been considered a new industrial stage in which several emerging technologies are converging to provide digital solutions. However, there is a lack of understanding of how companies implement these technologies. Thus, we aim to understand the adoption patterns of Industry 4.0 technologies in manufacturing firms. We propose a conceptual framework for these technologies, which we divided into front-end and base technologies. Front-end technologies consider four dimensions: Smart Manufacturing, Smart Products, Smart Supply Chain and Smart Working, while base technologies consider four elements: internet of things, cloud services, big data and analytics. We performed a survey in 92 manufacturing companies to study the implementation of these technologies. Our findings show that Industry 4.0 is related to a systemic adoption of the front-end technologies, in which Smart Manufacturing plays a central role. Our results also show that the implementation of the base technologies is challenging companies, since big data and analytics are still low implemented in the sample studied. We propose a structure of Industry 4.0 technology layers and we show levels of adoption of these technologies and their implication for manufacturing companies.

1. Introduction

The fourth industrial revolution – also named as Industry 4.0 – is one of the most trending topics in both professional and academic fields (Chiarello et al., 2018; Liao et al., 2017). This concept has Smart Manufacturing as its central element (Kagermann et al., 2013). It also considers the integration of the factory with the entire product lifecycle and supply chain activities (Wang et al., 2016b; Dalenogare et al., 2018), changing even the way people work (Stock et al., 2018). Industry 4.0 relies on the adoption of digital technologies to gather data in real time and to analyze it, providing useful information to the manufacturing system (Lee et al., 2015; Wang et al., 2016a). The advent of Internet of Things (IoT), cloud services, big data and analytics, made this possible, creating the cyber-physical system concept of Industry 4.0 (Wang et al., 2015; Lu, 2017).

The Industry 4.0 concept has a very complex technology architecture of the manufacturing systems (Lee et al., 2015), which is one of the main concerns in this new industrial stage. Therefore, the effective implementation of Industry 4.0 technologies is still a subject of research (Lee et al., 2015; Babiceanu and Seker, 2016; Dalenogare et al., 2018). Some prior works have proposed maturity models for the implementation of these technologies (e.g. Schuh et al., 2017; Lee et al., 2015; Lu and Weng, 2018; Mittal et al., 2018), while other works have studied the impact of these technologies on industrial performance (Dalenogare et al., 2018). However, there is a lack of studies providing empirical evidence about the way these technologies are adopted in manufacturing companies, leading to an important question: *what are the current Industry 4.0 technologies adoption patterns in manufacturing companies?*

In order to answer this question, we present an exploratory quantitative analysis of 92 manufacturing companies from the machinery and equipment sector. We aim to understand if manufacturing companies can be organized based on adoption patterns of Industry 4.0 technologies and if these patterns allow to define specific configurations of Industry 4.0 technologies. Such analysis helps us to understand what is needed for an effective implementation of Industry 4.0 technologies in manufacturing companies. We first propose a conceptual framework of Industry 4.0 technologies, into two main layers: front-end

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and base technologies. The first layer (front-end technologies) comprises four main dimensions of Industry 4.0: Smart Manufacturing, Smart Products, Smart Supply Chain and Smart Working, each of them representing a specific subset of technologies. The second layer (base technologies) considers technologies that provide connectivity and intelligence to the front-end technologies (e.g. IoT and analytics). Then, we apply a cluster analysis to define patterns of adoption of these two layers of technologies in the surveyed companies and to understand relationships among these technologies. As a key-finding, we propose a structure of Industry 4.0 technology layers and we show levels of adoption of these technologies and their implication for the implementation of the Industry 4.0 concept. These findings are summarized in a final framework representing a maturity pattern of the Industry 4.0 implementation in the sample studied.

2. Defining the Industry 4.0 concept

Industry 4.0 was coined in 2011 by a German initiative of the federal government with universities and private companies. It was a strategic program to develop advanced production systems with the aim of increasing productivity and efficiency of the national industry (Kagermann et al., 2013). This concept represents a new industrial stage of the manufacturing systems by integrating a set of emerging and convergent technologies that add value to the whole product lifecycle (Dalenogare et al., 2018; Wang et al., 2016b). This new industrial stage demands a socio-technical evolution of the human role in production systems, in which all working activities of the value chain will be performed with smart approaches (*Smart Working*) (Stock et al., 2018; Longo et al., 2017) and grounded in information and communication technologies (ICTs) (Raguseo et al., 2016).

Industry 4.0 is rooted in the advanced manufacturing or also called *Smart Manufacturing* concept, i.e. an adaptable system where flexible lines adjust automatically production processes for multiple types of products and changing conditions (Wang et al., 2016a; Schuh et al., 2017). This allows to increase quality, productivity and flexibility and can help to achieve customized products at a large scale and in a sustainable way with better resource consumption (Dalenogare et al., 2018; de Sousa Jabbour et al., 2018).

Industry 4.0 also considers the exchange of information and integration of the supply chain (called *Smart Supply Chain*), synchronizing production with suppliers to reduce delivery times and information distortions that produce bullwhip effects (Ivanov et al., 2016). This integration also enables companies to combine resources in collaborative manufacturing (Chien and Kuo, 2013; Lin et al., 2012), allowing them to focus on their core competences and share capabilities for product innovation in industry platforms, a joint effort to develop products and complementary assets and services, with more value-added (Gawer and Cusumano, 2014; Kortmann and Piller, 2016; Chen and Tsai, 2017).

The technologies embedded in the final products (*Smart Products*) are also part of the broader Industry 4.0 concept (Dalenogare et al., 2018). Smart Products can provide data feedback for new product development (Tao et al., 2018b) as well as they can provide new services and solutions to the customer (Porter and Heppelmann, 2015). Thus, some scholars consider the Smart Products as the second main objective of Industry 4.0, since they allow new business models such as the product-service systems, which create new opportunities for manufacturers and service providers (Zhong et al., 2017; Ayala et al., 2019).

3. A conceptual framework for Industry 4.0 technologies

Industry 4.0 technologies can be separated, at least, into two different layers according to their main objective, as proposed in our conceptual framework of Fig. 1. In the center of the framework we place what we call as '*Front-end technologies*' of Industry 4.0, which considers the transformation of the manufacturing activities based on

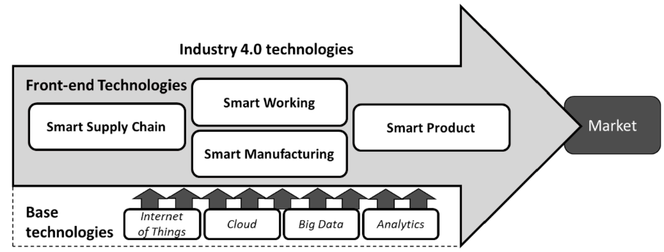

Fig. 1. Theoretical framework of Industry 4.0 technologies.

emerging technologies (Smart Manufacturing) and the way product are offered (Smart Products) (Dalenogare et al., 2018). It also considers the way raw materials and product are delivered (Smart Supply Chain) (Angeles, 2009) and the new ways workers perform their activities based on the support of emerging technologies (Smart Working) (Stock et al., 2018; Longo et al., 2017). We call *'front-end technologies'* to this technology layer because the four 'smart' dimensions are concerned with operational and market needs. Therefore, they have an end-application purpose for the companies' value chain, as shown in the schematic arrow represented in Fig. 1. It is worth noticing that the central dimension of the front-end technology layer is the Smart Manufacturing, while the other dimensions are interconnected to this one. The front-end layer relies on another layer represented in Fig. 1: the '*base technologies*' which comprises technologies that provide connectivity and intelligence for front-end technologies. This last layer is the one which enables the Industry 4.0 concept, differentiating this concept from previous industrial stages. This is because base-technologies allow front-end technologies to be connected in a complete integrated manufacturing system (Tao et al., 2018a; Thoben et al., 2017; Wang et al., 2016a). In the following subsections, we define each layer proposed in our framework of Fig. 1. We aim to understand how these technologies are used in manufacturing firms and if they follow implementation patterns.

3.1. Industry 4.0 front-end technologies

3.1.1. Smart Manufacturing and Smart Products

In the core of the Industry 4.0 concept, Smart Manufacturing technologies work as the central pillar of the internal operations activities (Ahuett-Garza and Kurfess, 2018), while Smart Product consider the external value-added of the products, when customer information and data are integrated with the production system (Dalenogare et al., 2018). These two dimensions consider technologies that have direct impact on manufactured products. Smart Manufacturing considers technologies for the product processing (production system), while Smart Products considers technologies related to the product offering. Therefore, we assume that Smart Manufacturing is the beginning and first purpose of Industry 4.0, while Smart Product is its extension. This vision follows the chronological recent evolution of the Industry 4.0 concept, which has its roots firstly in the advanced manufacturing systems and its connections with other processes of the company (Yin et al., 2018; Dalenogare et al., 2018).

Regarding the Smart Manufacturing dimension, we subdivided the related technologies into six main purposes: (i) vertical integration, (ii) virtualization, (iii) automation, (iv) traceability, (v) flexibility and (vi) energy management, as summarized in Table 1.

Factory's vertical integration comprises advanced ICT systems that integrate all hierarchical levels of the company – from shop floor to middle and top-management levels – helping decision-making actions to be less dependent of human intervention (Schuh et al., 2017). To reach vertical integration, the first step at shop floor is the digitalization of all physical objects and parameters with sensors, actuators and Programmable Logic Controllers (PLC) (Jeschke et al., 2017). The data is then gathered with Supervisory Control and Data Acquisition

Table 1
Smart Manufacturing technologies.

Categories	Technologies for Smart Manufacturing	Reference
Vertical integration	Sensors, actuators and Programmable Logic Controllers (PLC)	Jeschke et al. (2017); Lee et al. (2015)
	Supervisory Control and Data Acquisition (SCADA)	Jeschke et al. (2017)
	Manufacturing Execution System (MES)	Telukdarie et al. (2018); Jeschke et al. (2017)
	Enterprise Resource Planning (ERP)	Jeschke et al. (2017)
	Machine-to-machine communication (M2M)	Gilchrist (2016)
Virtualization	Virtual commissioning	Mortensen and Madsen (2018); Tao et al. (2018c)
	Simulation of processes (e.g. digital manufacturing)	Jeschke et al. (2017)
	Artificial Intelligence for predictive maintenance	Tao et al. (2018c)
	Artificial Intelligence for planning of production	Gilchrist (2016)
Automation	Machine-to-machine communication (M2M)	Gilchrist (2016)
	Robots (e.g. Industrial Robots, Autonomous Guided Vehicles, or similar)	Gilchrist (2016)
	Automatic nonconformities identification in production	Gilchrist (2016); Jeschke et al. (2017)
Traceability	Identification and traceability of raw materials	Angeles (2009)
	Identification and traceability of final products	
Flexibility	Additive manufacturing	Weller et al. (2015); D'Aveni (2015)
	Flexible and autonomous lines	Balogun and Popplewell (1999); Wang et al. (2016a)
Energy management	Energy efficiency monitoring system	Gilchrist (2016); Kagermann et al. (2013)
	Energy efficiency improving system	Jeschke et al. (2017); Kagermann et al. (2013)

(SCADA), for production control and diagnosis at the shop floor. At the managerial information layers, Manufacturing Execution Systems (MES) obtain data from SCADA, providing production status to the Enterprise Resource Planning (ERP) system. When all systems are properly integrated, the information of production orders also flows in the inverse way (downstream), from ERP to MES and then to SCADA, helping to deploy the enterprise resources into manufacturing orders (Tao et al., 2018c; Jeschke et al., 2017). Therefore, vertical integration provides more transparency and control of the production process and helps to improve the shop floor decision-making process. To enhance adaptability for different types of products, Smart Manufacturing comprises networked machines at shop floor, through machine-to-machine communication (M2M) (Kagermann et al., 2013). M2M consist in a communication system with interoperability, which makes machines capable to understand each other, facilitating their adaptation in manufacture lines (Gilchrist, 2016). This capability is supported by virtual commissioning, which emulates the different PLC-codes of machines and validates virtually setup procedures, avoiding extended downtime due to the long setup of equipment (Mortensen and Madsen, 2018). This simulation is more advanced with digital manufacturing, which besides PLC-codes also considers data from all virtualized objects of the shop floor and then simulates operations' processes, considering several parameters that can affect production (Jeschke et al., 2017).

Smart Manufacturing also promotes an enhanced automation (Kagermann et al., 2013). Robots can perform tasks with more precision than in the past, increasing productivity while being much less prone to fatigue (Thoben et al., 2017). In our work, we differentiate robots and automation from collaborative robots. The former is designed to automatize operational processes and, therefore, we included it as a part of the Smart Manufacturing dimension, while the latter is designed to work with humans, supporting tasks that help to enhance human's flexibility and productivity (Gilchrist, 2016). Therefore, were included collaborative robots as a technology of the Smart Working dimension, as we explain after.

Moreover, artificial intelligence gives support for Smart Manufacturing in many ways. In machines, advanced analytical tools can analyze data gathered from sensors to monitor and forecast machinery failures, overloads or any other problems. This enables predictive maintenance which helps to avoid downtimes due to unexpected failures during the production process (Tao et al., 2018c). Machines with artificial intelligence can also automatically identify product nonconformities in earlier stages of the production process, increasing quality control and reducing production costs (Tao et al., 2018c). Furthermore, artificial intelligence also complements systems like ERP, predicting long-term production demands and transforming them into daily production orders, considering last-minute orders and operations' restrictions (Gilchrist, 2016).

For internal traceability, sensors are applied in raw materials and finished products in the factory's warehouse. This optimized inventory control gives support for recall actions, through identification of specific components in batches of finished products. Internal traceability can also give support to adaptable systems with flexible lines (Angeles, 2009; Wang et al., 2016b), in which machines read products requirements in the sensors embedded in them, and perform the necessary actions to manufacture them. Flexible lines can also comprise modular machines that are easily plugged into a manufacturing line with minimum setup. This enables the production of different types of products at small batches, with minimum loss of productivity (Wang et al., 2016b; Balogun and Popplewell, 1999). In addition, to customize products, additive manufacturing is a promising technology of the Industry 4.0 concept. Additive manufacturing uses 3D printing of digital models that can be altered for customization, using the same resources to manufacture different goods. Additive manufacturing also promotes a sustainable production, as it only requires one process that generates less waste than traditional manufacturing. However, for large-scale productions, the use of additive manufacturing is still limited due to its low throughput speed (Weller et al., 2015; D'Aveni, 2015). Lastly, to enhance factory's efficiency, Smart Manufacturing also comprises energy management (monitoring and improving energy efficiency) (Kagermann et al., 2013). Efficiency monitoring relies on data collection of energy consumption in electrical power grids, while its improvement is achieved through intelligent systems for energy management that schedule intensive stages of production in times with favorable electricity rates (Gilchrist, 2016; Jeschke et al., 2017).

Manufacturing companies can focus on different needs they may have when they prioritize the implementation of the aforementioned Smart Manufacturing technologies. However, recent findings of the literature have shown that the industry varies in the benefits expected by those technologies for industrial performance and companies should think systemically the implementation of such technologies to achieve a higher maturity level of Industry 4.0 (Dalenogare et al., 2018). This suggests that the Smart Manufacturing technologies can be interrelated and create synergy for the Industry 4.0 purposes. This synergistic integration of the Smart Manufacturing technologies supported by IoT results in the so called cyber-physical systems (CPS) – i.e. the integration of the physical objects of the factory with the virtual dimension of the factory, including integrated data, artificial intelligence and simulation – (Wang et al., 2016a; Schuh et al., 2017; Tao et al., 2018c), which is one of the essential concepts of Industry 4.0. Therefore, we assume the following hypothesis regarding the adoption of Smart

Table 2
Smart Product technologies.

Categories	Technologies for Smart Products	Reference
Capabilities of Smart, connected products	Product's connectivity Product's monitoring Product's control Product's optimization Product's autonomy	Porter and Heppelmann (2014)

Manufacturing technologies:

H1. Manufacturing companies that aim a higher maturity level of Industry 4.0 will implement systemically most of the Smart Manufacturing technologies, since these technologies are interrelated.

On the other hand, the front-end technologies for Smart Products comprise smart components that enable digital capabilities and services with products' offering, as shown in Table 2. In this case, we consider technological capabilities needed for different levels of Smart Product, as proposed in the seminal work of Porter and Heppelmann (2014).

Embedded sensors allow connectivity of products in a network with other objects and systems. Sensors can provide monitoring capability in physical products, allowing customers to know the product condition and usage parameters. Products with embedded software connected to cloud services can be controlled through digital remote interfaces. With analytical algorithms, products can have optimization functions, enhancing products' performance based on predictive diagnoses that informs necessary corrections. Using artificial intelligence, products can autonomously optimize themselves. These capabilities extend products functions for customers, bringing new opportunities for manufacturers. Product monitoring also provides useful information for manufacturers, who can gather this data and identify patterns of product usage for market segmentation and new product development. This also enables digital product-service-systems (PSS), in which manufacturers can offer additional services with the product and even offer the product as a service (Zhong et al., 2017; Ayala et al., 2017). Although some companies can be focused on the external aspect of the digital technologies, i.e. Smart Products for the end customer, the Industry 4.0 concept assumes that both, internal Smart Manufacturing and external Smart Products should be connected and integrated (Tao et al., 2018a; Kagermann et al., 2013; Porter and Heppelmann, 2015). Such an approach was previously studied by Kamp et al. (2017) and Rymaszewska et al. (2017) who studied the connections of the digital products and services with internal processes. Therefore, we propose the following hypothesis:

H2. Manufacturing companies that are strongly engaged in Smart Product technologies will also show high maturity in Smart Manufacturing technologies, being both implementations related.

3.1.2. Smart Supply Chain and Smart Working

Two other complementary group of front-end technologies of Industry 4.0 are Smart Supply Chain and Smart Working. We considered them separately from Smart Manufacturing and Smart Products because these two latter have the purpose of adding value to *manufacturing* and *final products* while Smart Supply Chain and Smart Working dimensions have the purpose of providing efficiency to the complementary *operational activities*. Outside the factory, Smart Supply Chain includes technologies to support the horizontal integration of the factory with external suppliers to improve the raw material and final product delivery in the supply chain, which impact on operational costs and delivery time (Marodin et al., 2016, 2017a,b). On the other hand, inside the factory, Smart Working considers technologies to support workers tasks, enabling them to be more productive and flexible to attend the manufacturing system requirements (Stock et al., 2018).

Table 3
Smart Supply Chain and Smart Working technologies.

Technologies for Smart Supply Chain	References
Digital platforms with suppliers Digital platforms with customers Digital platforms with other company units	(Pfohl et al., 2017; Angeles, 2009; Simchi-Levi et al., 2004)
Technologies for Smart Working	**References**
Remote monitoring of production Remote operation of production	(Wang et al., 2016a; El Kadiri et al., 2016; Zhong et al., 2017)
Augmented reality for maintenance	(Elia et al., 2016; Scurati et al., 2018)
Virtual reality for workers training	(Elia et al., 2016; Gorecky et al., 2017)
Augmented and virtual reality for product development	(Elia et al., 2016; Tao et al., 2018b)
Collaborative robots	(Du et al., 2012; Wang et al., 2015)

Both Smart Supply Chain and Smart Working are considered as front-end since they have also a direct contribution to the operational performance of the company. Next, we explain in detail the specific technologies of these two dimensions, which are presented in Table 3.

First, the horizontal integration, supported by the Smart Supply Chain technologies, involves exchanging real-time information about production orders with suppliers and distribution centers (Pfohl et al., 2017). While Smart Manufacturing includes intra-logistics processes with technologies for internal traceability of materials and autonomous guided vehicles (Tao et al., 2018a; Zhou et al., 2017), other technologies are needed to connect factories to external processes (Pfohl et al., 2017). Digital platforms meet this requirement, as they provide easy on-demand access to information displayed in a cloud, integrating suppliers and manufacturers (Pfohl et al., 2017; Angeles, 2009). The tracking of goods can be remotely monitored, maintaining warehousing at optimized levels due to real-time communication with suppliers. In addition, when digital platforms with analytical capabilities are connected to meteorological systems, delivery delays can be avoided. Digital platforms can also reach customers by tracking product delivery and attending specific customer demands (Pfohl et al., 2017). Digital platforms can also integrate different factories of the company by sharing real-time information of the operations activities among them (Simchi-Levi et al., 2004).

On the other hand, Smart Working technologies aim to provide better conditions to the workers in order to enhance their productivity (Kagermann et al., 2013) and to provide them remote access to the shop floor information (Wang et al., 2016a). Thus, humans and machines are considered in the Industry 4.0 concept as an integrated socio-technical mechanism (Thoben et al., 2017). Industry 4.0 considers also remote control of the operations activities by means of mobile devices, which improves the decision-making processes and enhances the information visibility of the process, two aspects that contribute for the Smart Working as well (El Kadiri et al., 2016; Ahuett-Garza and Kurfess, 2018; Tao et al., 2018a,b,c; Thoben et al., 2017).

Virtual tools can be also considered part of Smart Working since they support the decision-making process. Augmented and virtual reality are two emerging technologies in this field that create partial and complete virtual environments (Elia et al., 2016; Gilchrist, 2016). In manufacturing maintenance, virtual reality accelerates workers trainings with an immersive simulation of the maintenance routines (Gorecky et al., 2017; Turner et al., 2016), while augmented reality supports workers with an interactive and real-time guidance for the necessary steps of the tasks to be made (Scurati et al., 2018). In product development activities, these tools create virtual models of the product, helping to detect flaws during the product usage without needing physical prototypes (Tao et al., 2018a; Guo et al., 2018).

Lastly, we also included collaborative robots in the Smart Working dimension. This is because collaborative robots are specifically designed for the interaction with humans and to support workers activities. In this way, manufacturing work is improved with the accuracy, reliability and efficiency of robots, without losing the flexibility of human work (Du et al., 2012; Wang et al., 2015). In this sense, the aim is to reduce low added value tasks of workers by the use of collaborative robots and taking advantage of workers potential for more advanced tasks in which robots are limited due to the flexibility of the tasks.

Therefore, considering that, as we explained above, both technologies – Smart Supply Chain and Smart Working – provide support for different needs of the Industry 4.0 production system, one focused on the connection of the manufacturing system with the supply chain and the other focused on integrating the worker with the manufacturing system, we propose the following hypothesis:

H3. Manufacturing companies that are strongly engaged in Smart Supply Chain (H3a) and Smart Working (H3b) technologies will also show high maturity in Smart Manufacturing technologies.

3.2. Industry 4.0 base technologies

We consider a second layer of Industry 4.0 technologies, which we called "base technologies" since they support all the other 'Smart' dimensions discussed above. The base technologies are composed by the so-called new ICT (Table 4), which includes Internet of Things (IoT), cloud services, big data and analytics (Tao et al., 2018a; Thoben et al., 2017; Wang et al., 2016a). These technologies are considered base because they are present in all the dimensions and in different technologies of such dimensions. They leverage the Industry 4.0 dimensions and make the interconnectivity possible as well as they provide the intelligence of the new manufacturing systems.

IoT represents the integration of sensors and computing in an internet environment through wireless communication (Tao et al., 2018c). Recent advancements in the internet successfully allowed the communication of several objects, achieving this concept. This was also supported by the cost-reduction of sensors in the recent years (Schuh et al., 2017), which enabled the sensing of any kind of object and their connection to a broader network (Boyes et al., 2018).

Cloud services enable on-demand network access to a shared pool of computing resources (Mell and Grance, 2009). This technology has the capacity to store data in an internet server provider which can be easily retrieved through remote access (Yu et al., 2015). Therefore, Cloud services facilitate the integration of different devices, since they do not need to be physically near and even though they can share information and coordinate activities (Yu et al., 2015; Thoben et al., 2017).

The combination of using IoT and Cloud permits different equipment to be connected, collecting huge amount of data, which results in the Big Data storage (Lu, 2017; Liu, 2013). Big data consists in the data gathering from systems and objects, such as sensor readings (Porter and Heppelmann, 2015). Together with analytics – e.g. data mining and machine learning, it is considered one of the most important drivers of the fourth industrial revolution and a key source of competitive advantage for the future (Tao et al., 2018a; Porter and Heppelmann, 2015; Ahuett-Garza and Kurfess, 2018). The main importance is due to the information it can generate. Big data is necessary to generate the digital twins of the factory and, subsequently, analytics enables advanced predictive capacity, identifying events that can affect production before it happens (Schuh et al., 2017). The combination of big data with analytics can support the self-organization of the production lines and can optimize decision-making activities in every dimension of an industrial business (Wang et al., 2016a; Babiceanu and Seker, 2016; Wamba et al., 2015).

Table 4
Base technologies for Industry 4.0

Base technologies	References
Internet of Things (IoT) Cloud computing Big data Analytics	(Wang et al., 2016a; Lu, 2017; Zhong et al., 2017; Gilchrist, 2016)

The four technologies aforementioned – IoT, cloud, big data and analytics – have different capabilities. IoT aims to solve communication issues among all objects and systems in a factory, while cloud services provide easy access to information and services. Lastly, big data and analytics are considered key enablers to advanced applications of Industry 4.0, since the intelligence of the system depends on the large amount of data accumulated (big data) and the capacity of analyzing with advanced techniques (analytics). Thus, focusing on the central element of Industry 4.0, we formulate our fourth and last hypothesis:

H4. The more advanced the company is in the Smart Manufacturing technologies of Industry 4.0, the stronger the presence of the base technologies will be.

4. Research method

4.1. Sampling

We performed a cross-sectional survey in manufacturing companies. We obtained our sample from the southern regional office of the Brazilian Machinery and Equipment Builders' Association (ABIMAQ-Sul). This association was chosen due to its current engagement in industrial policies and strategies to promote the Industry 4.0 concept, which shows a growing interest by the associate companies. We also choose this association for representing one of the strongest manufacturing sectors in this country. The sample is composed by 143 companies associated to ABIMAQ-Sul. The questionnaire was addressed to the Chief Executive Officers or Operations Directors of the companies. Two follow-ups were sent each after two weeks from the last one. We obtained a total of 92 complete questionnaires for the variables studied in this paper, representing a response rate of 64.33%. This high response rate is due to the way the questionnaire was administrated, since ABIMAQ-Sul office contacted all companies to inform about the survey, as well as it presented this research in the association's industrial seminars and sent the questionnaires by an institutional e-mail, following the collection process. Table 5 shows the composition of the

Table 5
Demographic characteristics of the sample.

Category	Description	(%)	Category	Description	(%)
Main industries attended by the manufacturing companies of the sample	Agriculture	48%	Company's size	Small (< 100 employees)	41%
	Biotechnology	1%			
	Chemicals	24%		Medium (100–500 employees)	37%
	Construction	10%			
	Energy	15%		Large (> 500 employees)	22%
	Food products	29%			
	Leather and related products	3%	Respondent's profile	Managers or directors	78%
	Mining	21%		Supervisors	10%
	Furniture	10%			
	Pharmaceutical	10%		Analysts	4%
	Pulp and paper	16%			
	Software and technology	17%		Other	8%
	Steelworks	18%			
	Transport	13%			
	Metal products	34%			
	Other manufacturing	24%			

sample regarding companies' size, respondents' profile and main markets attended by the companies of the sample.

4.2. Variables definition

Following our conceptual framework represented in Fig. 1, we developed a questionnaire to assess both the front-end and base technologies of Industry 4.0 (Tables 1–4). The questionnaire assessed the existence or not of a type of technology and the level of implementation of such technology in the manufacturing companies. We used a five-point Likert scale varying from 1 – Very low implemented to 5- Advanced implemented. Thus, the highest degree shows an advanced maturity of this technology. Since we aimed to classify companies regarding their implementation patterns of the Industry 4.0 concept, we also included in the questionnaire companies' information that may help us to better understand their profile. These characteristics were already presented in the demographic description shown in Table 5.

Before implementing the questionnaire, we refined the description of the technologies as well as its structure with a round of interviews with 15 scholars and seven practitioners. Scholars are affiliates to technological institutes of Southern Brazil dedicated to the develop of innovative solutions based on IoT technologies. Industry representatives are companies' CEOs that compose the directory board from ABIMAQ-Sul. They helped to align the questionnaire to the technical language of the companies.

4.3. Sample and method variance

We tested potential sample bias using Levene's test for equality of variances and *t*-test for the equality of means between early and late respondents. Aiming this, we grouped respondents into two main waves, the early respondents, i.e. those from the first e-mail (63 answers), and the late respondents, i.e. the remaining 29 answers. The tests indicated that only 2 of the 45 variables (technologies) showed statistical differences between both groups but only at $p < 0.01$, while there were no differences in any variable for $p < 0.05$. Following (Armstrong and Overton, 1977), we concluded that there are no evidences of differences of these groups compared to the population.

Regarding the common method variance (Podsakoff et al., 2003), we randomized the technologies list order to avoid that the respondent may directly associate technologies of the list. Furthermore, we sent our questionnaire to key respondents (CEO and Operations Directors), as explained in the sampling section (4.1.), in order to obtain a broader vision of the implementation level of the Industry 4.0 concepts in the companies. Finally, we calculated the Harman's single-factor test with an exploratory factor analysis to address common method bias, i.e. the variance due to the measurement method rather than to the measures they are assumed to represent (Podsakoff et al., 2003). This test with all variables resulted into a first factor that comprehended only 33% of the observed variance and that, therefore, there is no single factor accounting for the majority of the variance in the model. Nonetheless, to be completely sure of the absence of this potential problem, a multiple-respondent approach representing each company should be used, which was no possible in our survey, being a limitation of our study (Guide and Ketokivi, 2015).

4.4. Data analysis

The first step of data analysis was to identify companies with different maturity levels in the adoption of Smart Manufacturing technologies. At least two groups with distinct technological level were necessary to test our hypotheses, in order to discover different patterns between these groups that can explain Industry 4.0 adoption. Therefore, we followed a two-step cluster analysis for the identification of distinct groups with similar technological characteristics in the sample, as previously done by other studies (Marodin et al., 2016; Montoya et al., 2009). We clustered groups according to their similarity of adoption of Smart Manufacturing technologies, since our theoretical premise is that this is the central dimension of Industry 4.0. Following Milligan and Cooper (1985), we firstly performed a hierarchical cluster analysis (HCA), which determines the adequate number of groups for sample division. HCA was performed using Ward's method in the clustering process, with the Euclidean distance measure of similarity among respondents. The second stage considered the refinement of the cluster solution and the definition of variables that discriminated the clusters obtained. This was performed using a non-hierarchical K-means cluster algorithm (HAIR et al., 2009).

After obtaining the cluster compositions, we performed a demographic analysis of the cluster members. The aim of this step was to understand if the groups formed with cluster analysis presented different patterns of high implementation of the Smart Manufacturing technologies of Industry 4.0 (H1). We also used the demographic analysis and independence tests to understand the relationship of these groups of companies allocated in the different clusters with levels of Smart Products development (H2), Smart Working and Smart Supply Chain adoption (H3a and 3b) and of base technologies (H4). We used Pearson's Chi-squared standardized measure of association, which is used to reject the null hypothesis that there is no association between the variables. In a contingency table, Pearson's Chi-squared compares the frequencies of expected values of a variable with its current values. A higher value of association means that for the category in analysis (column), the variables (row) have a different value than the expected (Ross, 2010). In our analysis, the rejection of the null hypothesis supports our formulated hypothesis, indicating a different pattern of technology adoption between the clustered groups. According to HAIR et al. (2009), this measure is suitable for samples larger than 50 cases, with a minimum of five observations for each class. Therefore, we used the Fisher's exact test for the associations resulting in less than five observations (Cortimiglia et al., 2016).

5. Results

5.1. Results for the front-end technologies of Industry 4.0

Fig. 2 shows the dendrogram of the performed hierarchical cluster analysis using the Smart Manufacturing technologies (Table 1) as selection variables. The dendrogram represents the similarities between companies based on the adoption profile of these Smart Manufacturing technologies (Fig. 1). The results show that companies can be grouped into two or three main clusters. We choose to work with three groups to obtain more differentiation of Industry 4.0 patterns. We avoided to select more refined number of groups since this would lead to some clusters with little representativeness due to the low number of companies in them.

After we defined the number of clusters, we performed the K-means analysis to refine the cluster memberships. Table 6 shows the contribution of each of the Smart Manufacturing technologies for the definition of the clusters' composition. The average for the level of adoption of Smart Manufacturing technologies is statistically different among the three groups for all technologies except for flexible lines (see ANOVA F-values). The first cluster is characterized by technologies below the moderate level of adoption (≤3.00); the second is

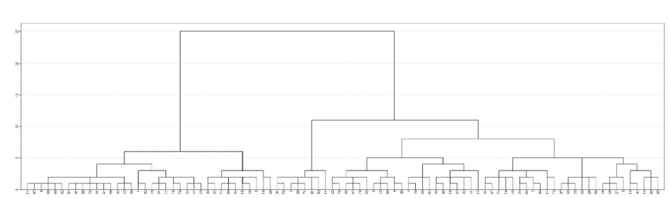

Fig. 2. Dendrogram for the selection of the number of clusters.

Table 6
K-means results for cluster variables.

Smart Manufacturing technologies (H1) [a]	Cluster Mean + S.D.						ANOVA F-value
	Cluster 1 *Low adopters*		Cluster 2 *Moderate adopters*		Cluster 3 *Advanced adopters*		
Sensors, actuators and PLCs	2.36	*± 1.22*	3.55	*± 1.00*	4.60	*± 0.63*	27.89***
Enterprise Resource Planning (ERP)	3.20	*± 1.15*	4.06	*± 1.00*	4.53	*± 1.06*	10.80***
Manufacturing Execution System (MES)	2.14	*± 0.90*	3.39	*± 1.00*	4.33	*± 0.72*	38.48***
Supervisory Control and Data Acquisition (SCADA)	2.32	*± 0.98*	3.21	*± 1.02*	4.07	*± 1.10*	18.61***
Energy efficiency monitoring system	1.75	*± 0.65*	2.15	*± 0.76*	4.07	*± 0.96*	54.72***
Energy efficiency improving system	1.77	*± 0.60*	2.15	*± 0.83*	4.07	*± 0.96*	52.23***
Identification and traceability of final products	2.32	*± 0.96*	3.64	*± 1.19*	4.00	*± 0.76*	23.12***
Identification and traceability of raw materials	2.18	*± 0.97*	3.52	*± 1.20*	4.00	*± 0.65*	25.43***
Simulation of processes (digital manufacturing)	2.20	*± 0.85*	2.73	*± 1.13*	4.00	*± 0.93*	19.22***
Machine-to-machine communication	1.80	*± 0.73*	2.79	*± 0.99*	3.93	*± 0.70*	40.01***
Industrial robots	1.80	*± 0.82*	2.94	*± 1.30*	3.80	*± 1.21*	23.00***
Artificial Intelligence for production	1.77	*± 0.60*	2.70	*± 0.85*	3.40	*± 1.06*	28.79***
Virtual commissioning	1.73	*± 0.66*	2.39	*± 0.97*	3.33	*± 1.29*	18.72***
Artificial Intelligence for predictive maintenance	1.68	*± 0.74*	2.42	*± 0.94*	3.33	*± 1.23*	19.95***
Automatic nonconformities identification	1.95	*± 0.61*	2.55	*± 0.83*	3.27	*± 1.10*	16.70***
Additive manufacturing	1.80	*± 0.67*	2.48	*± 1.18*	2.60	*± 1.24*	6.39**
Flexible lines	2.00	*± 0.89*	2.45	*± 1.23*	2.53	*± 1.36*	2.19
Number of companies	44		33		15		
Small size companies	63.6%		21.2%		6.7%		
Medium size companies	22.7%		54.5%		20.0%		
Large size companies	13.6%		24.2%		63.3%;;		

** $p < 0.05$; ***$p < 0.001$.
[a] Note: the grey scale represents levels of adoption of the considered technologies in each cluster, varying from high adoption (light grey) to low adoption (dark grey).

Table 7
Levels of adoption of Smart Products technologies.

Smart Product technologies (H2)	Adoption	Cluster 1 *Low adopters*	Cluster 2 *Moderate adopters*	Cluster 3 *Advanced adopters*	Test
Smart products with connectivity capability	Yes	14%	36%	73%	Fisher's test = 18.40***
	No	86%	64%	27%	
Smart products with monitoring capability	Yes	20%	45%	67%	Pearson's X^2 test = 1.84**
	No	80%	55%	33%	
Smart products with control capability	Yes	23%	39%	67%	Pearson's X^2 test = 9.66**
	No	77%	61%	33%	
Smart products with optimization capability	Yes	7%	18%	53%	Fisher's test = 3.86**
	No	93%	82%	47%	
Smart products with autonomy capability	Yes	7%	6%	53%	Fisher's test = 16.69***
	No	93%	94%	47%	
Total count		**44**	**33**	**15**	

** $p = 0.05$; *** $p = 0.001$.

characterized by higher levels of adoptions than the first group, but with mean values below the high level of implementation (≤4.00). Finally, the last group has the highest level of implementation of all the technologies and it has a subset of technologies with high level of implementation (≥4.0) while the other technologies are above the middle level of implementation (≥3.00). Therefore, we defined these three groups as low adopters (Cluster 1), moderate adopters (Cluster 2) and advanced adopters (Cluster 3), respectively, of the Industry 4.0 Smart Manufacturing technologies. Regarding the size of the companies constituting each of these clusters, it is worth noticing that the more advanced the cluster is in terms of technology adoption, the greater the concentration of large companies composing it.

The findings presented in the K-means results of Table 6 support H1. These findings show that the clusters (adoption pattern) are divided according to levels of implementation of the complete set of technologies. In other words, one could expect that some cluster may group companies with high implementation of one type of technologies while other clusters may group companies with high implementation of other type of technologies, but this did not happen. What the results show, as proposed in hypothesis H1, is that companies are clustered in a progressive implementation of the complete set of technologies, showing a strong interrelation among them, except for flexible lines which did not show statistical differences between groups. Therefore, as suggested in H1, the Smart Manufacturing technologies are complementary and not substitutable while companies are growing in maturity. Additionally, Table 6 presents three categories of technologies independently of the cluster analyzed. This can be seen in the classification presented in grey scale. The first category, represented with light grey color, is composed by technologies with the highest level of implementation in any cluster. This set of technologies considers those related to vertical integration: Sensors/PLCs + SCADA + MES + ERP systems, and those associated with energy efficiency and traceability. The second category of technologies – highlighted with moderate grey color – is composed by technologies focused on virtualization of the factory and automation. Finally, the cluster highlighted in dark grey color is represented by the less implemented technologies in the clusters.

In the second step, we associated the three clusters of maturity-levels with the adoption of different types of solutions for Smart Products, something part of the broader Industry 4.0 concept, as proposed in our hypothesis H2. These results are reported in Table 7 in which it can be seen that H2 is supported. The results show that Cluster 3, which is composed by companies with advance adoption of Smart

Table 8
Levels of adoption of Smart Supply Chain and Smart Working technologies.

Support Technologies		Adoption	Cluster 1	Cluster 2	Cluster 3	Fisher's exact test
			Low adopters	*Moderate adopters*	*Advanced adopters*	
Smart Supply Chain technologies (H3a)	Digital platforms with Suppliers	Yes	7%	9%	33%	6.38**
		No	93%	91%	67%	
	Digital platforms with customers	Yes	5%	9%	33%	7.81**
		No	95%	91%	67%	
	Digital platforms with other company units	Yes	9%	21%	53%	11.91**
		No	91%	79%	47%	
Smart Working technologies (H3b)	Remote monitoring of production	Yes	9%	39%	93%	37.17***
		No	91%	61%	7%	
	Collaborative robots	Yes	2%	9%	67%	28.30***
		No	98%	91%	33%	
	Remote operation of production	Yes	5%	3%	40%	12.95***
		No	95%	97%	60%	
	Augmented reality for maintenance	Yes	0%	6%	27%	10.24***
		No	100%	94%	73%	
	Virtual reality for workers training	Yes	0%	6%	27%	10.24***
		No	100%	94%	73%	
	Augmented and Virtual reality for NPD	Yes	2%	6%	33%	10.31***
		No	98%	94%	67%	
	Total count		**44**	**33**	**15**	

** p = 0.05; *** p = 0.001.

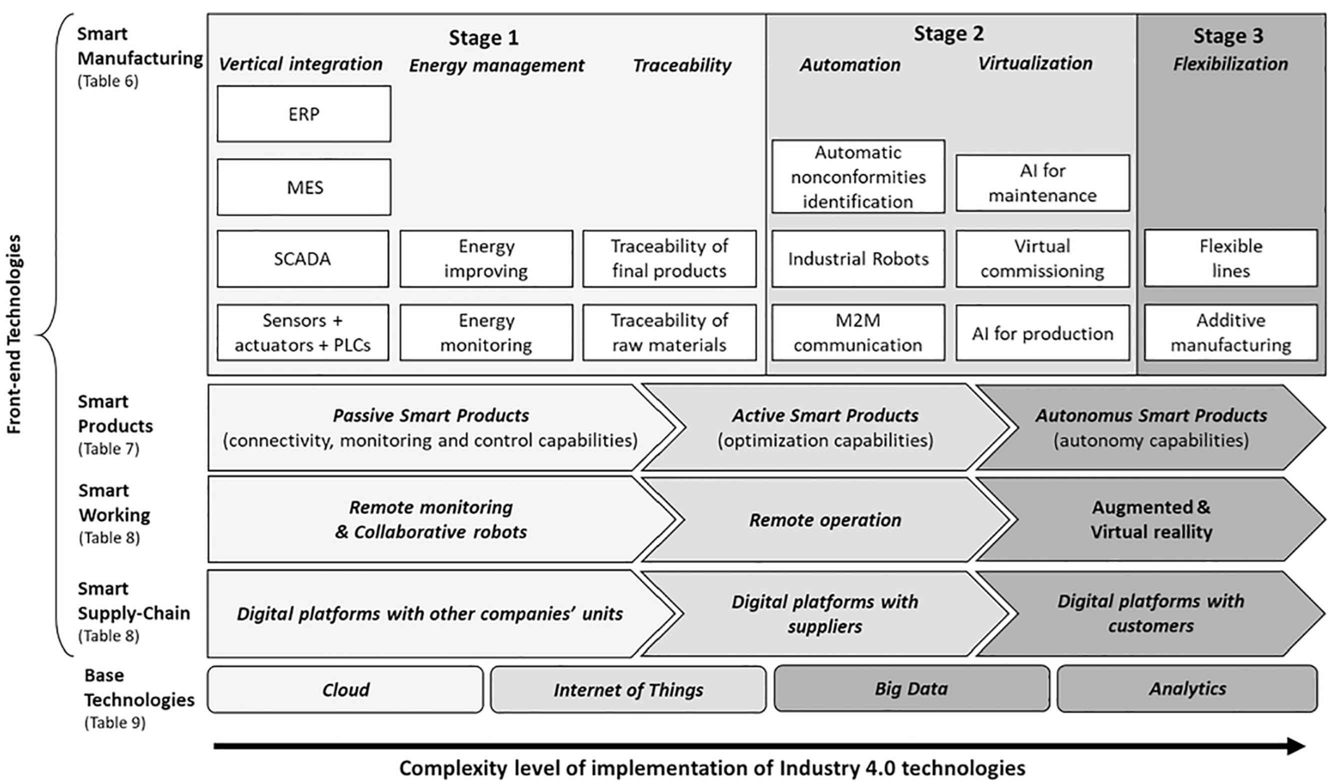

Fig. 3. Framework summarizing the findings of the adoption patterns of Industry 4.0.

Manufacturing, is the only one with high adoption of three capabilities for Smart Products: connectivity (73%), monitoring (67%) and control (67%). Thus, our findings show that there is a connection, at least at the advanced level of Industry 4.0 (Cluster 3), between the adoption of Smart Manufacturing and Smart Product technologies. On the other hand, optimization and autonomy are capabilities less implemented at the advanced level (47% of the companies of Cluster 3 did not adopt this capabilities), although they show a higher number of companies adopting them if compared to the other two clusters.

In the next step, we tested hypotheses H3a and H3b. The results are presented in Table 8, showing that H3a and H3b are partially supported by our findings. Firstly, regarding Smart Supply Chain technologies of Industry 4.0 (H3a), it is possible to see that the three types of platforms for integration with suppliers, customers and other units of the company show low levels of adoption in the three clusters. It is worth noticing that digital platforms for suppliers and customers' integration, which represent the horizontal integration of the Industry 4.0 concept, are very low adopted, even in companies with advanced level of implementation of Smart Manufacturing. Only platforms for the integration with other units showed a relatively high level of adoption (53%) in the advanced adopters of the Smart Manufacturing technologies (Cluster 3).

Regarding the Smart Working technologies (H3b) (Table 8), we also found only partial support for hypothesis H3b. In this case, only the use of remote monitoring of production and the use of collaborative robots presented a relatively higher level of adoption (93% and 67% of the companies) among the advanced adopters of Smart Manufacturing technologies. Remote operation of production showed a slightly higher level of adoption in Cluster 3 (40% of the companies) but the lack of adoption of this technology is still predominant in this cluster (60% of the companies). The less implemented technologies for Smart Working in the three clusters were augmented reality and virtual reality.

5.2. Results for the base technologies of Industry 4.0

In the final step, we analyzed how the base technologies are present in the implementation of the Smart Manufacturing technologies of Industry 4.0, as proposed in hypothesis H4. Our findings support H4 since the four base technologies are more adopted in Cluster 3 (advanced adopters of Smart Manufacturing). It is also possible to see that Cloud services is the adopted base technology in all clusters, being the most accessible solution used by the companies. On the other hand, Internet of Things, Big Data and Analytics follow a similar patter with low levels of adoption in Clusters 1 and 2.

6. Discussions

We summarized our findings in the framework of Fig. 3 to illustrate a holistic vision of the adoption patterns of Industry 4.0 technologies. The framework summarizes the results presented in Tables 6–9. We divided the structure following our initial conceptual framework of Fig. 1, which we expanded with the empirical findings. We also divided the implementation complexity based on the results from the three clusters, showing those more implemented (light grey color) to those less implemented (dark grey color) technologies. We represented these intensities as a growing complexity when implementing a sequence of stages. It is worth noticing that we are not proposing them as the ideal stages of implementation, but just the current situation of the companies studied. This framework can be compared with other prior proposals from the literature, such as Schuh et al. (2017), Lee et al. (2015) and Lu and Weng (2018). The main difference between these models and our framework is that they proposed ideal stages while ours present what is happening in an industrial sector based on empirical evidences. We also detail the technologies, while they focused mainly on capabilities required for Industry 4.0. Moreover, our model is broader, since it considers not only the internal Smart Manufacturing technologies as the other models does, but we also include many other important dimensions and technologies. We use this framework to guide the discussions below.

Our findings allowed us to verify some prior suggestions of the literature. One of them is that the level of implementation of the Industry 4.0 concept is dependent of the companies' size, as suggested by Kagermann et al. (2013) and Schuh et al. (2017). Our results (Table 6) show a relationship between large companies and advanced implementation of Industry 4.0. This is aligned with the general innovation literature, which affirms that large companies are more prone to invest in process and product innovation, since it requires high investments in technological infrastructure, something not viable for small companies (Frank et al., 2016). Moreover, these findings showed that advanced adopters are leading all the technologies and not some specific, which may indicate that the growing maturity in Industry 4.0 technologies implies in aggregating technological solutions as a 'Lego' instead of substituting one to another. This is represented in our framework (Fig. 3) as the progressive adding of technologies in the growing maturity of Industry 4.0.

Additionally, a surprising result from our findings regarding Smart Manufacturing adoption is that flexible lines is the only technology which was not strongly adopted in any of the three maturity clusters. This is in line with previous findings from Dalenogare et al. (2018) at the industry level. Flexible line has been proposed as one of the Industry 4.0 concepts, which can be also supported by the use of additive manufacturing to produce different components and products in the same line (Wang et al., 2016b; Weller et al., 2015; D'Aveni, 2015). However, previous studies on Industry 4.0 in emerging countries highlighted productivity the main industrial concern instead of flexibility (CNI, 2016). Since we studied an industrial sample focused on business-to-business solutions in which customization of the products might require more flexibility and adaptation of the plants, instead of large-scale production, we were expecting different results. Therefore, one of our concerns is that companies are just replicating an adoption pattern of Industry 4.0 from other business context focused on economies of scale and, consequently, on productivity. Other possibility is that companies see this as a very advanced level of implementation, being at the top of the maturity, as we show in the framework of Fig. 3. For example, making an existing production line more flexible will require not only to apply new technology but to change the layout and production methods. This might be financially restrictive or might require too many rearrangements that interrupt the operations routines. Thus, the role of flexible lines in Industry 4.0 require mores investigation in future research.

Regarding the connection between Smart Manufacturing and Smart Products, (tested in hypothesis H2), the extant literature suggests that Industry 4.0 can foster the implementation of digital solutions focused on the customer (Ardolino et al. 2018; Kamp et al., 2017; Opresnik and Taisch, 2015), stimulating the offering of Smart Products (Lerch and Gotsch, 2015). We could evidence such relationship in our results from Table 7, since the high adopters of the Smart Manufacturing concept are the same with strong implementation of some of the Smart Product capabilities. In this sense, we reinforce prior works of Kamp et al. (2017) and Rymaszewska et al. (2017) that highlighted potential returns of the digital Smart Products for the internal manufacturing processes of the company. However, the companies of our sample are only implementing what we called as 'passive' Smart products, which help to monitor and control, but not to optimize and to provide

Table 9
Levels of adoption of base technologies.

Base technologies (H4)	Adoption	Cluster 1 *Low adopters*	Cluster 2 *Moderate adopters*	Cluster 3 *Advanced Adopters*	Test
Internet of Things	Yes	18%	39%	67%	Pearson's X^2 test = 12.51**
	No	82%	61%	33%	
Cloud	Yes	43%	58%	60%	Pearson's X^2 test = 2.13
	No	57%	42%	40%	
Big Data	Yes	9%	27%	60%	Fisher's test = 15.20***
	No	91%	73%	40%	
Analytics	Yes	18%	36%	60%	Pearson's X^2 test = 9.62**
	No	82%	64%	40%	
Total count		**44**	**33**	**15**	

** p = 0.05; *** p = 0.001.

autonomy to the machines.

Our results showed partial evidence to the hypotheses H3a and H3b. The literature has highlighted the supply chain integration as one of the advantages of Industry 4.0 based on integrated platforms with suppliers (Pfohl et al., 2017; Angeles, 2009; Simchi-Levi et al., 2004). Our results show that, at least in the industrial sector considered in our sample, supply chain integration is still in the initial stages of development. The same limitation was found in the technologies for Smart Working activities, where only remote monitoring of production and collaborative robots were prominent among the advanced adopters of the Smart Manufacturing technologies. In this case, augmented and virtual reality are still low implemented. The same was reported in other studies that consider them still initial technologies (Elia et al., 2016). Therefore, we could state that these two dimensions might only grow after the consolidation of the internal Smart manufacturing dimension of Industry 4.0.

Regarding the base technologies, some interesting and counterintuitive results were found. Firstly, one could expect that cloud may be dependent of the implementation of IoT solutions, since the equipment should be first connected to generate data stored in the cloud (Wang et al., 2016a). However, the fact that cloud services is the first implemented technology may suggest that it is used not as a way to store real-time data from the equipment but simply used as a remote data storage. In this sense, cloud may represent only a remote storing of data, while the real-time data collection may be represented by the sequence of IoT + Big Data + Analytics, which are the following technologies in the framework of Fig. 3. As previously demonstrated by Dalenogare et al. (2018) at the industry-level, this is a set of technologies still very immature in traditional manufacturing sectors as the one considered in our sample. This is also aligned with Enrique et al. (2018) who showed that, in general, companies in Brazil need to grow in the use of ICT, as those considered here.

7. Conclusions

In this paper, we aimed to identify different patterns of adoption of two technology layers of Industry 4.0: base technologies and front-end technologies. Our results support our premise that Smart Manufacturing has a central role in Industry 4.0 and that it is connected with Smart Products, being strong interrelated. We also showed how other front-end technologies complement Smart Manufacturing, but they are still low implemented in the sample studied.

According to our findings, companies with an advanced level of implementation of Industry 4.0 tend to adopt most of the front-end technologies and not a specific subset. For the technologies adopted, a sequence of implementation steps can be drawn. We summarized this in a framework, which is the main contribution of our findings, showing how Industry 4.0 technologies are implemented and interrelated.

7.1. Practical implications

Our results can contribute for companies that look for technological upgrade. We provided insights about requirements for the implementation of Industry 4.0 technologies. This is important for managers since there is still considerable uncertainty about Industry 4.0, especially regarding technology requirements and potential benefits, as previous researches have shown (CNI, 2016; Dalenogare et al., 2018). Managers can use our framework to focus not only on the front-end technologies, but also on the base technologies that provide support for the implementation of Industry 4.0. Managers can also use our framework as a maturity implementation model to evolve in the Industry 4.0 concept. The framework shows levels of implementation of several technologies which were related to complexity levels for the implementation of the Industry 4.0 concept. Our findings suggest that companies should not stay only at the first stage described in our framework, focusing only on vertical integration, energy management and traceability. These are the most consolidated technologies of Industry 4.0. As shown in our results, advanced automation, virtualization and flexibilization are the frontiers regarding the complexity of implementation of Industry 4.0. Companies that master these higher levels of maturity can gain competitive advantage. These are stages where big data and analytics play a key-role, supporting tools such as artificial intelligence for operational aspects of the factory and for increasing workers productivity through augmented and virtual reality. We also showed also that even flexible lines are something aimed by the Industry 4.0 concept, it can be hard to be achieved due to the already established manufacturing arrangements. Therefore, managers who are starting new factories should think on this aspect before defining the manufacturing layout, so that this may not be a future restriction in the implementation of Industry 4.0.

7.2. Limitations and future research

This research has some limitations that open new avenues for future research. Firstly, our work considers a sample from a specific industrial sector which has its own characteristics. The machinery and equipment industry is intrinsically focused on business-to-business (B2B) activities, which are very different from business-to-consumer (B2C) models. B2B activities demand more specialized and customized solutions, resulting in stronger interaction and connection between the company and the customer. This naturally affects the relevance given to the different dimensions of the front-end technologies. Moreover, almost half of our sample has the agriculture sector as the main industrial market. This sector has grown very fast in the demand of IoT solutions for automated agriculture (e.g. European Commission, 2017; Porter and Heppelmann, 2014) and this opened more opportunities for Industry 4.0. These characteristics cannot be simply extrapolated to other kind of markets, especially those based on B2C activities. Another important characteristic of our sample is that we are considering a traditional manufacturing sector, which is positioned as a middle level of maturity in the digital transformation process, behind other more advanced sectors such as computers and electronics (CNI, 2016). Therefore, one should be careful to accept our findings as a general pattern for Industry 4.0 technologies. Nonetheless, the comparison made with prior works regarding the maturity levels of Industry 4.0 shown in our findings (e.g. Schuh et al., 2017; Lee et al., 2015; Lu and Weng, 2018; Dalenogare et al., 2018) makes us believe that our findings could be extended to other industrial fields. However, more empirical evidences are needed to validate this possible extension to other industries. Second, our study did not consider the effect of these technologies on industrial performance, which could be a very interesting issue for future research. The real benefit of Industry 4.0 is still a concern for practitioners and such a study could be helpful for theory and practice. Dalenogare et al. (2018) have recently studied such an impact but only at the industry-level, and they called the attention to the need of firm-level analysis. We moved our research a first step towards this direction, since we provided an empirical base for the understanding of how technologies are adopted and how they relate to each other. From this starting point, future research can advance in studying how these technologies impact on industrial performance at the firm level. Lastly, we demonstrated that large companies are more prepared for Industry 4.0, as expected. However, the higher maturity group also presented some small size companies that successfully adopted smart manufacturing technologies. Future research could deep in this kind of companies to understand what factors support them to innovate, since the literature indicates many barriers that small companies face in the digital transformation (e.g. Kagermann et al., 2013; Müller et al., 2018).

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