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The expected contribution of Industry 4.0 technologies for industrial performance

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ABSTRACT

Industry 4.0 is considered a new industrial stage in which vertical and horizontal manufacturing processes integration and product connectivity can help companies to achieve higher industrial performance. However, little is known about how industries see the potential contribution of the Industry 4.0 related technologies for industrial performance, especially in emerging countries. Based on the use of secondary data from a large-scale survey of 27 industrial sectors representing 2225 companies of the Brazilian industry, we studied how the adoption of different Industry 4.0 technologies is associated with expected benefits for product, operations and side-effects aspects. Using regression analysis, we show that some of the Industry 4.0 technologies are seen as promising for industrial performance while some of the emerging technologies are not, which contraries the conventional wisdom. We discuss the contextual conditions of the Brazilian industry that may require a partial implementation of the Industry 4.0 concepts created in developed countries. We summarize our findings in a framework, that shows the perception of Brazilian industries of Industry 4.0 technologies and their relations with the expected benefits. Thus, this work contributes by discussing the real expectations on the future performance of the industry when implementing new technologies, providing a background to advance in the research on real benefits of the Industry 4.0.

1. Introduction

Industry 4.0 is understood as a new industrial stage in which there is an integration between manufacturing operations systems and information and communication technologies (ICT) – especially the Internet of Things (IoT) – forming the so-called Cyber-Physical Systems (CPS) (Wang et al., 2015; Jeschke et al., 2017). This new industrial stage is affecting competition rules, the structure of industry and customers' demands (Gilchrist, 2016; Bartodziej, 2017). It is changing competition rules because companies business models are being reframed by the adoption of IoT concepts and digitization of factories (Dregger et al., 2016; Lasi et al., 2014; Wang et al., 2015). From the market point of view, digital technologies allow companies to offer new digital solutions for customers, such as internet-based services embedded in products (Ayala et al., 2017; Coreynen et al., 2017). From the operational perspective, digital technologies, such as CPS, are proposed to reduce set-up times, labor and material costs and processing times, resulting in higher productivity of production processes (Brettel et al., 2014; Jeschke et al., 2017).

Several countries have recently created local programs to enhance the development and adoption of Industry 4.0 technologies. In Germany – where this concept was born – this program was called "High-Tech Strategy 2020", in the United States was established the "Advanced Manufacturing Partnership", in China the "Made in China 2025" and in France the "*La Nouvelle France Industrielle*" (Kagermann et al., 2013; Rafael et al., 2014; Wahlster, 2013; Zhou, 2017; CNI, 2013; Liao et al., 2017). In Brazil, the program called "Towards Industry 4.0" (*Rumo à Indústria 4.0*) was created by the Brazilian Agency for Industrial Development (ABDI – *Agência Brasileira de Desenvolvimento Industrial*) together with other initiatives of the Ministry of Industry, Foreign Trade and Services (MDIC – *Ministério da Indústria, Comércio Exterior e Serviços*) (ABDI, 2017). All these programs, in both developed and emerging countries aim to disseminate the Industry 4.0 concepts and technologies in local firms.

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Nevertheless, it is well-known that the adoption of advanced technologies can be more challenging for emerging countries (Hall and Maffioli, 2008; Kumar and Siddharthan, 2013). Since the economies of emerging countries have been historically more focused on the extraction and commercialization of commodities, companies in these countries are frequently behind in terms of technology adoption, when compared to their counterparts in developed countries (Castellacci, 2008). Other factors such as ICT infrastructure, culture, level of education and economic and political instability can also interfere in the value perception and in the consequent level of investments in advanced technologies (Frank et al., 2016). Thus, even when the Industry 4.0 related technologies are presented by the literature as beneficial for firms, given the particular characteristics of emerging economies, an important question emerges: *what is the perception of industries in emerging countries about the benefits of Industry 4.0 related-technologies for industrial performance*?.

We aim to answer this question by analyzing the potential benefits for product development, operations and side-effects aspects expected by the Brazilian industry when implementing the Industry 4.0 related technologies. We analyze secondary data from a large survey recently applied in Brazil by the National Confederation of the Industries (*Confederação Nacional das Indústrias* – CNI), which comprises a sample of 2225 companies from different industrial segments of this emerging country. Our findings indicate that only some of the Industry 4.0 related technologies are expected as beneficial by the Brazilian industry and that it depends on the focus of the industrial sectors, i.e. focus in differentiation or cost. We also discuss some unanticipated findings regarding advance technologies with negative expected results on industrial performance.

The remaining sections of this paper are structured as follows. In Section 2, we provide the theoretical background for Industry 4.0 technologies and the expected benefits of their implementation, as well as their usefulness in emerging countries. Section 3 introduces the research method where we discuss the secondary data source and our methodological procedures for the data treatment and analysis. The results are presented in Section 4, followed by the discussions of the findings in Section 5 and the conclusions in Section 6.

2. Theoretical background

2.1. Industry 4.0 and the international technology diffusion-adoption theories

Some scholars and practitioners have considered four main industry changes throughout the history, while the Industry 4.0 is the last one and an ongoing industry transformation (Qin et al., 2016). The steam machine – between 1760 and 1840 – characterized the first industry revolution; the second was defined by the utilization of electricity in industrial processes in the end of the XIX century; the third revolution started in the decade of 1960 with the use of ICT and industrial automation. The fourth industrial revolution – or Industry 4.0 – emerged from several developed countries and it was consolidated in a German public-private initiative to build smart factories by the integration of physical objects with digital technologies (Brettel et al., 2014; Hermann et al., 2016). The key element that characterizes this new industrial stage is the deep change in the manufacturing systems connectivity due to the integration of ICT, IoT and machines in cyber-physical systems (CPS) (Kagermann et al., 2013; Schwab, 2017). As a result, the Industry 4.0 can be considered nowadays as a new industrial age based on the connectivity platforms used in the industry (Lasi et al., 2014; Parlanti, 2017; Reischauer, 2018). It considers the integration of several different dimensions of the business, with a main concern on manufacturing issues, based on advance manufacturing technologies (Saldivar et al., 2015; Fatorachian and Kazemi, 2018). In such a sense, Industry 4.0 can be understood as a result of the growing digitization of companies, especially regarding to manufacturing processes (Kagermann, 2015; Schumacher et al., 2016).

Following this concept, Industry 4.0 can be seen as a matter of technology diffusion and adoption. Emerging technologies of this new industrial age have been conceived in developed countries such as Germany, which is nowadays leading the diffusion of the concept to other countries interested in its adoption (Arbix et al., 2017; Bernat and Karabag, 2018). However, the diffusion-adoption process tends to be slow and it usually flows from developed countries to emerging countries (Phillips et al., 1994; Eaton and Kortum, 1999; Comin and Hobijn, 2004). Therefore, different behavior patterns could be seen when analyzing digital technologies in an emerging country such as Brazil comparing to the leading countries on this issue such as Germany. According to the diffusion-adoption theories, different aspects can produce such gaps between economies. Barriers to the diffusion and adoption are frequently present (Parente and Prescott, 1994) and the competitive environment of both the supplier side and the adopter industry also create differences (Robertson and Gatignon, 1986). As a consequence, emerging countries can have a different value perception of the diffused technologies (Alekseev et al., 2018; Luthra and Mangla, 2018) which may be based on different needs compared to developed countries (Kagermann, 2015).

Our study is based on the fact that the perceived value of technologies can be different in emerging countries, which can also change their adoption of these technologies (Castellacci, 2008; Castellacci and Natera, 2013). Instead of studying the technology diffusion-adoption flow, as previously done by several other scholars (e.g. Phillips et al., 1994; Comin and Hobijn, 2004), we focus on the current adoption and its expected benefits in the Brazilian industry. We first address the general benefits proposed by those enthusiastic on Industry 4.0. Second, we consider the Brazilian industrial context and the possible difficulties for the implementation of Industry 4.0 concepts. Then, we use empirical data to investigate the adoption levels and the expected benefits. We use the diffusion-adoption theory in order to understand better our findings.

2.2. Industry 4.0 and its expected benefits

The Industry 4.0 concepts are proposed to enable companies to have flexible manufacturing processes and to analyze large amounts of data in real time, improving strategic and operational decision-making (Kagermann et al., 2013; Porter and Heppelmann, 2014; Schwab, 2017). This new industrial stage has been possible due to the use of ICTs in industrial environments (Kagermann et al., 2013) and due to the cheapening of sensors, increasing their installation in physical objects (Brettel et al., 2014; Porter and Heppelmann, 2014; Bangemann et al., 2016). The advancements in these technologies allowed the development of embedded and connected systems (Jazdi, 2014; Kagermann et al., 2013; Brettel et al., 2014). These systems aim to monitor and control the equipment, conveyors and products through a cycle of feedbacks that collect a great quantity of data (big data) and update the virtual models with the information of the physical processes, resulting in a smart factory (Wang et al., 2015, 2016; Gilchrist, 2016). Therefore, since the development of digital manufacturing in the 1980s, different technologies have emerged and have been applied in production systems, such as cloud computing for on-demand manufacturing services (Yu et al., 2015), simulation for commissioning (Saldivar et al., 2015), additive manufacturing for flexible manufacturing systems (Kagermann et al., 2013; Wang et al., 2016), among others. Table 1 presents a list of ten types of technologies frequently associated to the Industry 4.0 concept (CNI, 2016; Gilchrist, 2016; Jeschke et al., 2017).

The technologies presented in Table 1 support the three main advantages that characterize Industry 4.0: vertical integration, horizontal integration and end-to-end engineering (Kagermann et al., 2013; Wang et al., 2015). The vertical integration refers to the integration of ICT systems in different hierarchical levels of an organization, representing the integration between the production and the management levels in a

Table 1
Technologies of the Industry 4.0

Technologies	Definition
Computer-Aided Design and Manufacturing [CAD/CAM]	Development of projects and work plans for product and manufacturing based on computerized systems (Scheer, 1994).
Integrated engineering systems [ENG_SYS]	Integration of IT support systems for information exchange in product development and manufacturing (Kagermann et al., 2013; Bruun et al., 2015; Abramovici, 2007).
Digital automation with sensors [SENSORING]	Automation systems with embedded sensor technology for monitoring through data gathering (Saldivar et al., 2015).
Flexible manufacturing lines [FLEXIBLE]	Digital automation with sensor technology in manufacturing processes (e.g. radio frequency identification – RFID – in product components and raw material), to promote Reconfigurable Manufacturing Systems (RMS) and to enable the integration and rearrangement of the product with the industrial environment in a cost-efficient way (Brettel et al., 2014; Abele et al., 2007).
Manufacturing Execution Systems (MES) and Supervisory control and data acquisition (SCADA) [MES/SCADA]	Monitoring of shop floor with real time data collection using SCADA and remote control of production, transforming long-term scheduling in short term orders considering restrictions, with MES (Jeschke et al., 2017).
Simulations/analysis of virtual models [VIRTUAL]	Finite Elements, Computational Fluid Dynamics, etc. for engineering projects and commissioning model-based design of systems, where synthesized models simulates properties of the implemented model (Saldivar et al., 2015; Babiceanu and Seker, 2016).
Big data collection and analysis [BIG_DATA]	Correlation of great quantities of data for applications in predictive analytics, data mining, statistical analysis and others (Gilchrist, 2016).
Digital Product-Service Systems [DIGITAL_SERV]	Incorporation of digital services in products based on IoT platforms, embedded sensors, processors, and software enabling new capabilities (Porter and Heppelmann, 2014).
Additive manufacturing, fast prototyping or 3D impression [ADDITIVE]	Versatile manufacturing machines for flexible manufacturing systems (FMS), transforming digital 3D models into physical products (Weller et al., 2015; Garrett, 2014).
Cloud services for products [CLOUD]	Application of cloud computing in products, extending their capabilities and related services (Porter and Heppelmann, 2014).

factory (Kagermann et al., 2013). On the other hand, the horizontal integration consists in the collaboration between enterprises, with resource and real time information exchange (Brettel et al., 2014). End-to-end engineering is the integration of engineering in the whole value chain of a product, from its development until after-sales (Kagermann et al., 2013; Brettel et al., 2014; Gilchrist, 2016).

The extant literature has suggested that this integration achieved by digital technologies can promote several benefits to the industry (Kagermann et al., 2013). For business operations, the communication between machines and products enables reconfigurable and flexible lines for production of customized products, even for small batches (Brettel et al., 2014; Wang et al., 2016). In addition, with the CPS for information processing, companies have more support for decision-making processes and have faster adaptation for several kinds of events, like production line breakdowns (Schuh et al., 2017). Therefore, these systems can increase the productivity of the companies, with better efficiency of resources utilization, through the combination of production with smart grids for energy savings, for example (Ali and Azad, 2013; Jeschke et al., 2017). Industry 4.0 also has opportunities and benefits for business growth. Through the horizontal integration concept, collaborative networks among enterprises combine resources, divide risks and quickly adapt to changes in the market, seizing new opportunities (Brettel et al., 2014). Collaboration is extended to customers also, through digital channels and smart products that integrate the firm with the customers, allowing also the delivery of higher value to the latter (Kiel et al., 2016; Porter and Heppelmann, 2014). Using additive manufacturing technology, enterprises can co-design products with customers, resulting in highly customized products, increasing their perceived value (Weller et al., 2015). Finally, with the service orientation of Industry 4.0 (Gilchrist, 2016) and horizontal integration, new business models can be developed, with new ways to deliver and capture value from customers (Kagermann et al., 2013; Chryssolouris et al., 2009).

From a socio-technical perspective (Hendrick and Kleiner, 2001), it is acknowledged that the adoption of the aforementioned emerging technologies of the Industry 4.0 are not supported by themselves. There are at least three complementary socio-technical dimensions to the technological one to consider the digitization process towards the Industry 4.0 implementation (Frank et al., 2015): (i) organization of work - new technologies need to rethink how the organization will operate (Brettel et al., 2014); (ii) human factors – new technologies require new competences and skills from the workers (Ras et al., 2017; Wei et al., 2017); and (iii) external environment – adoption of new technologies are dependent of the maturity where they are implemented (Schumacher et al., 2016). We focus on two of them, the *technological* opportunities and its relation with a specific *external environment* (i.e. an emerging country). Human factors and the organization of work can be enablers that potentialize the benefits of these technologies for business performance, as previously shown in the broader literature of technology management (Westerman et al., 2014). Thus, we consider only the first step, which is to verify the expected contribution of the technologies for industrial performance, being aware that such technologies may need a complementation of these other dimensions in a specific context.

2.3. Industry 4.0 in the context of emerging countries

As stated, Industry 4.0 was born in developed countries, where prior industrial stages are already mature regarding automation and ICT usage, two concepts of the third industrial revolution that converge in the Industry 4.0 (Kagermann et al., 2013). In this sense, emerging countries may face an important gap for the Industry 4.0 adoption due to the low maturity of prior industrial stages (Krawczyński et al., 2016; Guan et al., 2006). In the case of Brazil, the ICT adoption has significantly grown improving work productivity (Mendonça et al., 2008, 2009; Cortimiglia et al., 2012). However, as shown in the findings of Frank et al. (2016) in a large-scale survey of Brazilian industry, the investments on software acquisition has not leaded to good results in terms of market benefits or internal manufacturing process improvement. The authors suggest that companies are investing in software acquisition simply to automatize their operational routines instead of seeking advanced ICT tools that could give them a real competitive advantage in innovation development (Frank et al., 2016).

On the other hand, regarding manufacturing technologies, the same work of Frank et al. (2016) shows that machinery and equipment acquisition strategy resulted in poor results for innovation outcomes when compared to other innovation activities of industries in Brazil. As argued by these authors, one of the reasons is that most of the companies do not acquire leading technologies – as those from the Industry 4.0 –, but only those basics to update old industrial equipment, which is also in line with other prior works in emerging markets (e.g. Franco et al., 2011; Zuniga and Crespi, 2013). In this sense, the work of Nakata and Weidner (2012) showed that most population in emerging countries has lower incomes than in developed countries, what implies that the most consumed product are low cost, making lower price a more relevant factor in competitiveness than innovativeness. This market behavior can clearly influence technology investments. Usually, firms in emerging countries are focused on making investments in well-established technologies for the increase of productivity than in advanced technologies for the differentiation of products, as evidenced in prior studies, cited above. Thus, the two main pillars of Industry 4.0 – processing technologies and ICT – still seems weak in order to advance toward the fourth industrial revolution.

In addition, there are structural challenges that emerging economies may face and that can be a barrier for the Industry 4.0 establishment. One of them is that emerging economies growth are based on the low-cost workforce, especially for manufacturing activities, and it can discourage or delay investments in automation and other technologies, which usually are more expensive in these countries (Castellacci, 2008; Ramani et al., 2017). The supply chain of the manufacturing industry may be another constraint, which tend to be less integrated when compared to developed countries (Marodin et al., 2016, 2017b). Besides, the few investments in R&D (Olavarrieta and Villena, 2014), added to the economic and political instabilities and low quality of education and research institutions (Hall and Maffioli, 2008; Crisóstomo et al., 2011; Frank et al., 2016), configure a hard scenario for the adoption of Industry 4.0 technologies.

Finally, based on this prior research, it is clear that challenges for the adoption of Industry 4.0 technologies in emerging countries are different from those in developed countries, as it is proposed in the technology diffusion-adoption literature (Phillips et al., 1994). As the concept of Industry 4.0 is relatively new, there is a high uncertainty and lack of knowledge about the real impact and contribution of the Industry 4.0 related technologies in the context of emerging countries in general. In order to fill this gap, our study focuses on the contribution of these technologies in the Brazilian industry, as one representative of the emergent economies which has significantly increased the industrial activities in the recent years (Frank et al., 2016). Few studies have been conducted in this country on Industry 4.0 initiatives, while most of them come from consulting research and presents only descriptive information of this scenario. One of them is the survey conducted by Price Waterhouse Coopers (PWC) in 32 Brazilian industries (PWC, 2016), which shows a low level of digitization in several business processes. However, despite the low level of digitization, this survey shows that Brazilian enterprises expect bigger investments in digital technologies for the next years, with return in efficiency improvement, reduction of operational costs and additional business income (PWC, 2016). Other important source of information is the industrial survey conducted by the National Confederation of the Industry of Brazil (CNI, 2016), where a set of Industry 4.0 related technologies were considered and analyzed in the Brazilian industry. This survey shows that the level of implementation is still low, but that there are already some industrial sectors investing in these technologies and that an important part of the industry is concerned with this issue and is expecting new benefits from such investments. Following this last survey, we aim to deepen such analysis by investigating the association between the considered technologies and expected benefits in the CNI (2016) large-scale survey.

3. Research method

3.1. Sampling and measures

Our study focuses on a secondary data analysis of the dataset collected by the 'Special survey on Industry 4.0 in Brazil', conducted by the National Confederation of the Industries (CNI, 2016). CNI is an entity that represents the Brazilian industry and comprises 1250 employers' unions and almost 700,000 industrial businesses affiliated. CNI promotes the interests of the industry in Brazil and as well as research and development studies.[1] This large-scale industrial survey had the purpose of obtaining a current technological overview on Industry 4.0 in Brazilian industry. CNI elaborated a questionnaire and sent it by e-mail to operations managers of 7836 companies random selected from the population. The population of the survey is composed only by companies related to production activities (i.e. extractive and transformation sectors). The total amount of useful responses obtained was 2225 which represents a response rate of 28.39% (CNI, 2016). The final sample represents 40,8% small, 36,6% medium and 22,6% large industrial companies from 27 sectors in Brazil (see demographic details in Table 2). Given the demographic distribution of the complete responses (questionnaires) regarding companies' size, the industrial sectors, and the regional distribution of the data collected (which included all the industrialized States of the country), we have no reasons to believe the existence of biased patterns when compared to the incomplete responses, which were not included in the final sample (Hair et al., 2009, p.42–45). However, such level of details is not provided in the available secondary data from (CNI, 2016).

The questionnaire used in the survey is composed by six group of main questions[2]: (i) *Key-technologies*: a list of 11 digital technologies related to the Industry 4.0 where the companies indicate the technologies that they consider the most potential to enhancing the competitiveness of the Brazilian industry in the next five years; (ii) *Adopted technologies*: the same list of technologies where the companies indicate those technologies they are already using (iii) *Expected benefits*: a list of benefits expected from digital technologies where the companies indicate up to five benefits they expect to obtain with the technologies adopted; (iv) *Internal barriers*: a list of internal barriers the companies face in order to acquire digital technologies; (v) *External barriers*: a list of external barriers the companies face in order to acquire digital technologies (vi) *Industrial policy*: a list of possible actions the government should make to accelerate the digital technologies adoption by the Brazilian industries. For the purpose of this paper, we used data from the questions (ii) and (iii) of this survey, i.e. the digital technologies adopted and the expected benefits. Question (ii) asks: "*Indicate the digital technologies that your company already uses*". For this question, a list of 11 digital technologies are provided (see Section 3.2). Question (iii) asks "*Indicate the main benefits that your company expects to obtain by adopting digital technologies: (Indicate up to five items)"*. Here, a list of 14 benefits are provided (see Section 3.2). For both set of variables, the scale provided by the CNI database is in percentage (0%–100%), representing the relative amount of companies of each industrial sector that have adopted a specific technology (Question ii) or that are expecting a specific benefit (Question iii).

3.2. Variables selection

Since our main purpose is to understand the expected benefits of Industry 4.0 related technologies for industrial performance in Brazil, we defined as independent variables the technologies of Industry 4.0 adopted by the industrial sectors and as dependent variables the benefits expected by industrial sectors that are applying these technologies, which are both provided by the CNI (2016) survey. As presented in Table 3, the Industry 4.0 technologies are represented by 9 technologies and the expected benefits by 14 main benefits aligned with those highlighted in the literature. From the independent variables of our regression model, we did not include two technologies that are considered in the CNI survey. The first one was 'digital automation without

[1] Information source http://www.portaldaindustria.com.br/cni/en/about/about-cni/.

[2] The complete questionnaire is available at http://www.portaldaindustria.com.br/estatisticas/sondesp-66-industria-4-0/.

Table 2
Demographic characteristics of the industrial sectors considered in the sample.

Industrial sectors considered in the study	Mining	Rubber products
	Food products	Plastics products
	Beverages	Non-metallic mineral products
	Textiles products	Basic metals
	Wearing apparel	Metal products (not machinery and equipment)
	Leather and related products	Computers, electronics and opticals products
	Footwear and parts	Electrical equipment
	Wood products	Machinery and equipment
	Pulp and Paper	Motor vehicles, trailers and semi-trailers
	Printing and recorded media	Other transport equipment
	Coke and refined petroleum products	Furniture
	Chemicals	Repair and installation
	Soap and detergents	Other manufacturing
	Chemicals and pharmaceuticals	
Sample distribution	Total of companies in the 27 sectors: 2225	Large companies: 500 (22.6%)
		Medium companies: 815 (36.6%)
		Small companies: 910 (40.8%)

Table 3
Technologies and expected benefits considered in the research model.

Technologies (Independent Variables)	Expected benefits (Dependent variables)
Computer-Aided Design integrated with Computer-Aided Manufacturing [CAD/CAM]	Y1: Improvement of product customization
Integrated engineering systems [ENG_SYS]	Y2: Optimize automation processes[1]
Digital automation with sensors [SENSORING]	Y3: Increase energy efficiency[1]
Flexible manufacturing lines [FLEXIBLE]	Y4: Improvement of product quality
MES and SCADA systems [MES/SCADA2	Y5: Improve decision-making process[1]
Big data [BIG_DATA]	Y6: Reduction of operational costs
Digital Product-Services [DIGITAL_SERV]	Y7: Increase productivity
Additive manufacturing [ADDITIVE]	Y8: Increase worker safety[1]
Cloud services [CLOUD]	Y9: Create new business models[1]
	Y10: Reduction of product launch time
	Y11: Improving of sustainability
	Y12: Increase of processes visualization and control
	Y13: Reduce of labor claims
	Y14: Compensate for the lack of a skilled worker[1]

[1] These dependent variables were deleted from the model during the PCA procedure of variables reduction as explained in Section 3.3.

sensors', that was excluded because it is exclusively related to the classic automation of the third Industrial Revolution. The second variable excluded was Simulation/virtual models [VIRTUAL], because it did not follows a normal distribution in the data, presenting a high value of Kurtosis (4.269) (Hair et al., 2009), although it is directly related to the Industry 4.0 and was considered in Table 1. The data for the considered variables of our study are provided by CNI (2016) at an aggregate-level, as the percentage of companies in each industrial sector that indicated the adoption of a specific technology and the expectation for a specific benefit. Therefore, our study considers the analysis at the industrial sector level. Besides these variables, we also included two dummies as potential control variables in order to represent the three levels of technology intensity of the 27 industrial sectors under analysis (low, medium and high). These technological intensity levels are described in the CNI (2016) report. Table 3 summarizes the dependent and independent variables used in our regression model.

3.3. Variables reduction for regression analysis

To understand how the different Industry 4.0 related technologies are seen as beneficial for the industrial performance, we kept all Industry 4.0 technologies (Table 1) as single variables (not constructs) in order to differentiate the association of each of them to the expected performance outputs. We tested multicollinearity using the Variance Inflator Factor (VIF) to avoid potential multicollinearity among these independent variables in the regression model. On the other hand, we synthesized the 14 expected benefits presented in Table 3 (i.e. industrial performance) into main categories using a Principal Component Analysis (PCA).[3] PCA technique allowed us to obtain broader performance metrics based on the partial contribution of different but correlated measures (Hair et al., 2009). Such a strategy was also used in other prior works in the operations management field (e.g. Marodin et al., 2017a) and innovation field (e.g. Frank et al., 2016). This helped us to study the potential contribution of the technologies for the benefits of overall performance metrics when strong correlated outputs are considered. Based on Hair et al. (2009), we divided this procedure in two steps, the validation of PCA adequacy to the sample and the reduction of variables by means of the PCA technique, as explained next.

We used three criteria to evaluate the adequacy of the data to the PCA technique: the Kaiser-Meyer-Olkin (KMO) test for measure of sampling adequacy, Bartlett's test of sphericity, and the measure of sampling adequacy (MSA)[4] (Hair et al., 2009). All these tests suggested that the dependent variables can be reduced using PCA, since the KMO test was 0.501 (i.e. it equals the threshold value recommended), while the Barlett's test of sphericity presented a p-value < 0.001 (i.e. lower than the suggested $p < 0.05$ significance level) and the MSA test indicated that 75% of the variables had values higher than 0.5, as required by this test (Hair et al., 2009).

[3] PCA has been proposed as suitable also for small sample sizes (aggregated data, in our case), when the validation tests and the outputs are robust enough as those obtained in our results. For more details see MacCallum et al. (2001) and Dochtermann and Jenkins (2011).

[4] The statistical tests for both PCA and regression analysis were performed by using IBM® SPSS® Statistics version 20.

Table 4
Rotated Factor-Loading Matrix from PCA procedure.

List of expected benefits from the Industry 4.0	Factor loadings[a]			
	Product	Operational	Side-effects	Commu-nalities
Improvement of product customization	**<u>0.797</u>**	0.251	−0.171	0.727
Improvement of product quality	**<u>0.766</u>**	0.167	−0.309	0.711
Reduction of operational costs	0.306	**<u>0.865</u>**	0.026	0.843
Increase productivity	0.461	**<u>0.609</u>**	0.071	0.588
Reduction of product launch time	**<u>0.868</u>**	0.028	0.202	0.796
Improving of sustainability (externalities)	0.079	−0.076	**<u>0.935</u>**	0.886
Increase of processes visualization and control	−0.035	**<u>0.818</u>**	0.06	0.675
Reduce of labor claims (worker satisfaction)	−0.311	0.357	**<u>0.767</u>**	0.813
Eigenvalue	**2.986**	**1.919**	**1.135**	
% of variance explained (cumulative)	**37.32%**	**61.31%**	**75.49%**	
Cronbach's alpha	**0.807**	**0.750**	**0.720**	

[a] High factorial loadings (> 0.5) are represented in bold and underlined.

Then, we performed the PCA for the dependent variables (Table 4). We used a Varimax orthogonal rotation factor solution in order to reduce ambiguities often related to non-rotated analysis and achieve clearer and more meaningful factor solution from the PCA (Hair et al., 2009). We followed an iterative process to achieve the optimized solution where the optimal number of components were selected based on the eigenvalues, which should be higher than 1.0 (latent root criterion) and on the percentage of variance criterion, which considers that the optimal number of components are those that exceed 60% of the total variance and ideally more than 70%; in our case we used the latter percentage (Hair et al., 2009). In the initial solution, 6 of the 14 output variables (Y2, Y3, Y5, Y8, Y9 and Y14) showed no relation to any principal components (these variables are indicated in Table 3). Therefore, they were deleted from the outputs. Then, the PCA with Varimax was performed again for the eight remaining dependent variables, which were represented in three components that explain 75.49% of the variance, as shown in Table 4. The three main components were defined according to the variables with high factor loading (> 0.5) represented in them. The factorial scores for these new three outputs were obtained by means of the Thurnstones' method. Table 4 also shows the reliability analysis of the three constructs using Cronbach's alpha, being all of them above the threshold value of 0.7 (Hair et al., 2009). Hence, the final three factors are: Product expected benefits [PRODUCT], Operational expected benefits [OPERATION] and Side-effects expected benefits [SIDE-EFFECTS]. The first one (PRODUCT), includes all benefits regarding the product offered, measurement of customization, quality and launch time as dimensions of the product performance. The second construct (OPERATION) considers all the metrics regarding the internal industrial activity of the factory, including costs, productivity and process control of the factory.

Lastly, we called the third component as Side-effects expected benefits [SIDE-EFFECTS] because it considers the collateral effects related to the use of digital technologies of Industry 4.0. In this third component, two benefits are included: the improvement in sustainability (or reduction of externalities) and the reduction of labor claims. Despite the main goal of Industry 4.0, which is to increase productivity, the initiative aims to reach this goal with more efficient resources utilization, possible by the use of technologies such as additive manufacturing (Kagermann et al., 2013; De Sousa Jabbour et al., 2018). In addition, labor claims can be reduced due to different reasons in this initiative, as this new paradigm relies less on the human force (i.e. fewer workers with potential claims) and also because some technologies aims to help workers to perform their tasks (i.e. workers more assisted to do their job), e.g. human-machine collaboration systems (Gilchrist, 2016; Wang et al., 2015). Both benefits, improving sustainability and reducing labor claims, can be related into one component as they are usually not the primary objectives expected from industries when investing in digital technologies, so these benefits can be seen as derivative from the expected primary benefits from the Industry 4.0 (CNI, 2016). Table 5 presents the correlation matrix of the final set of variables used in our analysis. This table also shows the descriptive statistics such as mean, standard deviation and the skewness and kurtosis test to verify normality of the data.

4. Results

We used an ordinary least square (OLS) regression[5] to understand the association of Industry 4.0 related-technologies to three types of expected benefits: Product expected benefits [PRODUCT], Operational expected benefits [OPERATIONAL] and Side-effects expected benefits [SIDE-EFFECTS]. OLS regression should be used only if some standard requirements of the database are achieved, such as normality, linearity, and homoscedasticity (Hair et al., 2009). The skewness and kurtosis values reported in Table 5 suggest that the variables can be assumed as normal distributed, since they are below the threshold of 2.58 ($\alpha = 0.01$) (Hair et al., 2009). We also assessed data normality graphically by means of an examination of the residuals. We analyzed collinearity by plotting the partial regressions for the independent variables while homoscedasticity was visually examined in plots of standardized residuals against predicted value. All these requirements were met in our dataset. Moreover, multicollinearity could be also a problem for OLS regression (Hair et al., 2009). Therefore, we tested the variance inflation factor (VIF) among the independent variables, resulting in VIF < 3.5 for the independent variables and control variables, excepting for CAD/CAM, ENG_SYS and SENSORING which resulted in VIF < 8.14. As all these values were below the threshold VIF = 10.0, multicollinearity may not be a concern in our regression model (Hair et al., 2009).

We performed three independent regression models, one for each of the expected benefits (i.e. PRODUCT, OPERATIONAL and SIDE-EFFECTS). The results of the regression models for the three industrial expected benefits metrics are shown in Table 6. Two of the three models were significant at $p < 0.05$ and one did not show statistical significance. The first regression model ($F = 14.245$, $p < 0.001$) explained 84.9% of the variance of PRODUCT; while the second model ($F = 3.042$, $p = 0.024$) explained 46.3% of the OPERATIONAL variance. Lastly, we identified that SIDE-EFFECTS was not significant ($F = 0.751$, $p = 0.679$).

Regarding the association of the specific Industry 4.0 related technologies with the expecting PRODUCT, the following technologies presented positive and significant effects: integrated engineering systems for product development and manufacturing [ENG_SYS] ($\beta = 0.438$, $p = 0.063$); incorporation of digital services into products

[5] OLS regression was performed using IBM SPSS Statistics® version 20.

Table 5
Correlation matrix and descriptive analysis.

		MEAN (%)	S.D.	Skewness	Kurtosis	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	PRODUCT	0.24	0.06	0.402	0.596	–													
2	OPERATIONAL	0.36	0.05	−0.639	−0.112	0.000	–												
3	SIDE-EFFECTS	0.07	0.02	−0.284	−0.328	0.000	0.000	–											
4	CAD_CAM	0.27	0.17	0.542	−0.771	0.648**	0.402*	0.080	–										
5	ENG_SYS	0.14	0.08	0.352	−0.683	0.597**	0.446*	0.215	0.749**	–									
6	SENSORING	0.20	0.09	−0.080	−0.400	−0.191	0.335	0.281	−0.157	0.229	–								
7	FLEXIBLE	0.06	0.04	0.343	−0.327	0.191	0.207	0.062	−0.069	0.303	0.699**	–							
8	MES-SCADA	0.05	0.03	0.347	−0.747	−0.305	0.297	0.234	−0.113	0.300	0.714**	0.505**	–						
9	BIG_DATA	0.07	0.04	0.795	0.970	−0.279	0.487*	0.187	0.045	0.246	0.256	0.109	0.516**	–					
10	DIGITAL_SERV	0.03	0.02	1.054	2.517	0.381	0.306	−0.104	0.226	0.363	−0.020	0.256	0.073	0.353	–				
11	ADDITIVE	0.04	0.04	1.415	1.308	0.625**	0.124	0.356	0.522**	0.669**	0.107	0.314	0.139	0.323	0.463*	–			
12	CLOUD	0.06	0.03	0.043	0.069	0.064	−0.020	0.050	−0.191	−0.207	0.409*	0.418*	0.115	−0.078	0.041	0.042	–		
13	Control_tech_low	0.48	0.51	0.079	−2.160	0.014	−0.395*	−0.228	−0.348	−0.298	−0.465*	−0.239	−0.244	−0.345	−0.229	−0.264	−0.114	–	
14	Control_tech_high	0.26	0.45	1.164	−0.702	0.279	0.415*	0.045	0.496**	0.444*	0.173	0.283	0.049	0.087	0.491**	0.356	0.225	−0.570**	–

$^{**}p < 0.01$; $^{*}p < 0.05$.

Table 6
Results of the regression analysis [a].

	Expected benefits for …		
	Product	Operational	Side-Effects
CAD_CAM	0.310	**0.774****	−0.306
ENG_SYS	**0.438***	−0.129	0.118
SENSORING	−0.189	**0.778***	0.303
FLEXIBLE	0.212	0.062	−0.409
MES-SCADA	−0.246	−0.345	0.078
BIGDATA	−**0.388*****	**0.658*****	−0.040
DIGITAL_SERV	**0.286****	0.192	−0.308
ADDITIVE	**0.261****	−**0.529****	**0.622***
CLOUD	**0.255****	−0.149	0.009
Control_tech_low	0.257	0.379	−0.300
Control_tech_high	**0.426***	0.241	−0.126
F-value	14.245***	3.042**	0.751
R^2	0.913	0.690	0.355
Adjusted R^2	0.849	0.463	−0.118

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.
[a] Significant effects are represented in bold and underlined.

[DIGITAL_SERV] (β = 0.286, p = 0.022); additive manufacturing [ADDITIVE] (β = 0.261, p = 0.050); and Cloud Services [CLOUD] (β = 0.255, p = 0.043). In addition, one technology is negatively associated to the expected outcome of this expected benefits metric: big data analysis [BIG_DATA] (β = −0.388, p = 0.004).

In the second expected benefits metric, OPERATIONAL, the technologies with positive and significant association were: Computer-Aided Design with Computer-Aided Manufacturing [CAD/CAM] (β = 0.774, p = 0.046); digital automation with sensors for process control [SENSORING] (β = 0.778, p = 0.064) and Big Data [BIG_DATA] (β = 0.658, p = 0.008). On the other hand, additive manufacturing [ADDITIVE] had a negative association (β = −0.529, p = 0.036) to this expected benefits metric. ADDITIVE also showed a positive association to SIDE-EFFECTS (β = 0.622, p = 0.081), although the complete model for SIDE-EFFECTS was not statistical significant.

Furthermore, we performed a statistical power analysis of our two significant models (PRODUCT and OPERATION) based on (Cohen et al., 2003). We first estimated the population effect size of R^2 using Cohen's f^2 estimation.[6] For the PRODUCT model we obtained a $f^2 = 10.45$, which represents a statistical power of > 0.99 at α = 0.01, while for the OPERATION regression model the f^2 was 2.23, which represents a statistical power of ≈0.93 at α = 0.01. We also considered the statistical power of the partial coefficients using Cohen's f^2 estimation for the predictors[7] and the range of effects suggested by them: 0.02– small effect, 0.15 – medium effect, and 0.35 – large effect (Cohen et al., 2003, p. 95). Considering the statistical significant independent variables in the PRODUCT model, two of them showed large effects: BIGDATA (0.78) and DIGITAL_SERV (0.44), while all the others showed medium effect (≥0.27). For the significant regressors in the OPERATION model, two technologies indicate large effect: BIGDATA (0.63) and ADDITIVE (0.35), while the other two CAD_CAM and SENSORING presented medium effects (0.32 and 0.27 respectively). Therefore, we can conclude that the significant effects have also satisfactory statistical power in our sample.

5. Discussions

We summarized our findings in Fig. 1, aiming to illustrate the connections between the different Industry 4.0 related technologies and the expected benefits. We use this framework (Fig. 1) to guide the

[6] According to Cohen et al. (2003, p. 92): $f^2 = \frac{R^2}{(1-R^2)}$.

[7] According to Cohen et al. (2003, p. 94): $f^2 = \frac{sr^2}{(1-R^2)}$; where sr^2 represents

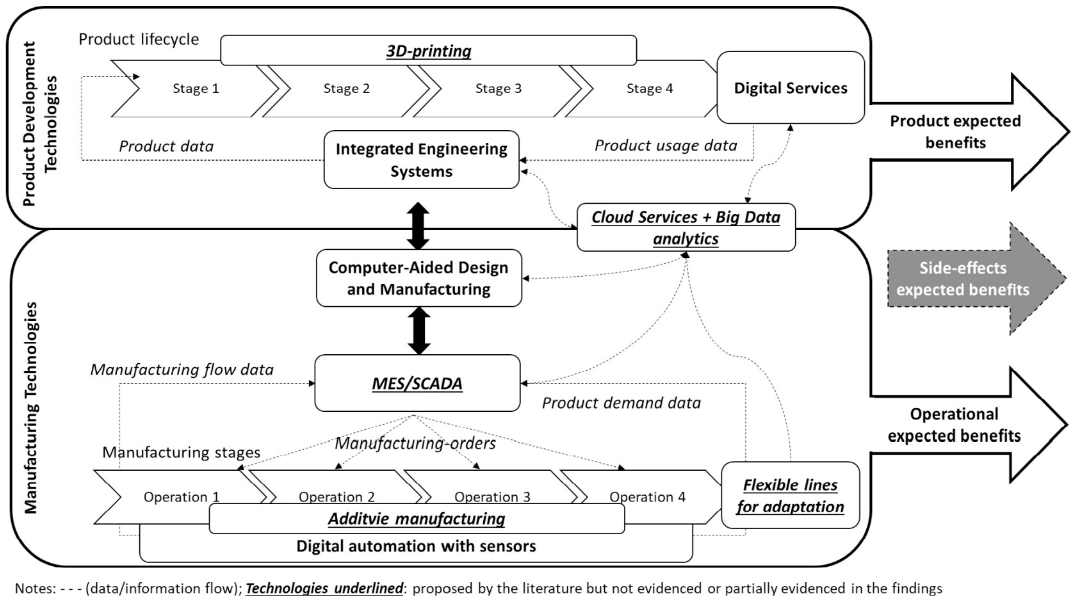

Fig. 1. Framework summarizing the findings and discussions of the paper.

discussion of our findings and to clarify how these Industry 4.0 technologies can be understood in the Brazilian context. Firstly, we divided our framework (Fig. 1) in two set of technologies as our findings showed in Table 6 The first set is related to (i) *Product Development Technologies* of the Industry 4.0 while the second set is related to (ii) *Manufacturing Technologies* of the Industry 4.0. We divided technologies in these two groups because, as we shown in our results, the industrial sectors have different expectations for them. According to our findings of Table 6, technologies that are expected to contribute for Product Performance (i.e. *Product Development Technologies*) are ENG_SYS, DIGITAL_SERV, ADDITIVE and CLOUD, while the technologies expected to bring benefits for operational performance (i.e. *Manufacturing Technologies*) are CAD_CAM, SENSORING and BIGDATA. Two technologies, integrated engineering systems [ENG_SYS] and Computer-Aided Design and Manufacturing [CAD/CAM] are considered integration systems in the interface between product and operational processes, as shown in Fig. 1 (Tao et al., 2018a). Next, we discuss in detail the configuration of this framework based on our findings and on prior evidences from the literature.

Firstly, regarding the *Product Development Technologies* (Fig. 1), *additive manufacturing* [ADDITIVE], which in product development is represented by 3D-printing, is associated with the expected benefits for new product development. This expectation is aligned with the literature, which highlights that the use of additive technology brings several advantages since products can be digitally modified before their physical production, reducing the processing times, resources and tools needed. This technology accelerates product innovation and assists co-design activities, promoting more customized products (Yin et al., 2017). While additive manufacturing (3D-printing) promotes customization of the products, our findings (Table 6) show that the industry also expects *digital services in products* [DIGITAL_SERV] and *Cloud Services [CLOUD]* to increase the value perceived by the customers (Fig. 1). According to Porter and Heppelmann (2014) digital services connected in the cloud are a global trend in companies, allowing them to launch smart products with embedded sensors, processors, software and connected via internet, which enables new functions and capabilities related to their monitoring, control, optimization and autonomy. With the Internet of Things (IoT), products can communicate with other products and systems of products, optimizing overall results and enabling after-sales service solutions. These technologies should improve the performance of extant products and the development of new products, and its utilization shows some degree of differentiation strategies expected by Brazilian industrial sectors. However, as the (CNI, 2016) report state, there are still few industrial sectors that incorporate digital services in their products with cloud systems and that use additive manufacturing.

On the other hand, the use of Big Data collection and analysis [BIG_DATA] showed a negative association to the benefits expected for product performance. This is a surprising result for us, since the literature describes this technology as of great potential to leverage innovation, competition and productivity in business processes (Wamba et al., 2015). While the industry is expecting positive outcomes for integrating data in the cloud (i.e. CLOUD was positive), they do not present an optimistic perspective for the latter technology. In other words, IoT technologies are perceived as useful for real-time processing but not for data storage and analysis. This may suggest that the Brazilian industry still lags in the implementation of one of the most promising tools in the Industry 4.0 for product improvement and innovation (Wamba et al., 2015). Therefore, even though these technologies have been widely diffused in developed countries, their diffusion and adoption in Brazil is still behind the competitive level expected. Such problem can be corroborated with a recent industrial survey conducted by PwC consulting (PWC, 2016) that indicates that around 63% of Brazilian companies considered themselves in a weak maturity level for Big data analytics, 30% in a middle maturity level and those that represented the remaining 7% outsourced data analytics competencies. As most industrial sectors do not have the capacity to properly analyze the large amount of data they generate, we conclude that this lack of knowledge might impair the perception of usefulness for the development of new products, which represents a diffusion-adoption gap for the Industry 4.0 in Brazil.

Regarding the interface between the (i) *Product Development Technologies* and (ii) *Manufacturing Technologies*, our findings (Table 6) showed that there are two complementary integration technologies: ENG_SYS, which is positively associated to PRODUCT expected benefits, and CAD/CAM, which is positively associated to OPERATIONAL expected benefits (Fig. 1). We argue that based on the findings and on the fact that ENG_SYS work with the integration of the whole product lifecycle data, from the product conception to its production and commercialization (Abramovici, 2007; Stark, 2011; Bruun et al., 2015). This technology can aid different industrial sectors to overcome the well-known communication and coordination barriers they face when involving suppliers in a collaborative NPD for complex products (Langner and Seidel, 2009; Peng et al., 2014). Moreover, as horizontal integration is one of the main Industry 4.0 characteristics, integrated engineering systems also have an important role for connecting people, objects and systems through digital platforms, what clearly simplify the orchestration of services and applications in industrial activities (Kagermann et al., 2013). On the other hand, CAD/CAM can help the operational aspects for vertical integration, since it can help to translate the product lifecycle data from end-to-end engineering into product design specifications, enhancing the visibility of manufacturing processes still in the design phase (Jeschke et al., 2017).

Following the *Manufacturing Technologies* dimension, surprisingly neither MES/SCADA nor flexible manufacturing lines [FLEXIBLE] were significantly associated to the OPERATIONAL expected benefits. Based on the extant literature, we were expecting a positive association of them, jointly with the integration systems (ENG_SYS and CAD/CAM) and the digital automation with sensors [SENSORING], as a set of standard technologies for the Industry 4.0 manufacturing system. While ENG_SYS and CAD/CAM integrate product development data with manufacturing processes (Miranda et al., 2017), SENSORING enables data collection in the manufacturing process (Konyha and Bányai, 2017), which could be used by the flexible manufacturing lines [FLEXIBLE] to reconfigure or adapt the processing sequence, schedule, etc. (Wang et al., 2015) with MES/SCADA support (Jeschke et al., 2017). In other words, these technologies should form a system that enables both, horizontal and vertical integration (Zhou et al., 2015). ENG_SYS contributes for information sharing among functional areas in the factory, both internally and externally, which in the latter constitutes the horizontal integration. FLEXIBLE and MES/SCADA contribute to the integration among process stages in the hierarchical areas. The first aims to build reconfigurable lines with sensor technology, in order to ease the change the product types in the production lines (Brettel et al., 2014; Steimer et al., 2016), while MES/SCADA generate daily production orders from the ERP, considering several restrictions from machine data (Jeschke et al., 2017), SENSORING acts at the most basic levels of the equipment operation (Gerber et al., 2013). One reason because MES/SCADA and FLEXIBLE might be not statistically associated to the OPERATIONAL expected benefits is because they are in very early stage of adoption in the Brazilian industry, since only around 8% of the industry has adopted these technologies for operational processes, according to the CNI report (CNI, 2016). Thus, several industrial sectors may not be aware of their contribution for operational benefits.

Digital automation with sensors for process control [SENSORING] showed a significant association to the OPERATIONAL expected benefits, being one of the most implemented technologies (around 27%) in the industries of the survey (CNI, 2016). Even though this is one of the less advanced technologies in the Industry 4.0 concept (Yu et al., 2015), it provides the basis for production cells control and data collection of manufacturing flow and cells demand, aiming to provide inputs for the flexible lines and the MES/SCADA, as shown in Fig. 1. SENSORING also allows to create operational big data [BIG_DATA] – also positively significant in our findings – for further analysis aiming for predicting maintenance, machine-learning (self-adapting), and scheduling or to provide information for the Manufacturing Execution System (MES) and for new design and manufacturing in the CAD/CAM system (Tao et al., 2018b), as we show in the framework of Fig. 1. On the other hand, it is worth noticing that cloud services [CLOUD] did not show significant association to the OPERATIONAL expected benefits while BIG_DATA did, as we explained before. Based on prior studies (e.g. Gilchrist, 2016; Jeschke et al., 2017) we expected a joint contribution of these technologies. One possible reason is that CLOUD is associated with external data warehousing and this is still a concern in the industry due to data security, which represent a barrier for its implementation (Wang et al., 2015).

The last Industry 4.0 technology at the operational level is additive manufacturing [ADDITIVE] which we represented in Fig. 1 as overlapped with different manufacturing operations. This means that ADDITIVE could be used in different operation stages and for different production purposes. However, our findings showed a negative association of this technology with OPERATIONAL expected benefits. According to Weller et al. (2015), additive manufacturing still has several restrictions for its application in manufacturing processes, such as the availability of materials and lack of defined quality standards. Moreover, although this technology can improve product development, this equipment has still low production throughput speed, when compared to conventional manufacturing, which may affect larger-scale production levels with cost efficiency, as suggested by our results.

Finally, regarding the SIDE-EFFECTS expected benefits, Fig. 1 represents it as a possible secondary perceived benefit from the Industry 4.0. Our results indicated a positive association with additive manufacturing. However, the complete model for SIDE-EFFECTS was not statistically significant – even when ADDITIVE has a positive association to this output – suggesting that this performance is not expected with the use of most of the Industry 4.0-related technologies. This is an unexpected finding, since the improvement of resource consumption efficiency is one of the main areas of Industry 4.0 (Kagermann et al., 2013), and the technologies analyzed in this paper are suggested to contribute to sustainability (e.g. Kiel et al., 2016; Stock and Seliger, 2016; Man and Strandhagen, 2017; De Sousa Jabbour et al., 2018), and indirectly for labor claim reduction, by automatizing the production process which reduces the need for manpower (e.g. Hozdić, 2015). The concern with Industry 4.0 as a way to deal with these side-effects aspects has been addressed in studies of developed economies. However, when considering emerging economies such as Brazil, other aspects may be priority in the industry's concern. As acknowledged by the CNI report (CNI, 2016), the main efforts of Brazilian industries with digital technologies has been to increase productivity, while the side-effects benefits are not yet a clear objective of the industry when investing in Industry 4.0 technologies. Therefore, they could be a secondary benefit only perceived after the achievement of product and operational benefits. This is also in line with the general literature about sustainability in industry, which evidences differences in such concern between developed and emerging countries (Hansen et al., 2018; Viotti, 2002).

6. Conclusions

In this paper we analyzed the perception of the Brazilian Industry about the benefits of Industry 4.0 related-technologies for three industrial performance metrics: product, operational and side-effects. Our results showed that some of these technologies are positively associated to the expected industrial benefits while others are still at a very early stage of adoption and, thus, without clear expected benefits. We discussed reasons for the lack of expectation of benefits for some of the promising technologies of the Industry 4.0 in this specific emerging industry.

Our main contribution to the state-of-the-art is that we show how these technologies are used and seen in an emerging economy, since most of the studies on this matter have been conducted in developed countries. In this sense, we showed how different set of technologies are associated with different expected benefits. We showed that the Brazilian industry has not yet taken advantage from some promising technologies such as product big data analysis, cloud services for manufacturing, among other technologies for the digitalization of the factory and for the analysis of the product performance. A further contribution is that we could not find any relation between the Industry 4.0 and the expected benefits for sustainability and labor claims [SIDE-EFFECTS], which represents a different pattern when comparing to developed economies. Based on prior evidences from developed countries, we argued that since side-effects tend to be at the second level of priority in the industries, after achieving operational and product performance benefits, the Brazilian industry is still not focused on this aspect, but this deserves future investigation.

6.1. Practical implications

Our results can be useful for both, operations managers and industrial policy-makers. For operations management, our results showed which are expected to be the most powerful technologies to enhance product and operational performance in the Brazilian context, according to the industry perception. Companies that want to initiate their digitalization journey towards the Industry 4.0 should first think, before implementing any technology, what are their strategic goals. Thus, companies with a focus on differentiation should prioritize the implementation of those technologies pointed as significantly associated to the *Product Development Technologies* dimension (Fig. 1), according to what is expected by the industry and the literature; while companies with a focus on low cost, productivity or operational flexibility should prioritize those Industry 4.0 technologies that have significant contribution for the *Manufacturing Technologies* dimension. On the other hand, industrial policy-makers in emerging countries can use our findings as a guideline about what technologies still need to be developed for the industry to achieve the competitiveness standards of developed countries. For instance, big data, cloud services and additive manufacturing (e.g. 3D printing) are strong industrial trends in developed countries that should be considered for the future of the emerging countries. However, this field needs further debates regarding the industrial policy approaches to foster the national competitiveness of the country.

6.2. Limitations and future research

The use of a secondary dataset for our analysis allowed us to obtain a broad overview of a still little explored emerging industry. However, some limitations are present due to this kind of research. Firstly, our results have limitations on the statistical inferences since we considered expecting benefits from the industry 4.0 technologies and not current benefits obtained from them. This is because the implementation of many of these technologies are recent and the benefits are not feasible to be obtained in the short-term. Future works can use our findings to advance in the study of real improvements, which could be done only in the middle or long-term of this new industrial trend. Experimental studies can provide quicker answers to these aspects when compared with survey studies. However, it is well known that experimental studies have also limitations regarding the generalization of the results.

Furthermore, we used aggregated-level data analysis and thus we studied the industrial sector behavior. In this sense, we call the attention to the risk of ecological fallacy, when macro-level analysis using aggregate data is used in micro-level conclusions (firm-level) (Clark and Avery, 1976). In this sense, our results are only valid at the industry-level behavior. Other future studies could, therefore, deepen our research by conducting company-level surveys. We also studied a cross-sectional sample, thus future longitudinal studies on the effect of the Industry 4.0 technologies could evidence patterns and maturity levels of the adoption of such technologies. We know that future research is called to address the endogeneity problems that can be present in large-scale survey studies (Bascle, 2008), especially because the adoption of technologies might depend not only on internal decisions but on the access to public funds and other kind of governmental incentives (Frank et al., 2016). There are other inherent aspects regarding endogeneity in operations management that we did not addressed in this work and are part of an emerging discussion in this field (Ketokivi and McIntosh, 2017). We were aware about these limitations, but due to the limitation of information in our dataset we cannot include instrumental variables that may be helpful to test alternative models to the OLS models used in this paper. Finally, we mentioned in our work that, from a socio-technical perspective, organizational and human factors are very relevant to the implementation of technologies. Since we delimited our research only to technological factors in a specific environment, future studies could expand to these other two factors, in order to consider how they facilitate or not the implementation of the technologies addressed in our work.

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References

ABDI - Agência Brasileira de Desenvolvimento Industrial, 2017. Inovação, Manufatura Avançada e o Futuro da Indústria. Available at: www.abdi.com.br/Estudo/ABDI_Inovacao_Manufatura_Vol01.pdf.

Abele, E., Wörn, A., Fleischer, J., Wieser, J., Martin, P., Klöpper, R., 2007. Mechanical module interfaces for reconfigurable machine tools. Prod. Eng. 1, 421–428. https://doi.org/10.1007/s11740-007-0057-1.

Abramovici, M., 2007. Future Trends in Product Lifecycle Management (PLM), in: the Future of Product Development. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 665–674. https://doi.org/10.1007/978-3-540-69820-3_64.

Alekseev, A., Evdokimov, S., Tarasova, A., Khachaturyan, K., Khachaturyan, A., 2018. Financial strategy of development of industry 4.0 in the countries with developing economy. Rev. Espac. 39.

Ali, A.B.M.S., Azad, S., 2013. Demand Forecasting in Smart Grid. pp. 135–150. https://doi.org/10.1007/978-1-4471-5210-1_6.

Arbix, G., Salerno, M., Zancul, E., Amaral, G., Lins, L., 2017. Advanced manufacturing: what is to Be learnt from Germany, the US, and China. Novos Estud. CEBRAP 36, 29–49.

Ayala, N.F., Paslauski, C.A., Ghezzi, A., Frank, A.G., 2017. Knowledge sharing dynamics in service suppliers' involvement for servitization of manufacturing companies. Int. J. Prod. Econ. 193, 538–553. https://doi.org/10.1016/j.ijpe.2017.08.019.

Babiceanu, R.F., Seker, R., 2016. Big Data and virtualization for manufacturing cyber-physical systems: a survey of the current status and future outlook. Comput. Ind. 81, 128–137. https://doi.org/10.1016/j.compind.2016.02.004.

Bangemann, T., Riedl, M., Thron, M., Diedrich, C., 2016. Integration of classical components into industrial cyber–physical systems. Proc. IEEE 104, 947–959. https://doi.org/10.1109/JPROC.2015.2510981.

Bartodziej, C.J.C.J., 2017. The Concept Industry 4.0. Springer Fachmedien Wiesbaden, pp. 27–50.

Bascle, G., 2008. Controlling for endogeneity with instrumental variables in strategic management research. Strat. Organ. 6, 285–327. https://doi.org/10.1177/1476127008094339.

Bernat, S., Karabag, S.F., 2018. Strategic alignment of technology: organising for technology upgrading in emerging economy firms. Technol. Forecast. Soc. Change. https://doi.org/10.1016/J.TECHFORE.2018.05.009.

Brettel, M., Friederichsen, N., Keller, M., Rosenberg, M., 2014. How virtualization, decentralization and network building change the manufacturing Landscape . Int. J. Mech. Ind. Sci. Eng. 8, 37–44.

Bruun, H.P.L., Mortensen, N.H., Harlou, U., Wörösch, M., Proschowsky, M., 2015. PLM system support for modular product development. Comput. Ind. 67, 97–111. https://doi.org/10.1016/j.compind.2014.10.010.

Castellacci, F., 2008. Technological paradigms, regimes and trajectories: manufacturing and service industries in a new taxonomy of sectoral patterns of innovation. Res. Pol. 37, 978–994. https://doi.org/10.1016/j.respol.2008.03.011.

Castellacci, F., Natera, J., 2013. The dynamics of national innovation systems: a panel cointegration analysis of the coevolution between innovative capability and absorptive capacity. Res. Pol. 42, 579–594. https://doi.org/10.1016/j.respol.2012.10.006.

Chryssolouris, G., Mavrikios, D., Papakostas, N., Mourtzis, D., Michalos, G., Georgoulias, K., 2009. Digital manufacturing: history, perspectives, and outlook. Proc. Inst. Mech. Eng. Part B J. Eng. Manuf 223, 451–462. https://doi.org/10.1243/09544054JEM1241.

Clark, W.A.V., Avery, K.L., 1976. The effects of data aggregation in statistical analysis. Geogr. Anal. 8, 428–438. https://doi.org/10.1111/j.1538-4632.1976.tb00549.x.

CNI - Conseil national de l'industrie, 2013. The New Face of Industry in France. French National Industry Council, Paris.

CNI - Confederação Nacional da Indústria, 2016. Industry 4.0: a New Challenge for Brazilian Industry. Available at: https://bucket-gw-cni-static-cms-si.s3.amazonaws.com/media/filer_public/54/02/54021e9b-ed9e–4d87-a7e5-3b37399a9030/challenges_for_industry_40_in_brazil.pdf.

Cohen, J., Cohen, P., Stephen, G., 2003. Applied Multiple Regression/correlation Analysis for the Behavioral Sciences, third ed. Taylor & Francis, UK.

Comin, D., Hobijn, B., 2004. Cross-country technology adoption: making the theories face the facts. J. Monet. Econ. 51, 39–83.

Coreynen, W., Matthyssens, P., Van Bockhaven, W., 2017. Boosting servitization through digitization: pathways and dynamic resource configurations for manufacturers. Ind.

Market. Manag. 60, 42–53. https://doi.org/10.1016/j.indmarman.2016.04.012.
Cortimiglia, M.N., Frank, A.G., Miorando, R.F., 2012. ICT trends in Brazil. IT Prof. 14, 31–38. https://doi.org/10.1109/MITP.2012.70.
Crisóstomo, V.L., López-Iturriaga, F.J., Vallelado, E., 2011. Financial constraints for innovation in Brazil. Lat. Am. Bus. Rev. 12, 165–185. https://doi.org/10.1080/10978526.2011.592797.
De Sousa Jabbour, A., Jabbour, C., Foropon, C., Godinho Filho, M., 2018. When titans meet–Can industry 4.0 revolutionise the environmentally-sustainable manufacturing wave? The role of critical success factors. Technol. Forecast. Soc. Change 132, 18–25. https://doi.org/10.1016/j.techfore.2018.01.017.
Dochtermann, N.A., Jenkins, S.H., 2011. Multivariate methods and small sample sizes. Ethology 117, 95–101. https://doi.org/10.1111/j.1439-0310.2010.01846.x.
Dregger, J., Niehaus, J., Ittermann, P., Hirsch-Kreinsen, H., Ten Hompel, M., 2016. The digitization of manufacturing and its societal challenges: a framework for the future of industrial labor. In: 2016 IEEE International Symposium on Ethics in Engineering, Science and Technology (ETHICS). Institute of Electrical and Electronics Engineers Inc., pp. 1–3. https://doi.org/10.1109/ETHICS.2016.7560045.
Eaton, J., Kortum, S., 1999. International technology diffusion: theory and measurement. Int. Econ. Rev.. (Philadelphia) 40, 537–570. https://doi.org/10.1111/1468-2354.00028.
Fatorachian, H., Kazemi, H., 2018. A critical investigation of Industry 4.0 in manufacturing: theoretical operationalisation framework. Prod. Plann. Contr. 1–12. https://doi.org/10.1080/09537287.2018.1424960.
Franco, E., Ray, S., Ray, P.K., 2011. Patterns of innovation practices of multinational-affiliates in emerging economies: evidences from Brazil and India. World Dev. 39, 1249–1260. https://doi.org/10.1016/j.worlddev.2011.03.003.
Frank, A.G., Cortimiglia, M.N., Ribeiro, J.L.D., Oliveira, L.S. de, 2016. The effect of innovation activities on innovation outputs in the Brazilian industry: market-orientation vs. technology-acquisition strategies. Res. Pol. 45, 577–592. https://doi.org/10.1016/j.respol.2015.11.011.
Frank, A.G., Ribeiro, J.L.D., Echeveste, M.E., 2015. Factors influencing knowledge transfer between NPD teams: a taxonomic analysis based on a sociotechnical approach. R D Manag. 45, 1–22. https://doi.org/10.1111/radm.12046.
Garrett, B., 2014. 3D printing: new economic paradigms and strategic shifts. Glob. Pol. 5, 70–75. https://doi.org/10.1111/1758-5899.12119.
Gerber, T., Bosch, H., Johnsson, C., 2013. Vertical Integration of Decision-relevant Production Information into IT Systems of Manufacturing Companies. pp. 263–278.
Gilchrist, A., 2016. Industry 4.0: the Industrial Internet of Things. Apress, Berkeley.
Guan, J.C., Mok, C.K., Yam, R.C.M., Chin, K.S., Pun, K.F., 2006. Technology transfer and innovation performance: evidence from Chinese firms. Technol. Forecast. Soc. Change 73, 666–678. https://doi.org/10.1016/j.techfore.2005.05.009.
Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E., 2009. Multivariate Data Analysis: a Global Perspective. Prentice Hall, Upper Saddle River.
Hall, B., Maffioli, A., 2008. Evaluating the impact of technology development funds in emerging economies: evidence from Latin America. Eur. J. Dev. Res. 20, 172–198. https://doi.org/10.3386/w13835.
Hansen, U., Nygaard, I., Romijn, H., Wieczorek, A., 2018. Sustainability Transitions in Developing Countries: Stocktaking, New Contributions and a Research Agenda, vol. 84. pp. 198–203. https://doi.org/10.1016/j.envsci.2017.11.009.
Hendrick, H., Kleiner, B., 2001. Macroergonomics: an Introduction to Work System Design. Human Factors and Ergonomics Society, Santa Monica, CA.
Hermann, M., Pentek, T., Otto, B., 2016. Design principles for industrie 4.0 scenarios. In: 2016 49th Hawaii International Conference on System Sciences (HICSS). IEEE. https://doi.org/10.1109/HICSS.2016.488.
Hozdić, E., 2015. Smart factory for industry 4.0: a review. Int. J. Mod. Manuf. Technol. 7, 28–35.
Jazdi, N., 2014. Cyber physical systems in the context of Industry 4.0. In: 2014 IEEE International Conference on Automation, Quality and Testing, Robotics, pp. 1–4. https://doi.org/10.1109/AQTR.2014.6857843.
Jeschke, S., Brecher, C., Meisen, T., Özdemir, D., Eschert, T., 2017. Industrial Internet of Things and Cyber Manufacturing Systems. Springer. https://doi.org/10.1007/978-3-319-42559-7_1.
Kagermann, H., 2015. Change through digitization—value creation in the age of industry 4.0. In: Management of Permanent Change. Springer Fachmedien Wiesbaden, Wiesbaden, pp. 23–45. https://doi.org/10.1007/978-3-658-05014-6_2.
Kagermann, H., Wahlster, W., Helbig, J., 2013. Recommendations for Implementing the Strategic Initiative INDUSTRIE 4.0. Final report of the Industrie 4.0 WG.
Ketokivi, M., McIntosh, C.N., 2017. Addressing the endogeneity dilemma in operations management research: theoretical, empirical, and pragmatic considerations. J. Oper. Manag. 52, 1–14. https://doi.org/10.1016/J.JOM.2017.05.001.
Kiel, D., Arnold, C., Collisi, M., Voigt, K., 2016. The impact of the industrial internet of things on established business models. In: Proceedings of the 25th International Association for Management of Technology (IAMOT) Conference, pp. 673–695.
Konyha, J., Bányai, T., 2017. Sensor networks for smart manufacturing processes. Solid State Phenom. 261, 456–462. https://doi.org/10.4028/www.scientific.net/SSP.261.456.
Krawczyński, M., Czyżewski, P., Bocian, K., 2016. Reindustrialization: a challenge to the economy in the first quarter of the twenty-first century. Found. Manag. 8. https://doi.org/10.1515/fman-2016-0009.
Kumar, N., Siddharthan, N., 2013. Technology, Market Structure and Internationalization: Issues and Policies for Developing Countries.
Langner, B., Seidel, V.P., 2009. Collaborative concept development using supplier competitions: insights from the automotive industry. J. Eng. Technol. Manag. 26, 1–14. https://doi.org/10.1016/j.jengtecman.2009.03.007.
Lasi, H., Fettke, P., Kemper, H.-G., Feld, T., Hoffmann, M., 2014. Industry 4.0. Bus. Inf. Syst. Eng. 6, 239–242. https://doi.org/10.1007/s12599-014-0334-4.
Liao, Y., Deschamps, F., Loures, E. de F.R., Ramos, L.F.P., 2017. Past, present and future of Industry 4.0-a systematic literature review and research agenda proposal. Int. J. Prod. Res. 55, 3609–3629. https://doi.org/10.1080/00207543.2017.1308576.
Luthra, S., Mangla, S., 2018. Evaluating challenges to Industry 4.0 initiatives for supply chain sustainability in emerging economies. Process Saf. Environ. Protect. 117, 168–179. https://doi.org/10.1016/j.psep.2018.04.018.
MacCallum, R.C., Widaman, K.F., Preacher, K.J., Hong, S., 2001. Sample size in factor analysis: the role of model error. Multivariate Behav. Res. 36, 611–637. https://doi.org/10.1207/S15327906MBR3604_06.
Man, J.C. de, Strandhagen, J.O., 2017. An industry 4.0 research agenda for sustainable business models. Proced. CIRP 63, 721–726. https://doi.org/10.1016/j.procir.2017.03.315.
Marodin, G.A., Frank, A.G., Tortorella, G.L., Fetterman, D.C., 2017a. Lean production and operational performance in the Brazilian automotive supply chain. Total Qual. Manag. Bus. Excel. 1–16. https://doi.org/10.1080/14783363.2017.1308221.
Marodin, G.A., Frank, A.G., Tortorella, G.L., Saurin, T.A., 2016. Contextual factors and lean production implementation in the Brazilian automotive supply chain. Supply Chain Manag. An Int. J. 21, 417–432. https://doi.org/10.1108/SCM-05-2015-0170.
Marodin, G.A., Tortorella, G.L., Frank, A.G., Godinho Filho, M., 2017b. The moderating effect of Lean supply chain management on the impact of Lean shop floor practices on quality and inventory. Supply Chain Manag. An Int. J. 22, 473–485. https://doi.org/10.1108/SCM-10-2016-0350.
Mendonça, M.A.A., Freitas, F., de Souza, J.M., 2008. Information technology and productivity: evidence for Brazilian industry from firm-level data. Inf. Technol. Dev. 14, 136–153. https://doi.org/10.1002/itdj.20091.
Mendonça, M.A.A. de, Freitas, F. de A., Souza, J.M. de, 2009. Tecnologia da informação e produtividade na indústria brasileira. Rev. Adm. Empres. 49, 74–85. https://doi.org/10.1590/S0034-75902009000100009.
Miranda, J., Pérez-Rodríguez, R., Borja, V., Wright, P.K., Molina, A., 2017. Sensing, smart and sustainable product development (S ^{3} product) reference framework. Int. J. Prod. Res. 1–22. https://doi.org/10.1080/00207543.2017.1401237.
Nakata, C., Weidner, K., 2012. Enhancing new product adoption at the base of the pyramid: a contextualized model. J. Prod. Innovat. Manag. 29, 21–32. https://doi.org/10.1111/j.1540-5885.2011.00876.x.
Olavarrieta, S., Villena, M.G., 2014. Innovation and business research in Latin America: an overview. J. Bus. Res. 67, 489–497. https://doi.org/10.1016/j.jbusres.2013.11.005.
Parente, S.L., Prescott, E.C., 1994. Barriers to technology adoption and development. J. Polit. Econ. 102, 298–321. https://doi.org/10.1086/261933.
Parlanti, R., 2017. Smart shopfloors and connected platforms in Industry 4.0. Electron. World 123, 26–28.
Peng, D.X., Heim, G.R., Mallick, D.N., 2014. Collaborative product development: the effect of project complexity on the use of information technology tools and new product development practices. Prod. Oper. Manag. 23, 1421–1438. https://doi.org/10.1111/j.1937-5956.2012.01383.x.
Phillips, L.A., Calantone, R., Lee, M., 1994. International technology adoption. J. Bus. Ind. Market. 9, 16–28. https://doi.org/10.1108/08858629410059762.
Porter, M., Heppelmann, J., 2014. How smart, connected products are transforming competition. Harv. Bus. Rev. 92, 64–88.
PWC - PricewaterhouseCoopers, 2016. Indústria 4.0: Digitização Como Vantagem Competitiva No Brasil. Available at: https://www.pwc.com.br/pt/publicacoes/servicos/assets/consultoria-negocios/2016/pwc-industry-4-survey-16.pdf.
Qin, J., Liu, Y., Grosvenor, R., 2016. A categorical framework of manufacturing for industry 4.0 and beyond. Proced. CIRP 52, 173–178. https://doi.org/10.1016/j.procir.2016.08.005.
Rafael, R., Shirley, A.J., Liveris, A., 2014. Report to the President Accelerating U.S. Advanced Manufacturing. The President's Council of Advisors on Science and Technology, Washington, DC.
Ramani, S.V., Thutupalli, A., Urias, E., 2017. High-value hi-tech product introduction in emerging countries. Qual. Market Res. Int. J. 20, 208–225. https://doi.org/10.1108/QMR-01-2017-0034.
Ras, E., Wild, F., Stahl, C., Baudet, A., 2017. Bridging the skills gap of workers in industry 4.0 by human performance augmentation tools: challenges and roadmap. In: Proceedings of the 10th International Conference on PErvasive Technologies Related to Assistive Environments, pp. 428–432.
Reischauer, G., 2018. Industry 4.0 as policy-driven discourse to institutionalize innovation systems in manufacturing. Technol. Forecast. Soc. Change 132, 26–33. https://doi.org/10.1016/J.TECHFORE.2018.02.012.
Robertson, T., Gatignon, H., 1986. Competitive effects on technology diffusion. J. Market. 50, 1–12.
Saldivar, A.A.F., Li, Y., Chen, W., Zhan, Z., Zhang, J., Chen, L.Y., 2015. Industry 4.0 with cyber-physical integration: a design and manufacture perspective. In: 2015 21st International Conference on Automation and Computing (ICAC). IEEE, pp. 1–6. https://doi.org/10.1109/IConAC.2015.7313954.
Scheer, A.-W., 1994. Cim: Computer Integrated Manufacturing towards the Factory of the Future. Secaucus. Springer Verlag, New Jersey, U.S.A.
Schuh, G., Anderi, R., Gausemeier, J., 2017. Industrie 4.0 Maturity Index. Managing the Digital Transformation of Companies (acatech STUDY) Available at: http://www.acatech.de/fileadmin/user_upload/Baumstruktur_nach_Website/Acatech/root/de/Publikationen/Projektberichte/acatech_STUDIE_Maturity_Index_eng_WEB.pdf.
Schumacher, A., Erol, S., Sihn, W., 2016. A maturity model for assessing industry 4.0 readiness and maturity of manufacturing enterprises. Proced. CIRP 52, 161–166.
Schwab, K., 2017. The Fourth Industrial Revolution, first ed. World Economic Forum.
Stark, J., 2011. Product Lifecycle Management, Product Lifecycle Management. Decision Engineering. Springer, London. https://doi.org/https://doi.org/10.1007/978-0-85729-546-0_1.

Steimer, C., Cadet, M., Aurich, J.C., Stephan, N., 2016. Approach for an integrated planning of manufacturing systems based on early phases of product development. Proced. CIRP 57, 467–472. https://doi.org/10.1016/j.procir.2016.11.081.

Stock, T., Seliger, G., 2016. Opportunities of sustainable manufacturing in industry 4.0. Proced. CIRP 40, 536–541. https://doi.org/10.1016/j.procir.2016.01.129.

Tao, F., Cheng, J., Qi, Q., Zhang, M., Zhang, H., Sui, F., 2018a. Digital twin-driven product design, manufacturing and service with big data. Int. J. Adv. Manuf. Technol. 94, 3563–3576. https://doi.org/10.1007/s00170-017-0233-1.

Tao, F., Qi, Q., Liu, A., Kusiak, A., 2018b. Data-driven smart manufacturing. J. Manuf. Syst. https://doi.org/10.1016/J.JMSY.2018.01.006.

Viotti, E.B., 2002. National Learning Systems: a new approach on technological change in late industrializing economies and evidences from the cases of Brazil and South Korea. Technol. Forecast. Soc. Change 69, 653–680. https://doi.org/10.1016/S0040-1625(01)00167-6.

Wahlster, W., 2013. SemProM: Foundations of Semantic Product Memories for the Internet of Things. Springer Science & Business Media. https://doi.org/10.1007/978-3-642-37377-0.

Wamba, F.S., Akter, S., Edwards, A., Chopin, G., Gnanzou, D., 2015. How "big data" can make big impact: findings from a systematic review and a longitudinal case study. Int. J. Prod. Econ. 165, 234–246. https://doi.org/10.1016/j.ijpe.2014.12.031.

Wang, L., Törngren, M., Onori, M., 2015. Current status and advancement of cyber-physical systems in manufacturing. J. Manuf. Syst. 37, 517–527. https://doi.org/10.1016/j.jmsy.2015.04.008.

Wang, S., Wan, J., Li, D., Zhang, C., 2016. Implementing smart factory of industrie 4.0: an outlook. Int. J. Distributed Sens. Netw., 3159805. https://doi.org/10.1155/2016/3159805.

Wei, Z., Song, X., Wang, D., 2017. Manufacturing flexibility, business model design, and firm performance. Int. J. Prod. Econ. 193, 87–97. https://doi.org/10.1016/J.IJPE.2017.07.004.

Weller, C., Kleer, R., Piller, F.T., 2015. Economic implications of 3D printing: market structure models in light of additive manufacturing revisited. Int. J. Prod. Econ. 164, 43–56. https://doi.org/10.1016/j.ijpe.2015.02.020.

Westerman, G., Bonnet, D., McAfee, A., 2014. Leading Digital: Turning Technology into Business Transformation. Harvard Business Press.

Yin, Y., Stecke, K.E., Li, D., 2017. The evolution of production systems from Industry 2.0 through Industry 4.0. Int. J. Prod. Res. 1–14. https://doi.org/10.1080/00207543.2017.1403664.

Yu, C., Xu, X., Lu, Y., 2015. Computer-integrated manufacturing, cyber-physical systems and cloud manufacturing – concepts and relationships. Manuf. Lett. 6, 5–9. https://doi.org/10.1016/j.mfglet.2015.11.005.

Zhou, J., 2017. Intelligent Mannfacturing-main Direction of " Made in China 2025 " 3969. https://doi.org/10.3969/j.issn.1004-132X.2015.17.001.

Zhou, K., Liu, Taigang, Zhou, Lifeng, Liu, T., Zhou, L., 2015. Industry 4.0: towards future industrial opportunities and challenges. In: 2015 12th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD), pp. 2147–2152. https://doi.org/10.1109/FSKD.2015.7382284.

Zuniga, P., Crespi, G., 2013. Innovation strategies and employment in Latin American firms. Struct. Chang. Econ. Dyn. 24, 1–17. https://doi.org/10.1016/j.strueco.2012.11.001.

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