GESTÃO & PRODUÇÃO

ISSN 0104-530X (Print)
ISSN 1806-9649 (Online)

ORIGINAL ARTICLE

Adoption of Industry 4.0 technologies: an analysis of small and medium-sized companies in the state of São Paulo, Brazil

Adoção de tecnologias da Indústria 4.0: uma análise com pequenas e médias empresas do estado de São Paulo, Brasil

Antonio Arnaldo Baio Junior[1], Marcelo José Carrer[1]

[1]Universidade Federal de São Carlos – UFSCar, Departamento de Engenharia de Produção, Programa de Pós-graduação em Engenharia de Produção, São Carlos, SP, Brasil. E-mail: marcelocarrer@dep.ufscar.br

How to cite: Baio Junior, A. A., & Carrer, M. J. (2022). Adoption of Industry 4.0 technologies: an analysis of small and medium-sized companies in the state of São Paulo, Brazil. *Gestão & Produção*, 29, e122. https://doi.org/10.1590/1806-9649-2022v29e122

Abstract: This paper analyzed the level of adoption and compared characteristics of adopters and non-adopters of Industry 4.0 technologies. Primary data for the year 2021 were collected by means of a structured questionnaire applied to 30 small and medium-sized companies of the metallurgical sector, who operate with machining processes, in the state of São Paulo. Data were analyzed using descriptive statistical measures and correlation estimates. The technologies adopted by the companies in the sample were: Cloud Computing (10 companies), Horizontal and Vertical Integration Systems (5 companies), Big Data (4 companies) and Industrial Internet of Things (4 companies). The comparative analysis between the characteristics of adopters and non-adopters showed that: (I) adopters have, much more frequently, employees with ICT capabilities and also more frequently hire ICT consulting services; (II) the use of ERP and MRP systems is much higher among companies that adopt Industry 4.0 technologies; (III) adopters participate more frequently in cooperation programs with Universities, Science and Technology Institutes or Research and Technological Development Promotion Agencies; (IV) companies that adopt 4.0 technologies have a greater perception of relative advantage and compatibility of these technologies.

Keywords: Industry 4.0; Technologies; Adoption; Small and medium-sized companies.

Resumo: Este artigo teve os objetivos de analisar o nível de adoção e comparar características de adotantes e não adotantes de tecnologias da Indústria 4.0. Dados primários do ano de 2021 foram coletados por meio de um questionário estruturado com 30 pequenas e médias empresas do setor metalúrgico, que operam com processos de usinagem, no estado de São Paulo. Os dados foram analisados por meio de medidas de estatística descritiva e coeficientes de correlação. As tecnologias 4.0 adotadas pelas empresas da amostra foram: Computação em Nuvem (10 empresas), Sistemas de Integração Horizontal e Vertical (5 empresas), Big Data (4 empresas) e Internet das Coisas Industrial (4 empresas). A análise comparativa entre as características das empresas adotantes e não adotantes mostrou que: (I) as adotantes possuem, com frequência muito maior, funcionários com competências em TICs e também contratam mais frequentemente serviços de consultoria em TICs; (II) o uso de sistemas de ERP e MRP é muito maior entre as empresas adotantes de tecnologias da Indústria 4.0; (III) as empresas adotantes

Received: July 11, 2022 - Accepted: Sept. 27, 2022
Financial support: CNPq (project no. 303341/2019-0) – Scientific Productivity Fellowship - PQ2.

participam com mais frequência de programas de cooperação com Universidades, Institutos de Ciência e Tecnologia ou Agências de Fomento à Pesquisa e Desenvolvimento Tecnológico; (IV) as empresas que adotam tecnologias 4.0 possuem maior percepção de vantagem relativa e compatibilidade dessas tecnologias.

Palavras-chave: Indústria 4.0; Tecnologias; Adoção; Pequenas e médias empresas.

1 Introduction

The term Industry 4.0 was initially adopted in 2011 at a fair in Hanover, Germany. The development of the concept stemmed from an initiative by the German government involving universities and private companies from that country. It was a strategic program whose goal was to develop and promote advanced production systems in order to increase the productivity and efficiency of the German industry (Drath & Horch, 2014). The main idea of the concept consisted in integrating emerging and converging technologies, aiming to add value to the whole life cycle of a product (Kagermann et al., 2011). To do so, the human role would need to be developed in terms of production and diffusion of smart approaches throughout the value chain based on information and communication technologies (Dalenogare et al., 2018; Horváth & Szabó, 2019).

Similar strategies have also been proposed in other industrialized countries like “Industrial Internet of Things” in the USA, “Future of Manufacturing” in the United Kingdom, “Factories of the Future” in the European Union and “Internet Plus” in China (Büchi et al., 2020). It seems that industry 4.0 will lead the future of production systems in developed countries, whose effects will manifest in the economic, organizational, political and social scopes.

It is considered a paradigm shift in industrial production, based on the advanced digitalization of factories, the internet and the intelligence of devices, machines and production systems (Raj et al., 2020; Tortorella et al., 2020). According to some authors, it is a technological revolution in the production system of products and services which is called “The Fourth Industrial Revolution” (Drath & Horch, 2014; Sousa Jabbour et al., 2018; Dalenogare et al., 2018; Frank et al., 2019; Horváth & Szabó, 2019; Tortorella et al., 2020).

The focus of this revolution is on the integration and connectivity of different production, distribution and commercialization processes, whose final objective is to improve company and value chain performance (Dalenogare et al., 2018; Büchi et al., 2020; Tortorella et al., 2020). New technologies, such as the Internet of Things (IoT), networked wireless sensors, mobile internet, big data, cloud computing, embedded systems, additive manufacturing and autonomous robots have been adopted by companies in different economic sectors (Raguseo, 2018; Maroufkhani et al., 2020; Raj et al., 2020). This new paradigm has the potential to affect the organization of business activities, business relationships between companies, industrial competition structure, business models, institutional environment and market demands (Horváth & Szabó, 2019; Büchi et al., 2020).

In spite of the potential benefits of Industry 4.0 technologies, a study of the World Economic Forum (Leurent et al., 2019) shows that few companies are able to effectively integrate Industry 4.0 technologies to obtain significant financial and economic advantages. Problems regarding human resources qualification and organization, lack of skills to manage digital technologies, absence of strategies for the use of digital technologies, shortage of financial resources and problems related to connectivity and data security have been reported as barriers for the adoption and effective use of these technologies by organizations (Dalenogare et al., 2018; Horváth & Szabó, 2019; Raj et al., 2020).

In Brazil, *Agência Brasileira de Desenvolvimento Industrial* (ABDI) and *Federação das Indústrias do Estado de São Paulo* (Fiesp) started a program called "*Rumo à Indústria 4.0*" (Towards Industry 4.0) in 2017. The program aimed to spread the concepts and technologies of Industry 4.0 to local companies. In 2019, the Brazilian Ministries of Economy and Science, Technology, Innovations and Communications launched *Câmara Brasileira da Indústria* 4.0 (Brazilian Chamber of Industry 4.0), whose goal is to promote the adoption of Industry 4.0 concepts and practices in Brazil and, therefore, boost Brazilian companies' competitivity and productivity (Brasil, 2019). Despite the aforementioned initiatives, the adoption level of Industry 4.0 technologies by Brazilian companies is still low, especially among small and medium-sized companies.

According to studies by Fiesp and Senai (SICAB, 2018), the subject "Industry 4.0" is still little known among Brazilian companies. In an investigation with a sample of 277 companies, only 41% of the companies adopted lean manufacturing, an important precondition for Industry 4.0 technologies. Moreover, 32% of the analyzed organizations stated that they did not have knowledge of the Fourth Industrial Revolution, Industry 4.0 or Advanced Manufacturing. Therefore, it is safe to say that this theme needs further investigations.

In this context, this paper aims to analyze the level of adoption of Industry 4.0 technologies and to compare the characteristics of adopters and non-adopters of these technologies. To achieve these aims, we collected primary data from a sample of 30 small and medium-size companies of the metallurgical industry that use machining processes in the state of São Paulo. Data were analyzed by descriptive statistics, means and frequency comparison tests and correlation analysis.

The results of this article can be particularly useful to promote the diffusion of Industry 4,0 technologies and boost the competitivity of national industry, especially for small and medium-sized companies. The technology diffusion strategies adopted by innovation systems agents must consider the characteristics that differentiate companies which adopt technologies from those that do not adopt them. On the one hand, the characterization of companies that adopt the Industry 4,0 technologies may function as benchmarking to develop technological diffusion strategies and policies. On the other hand, the characterization could help identify the barriers that prevent some companies from adopting these technologies, an issue that should also be addressed by innovation diffusion strategies and policies.

In addition to this introduction, this article is divided in other four sections. The next section approaches the technologies of Industry 4.0 and the theoretical framework for the adoption and diffusion of innovations. The third section contains the methodology used. The fourth section presents an empirical analysis of the adoption and of the characteristics of adopters and non-adopters of Industry 4.0 technologies. Finally, the conclusion of this study is in section 5.

2 Theoretical framework

2.1 Industry 4.0 technologies

The expression “Industry 4.0” encompasses the adoption of integrated and connected industrial automation systems that help to manage all the processes in supply and value chains (Yin et al., 2017; Reischauer, 2018). Therefore, this technological advance is characterized by the growing digitalization and connectivity of the activities regarding the production of goods and services (Dalenogare et al.., 2018). Integrated and connected sensors and systems monitor and collect large amounts of data and then feed managerial software, enabling factories to become smart (Rubmann et al., 2015; Dalenogare et al., 2018; Wang et al., 2016), which in turn allows analyses that might prevent mistakes in decision making, reduce waste, increase the speed of processes, improve quality and reduce costs (Raguseo, 2018).

Vertical and horizontal networks reduce response time and have the potential to optimize the use of resources throughout production chain, thus meeting economic, social and environmental demands better (Kagermann et al., 2011; Dalenogare et al., 2018). Information and communications technologies (ICT) are the central element to Industry 4.0 (Wang et al., 2016; Lu, 2017; Tortorella et al., 2020). Such technology enables data collection, processing, sharing and analysis in real time, providing the whole production system with useful information (Frank et al., 2019).

Furthermore, Industry 4.0 technologies allow the integration between information and manufacturing systems, which strongly affects decisions regarding allocation and use of production factors inside organizations as well as market relationships among organizations in their supply chains (Taştan & Gönel, 2020; Horváth & Szabó, 2019). Process optimization, waste reduction, better use of production factors, bigger product customization and reduction of production and delivery time are some of the potential benefits of the adoption of technologies (Horváth & Szabó, 2019; Bag et al., 2020; Büchi et al., 2020; Bag et al., 2021).

Zezulka et al. (2016) and Roblek et al. (2016) defined six key elements to Industry 4.0: (1) digitalization, optimization and customization of the production of goods and services; (2) automation and fast supply chain adaptation; (3) intense man-machine interaction; (4) supply of high value-added products and services; (5) automatic sharing of data and information inside and among organizations and (6) new business models.

Frank et al. (2019) proposed a division of the technologies that characterize Industry 4.0 into two large groups: (1) core technology: internet of things, cloud, big data and analysis software; (2) front-end technologies: smart supply chain (e.g.: digital platforms with suppliers, clients and organizations), smart work (e.g.: remote production monitoring, remote production operation, collaborative robots, virtual reality training, etc.), smart manufacturing (sensors, ERP, MRP, materials traceability, artificial intelligence machines, process simulations, etc.) and smart products (e.g.: products that have a connectivity interface with clients). The digital technologies in the first group offer connectivity and “intelligence” for companies to develop front-end competencies and technologies. The latter optimize the decision-making process, increase efficiency of use of production factors and provide sustainable competitive advantage to organizations (Frank et al., 2019; Bag et al., 2021).

The technologies presented in Table 1 are considered the “pillars of Industry 4.0”. These technologies have complementarities and might be adopted partially or an integrated way by an organization (Horváth & Szabó, 2019; Bag et al., 2021).

Table 1. Industry 4.0 technologies .

Technology	Definition	Impacts	References
Big data	Big Data can be understood as the collection and organization of a large amount of data at high speed in computerized and connected systems, allowing predictive analyses for decision making. This technology is driven mainly by the diffusion of computers, mobile devices, social media and technologies related to the internet of things (e.g.: RFID technology – radio-frequency identification). The data that feed Big Data can be collected through sensors, satellites, social media, photos, videos and GPS signal.	The adoption of Big Data allows organizations to collect, store, organize, manage and analyze large amounts of data at the right speed and time. The potential benefits of Big Data are an increase in the flexibility of production lines, machining and project cycle time reduction, quality improvement of goods and services, optimization in the use of production resources, greater capacity to understand market demands in real time and greater customization of products and services.	McAfee & Brynjolfsson (2012; Raguseo (2018); Wamba et al. (2014); Rubmann et al. (2015); Hiba et al. (2015); Leurent et al. (2019); Wang et al. (2018); Maroufkhani et al. (2020)
Simulation	Simulation is a method used to study the performance of a system through the formulation of a mathematical model, which must reproduce, as accurately as possible, the characteristics of the original system. It is a key technology to the development of exploratory computer models of planning that enable the optimization of decisions, projects and the efficiency of resource use in complex and smart production systems. Advanced technologies related to sensors and communications allow the connection of facilities and machines to a virtual environment through the internet and applications, thus enabling a simulation of the physical environment in real time.	The simulation might encompass workers, machines and products, allowing tests of different forms of resource coordination, which are always performed on the virtual environment before they are implemented in the physical world. The simulation of cyber-physical systems allows us to optimize the decision-making process, with a faster adaptation to various types of events, for example, production line downtime due to equipment breaking down. Thus, there are benefits regarding the efficiency of use of resources and production cost reduction.	Dalenogare et al. (2018); Gunal (2019); Cruz-Mejía et al. (2019)

Table 1. Continued…

Technology	Definition	Impacts	References
Integration of horizontal and vertical systems	Vertical systems are adopted to coordinate the activities in a company, encompassing its organizational structure, human resources, fixed assets, development of new products, etc. Vertical integration aims to connect information and communications systems in different hierarchical levels in the company. On the other hand, the integration of the horizontal system refers to the relationships with clients and suppliers throughout the value chain, generating greater collaboration between companies through resource and information sharing in real time. With data integration, value chains can be automatized, which integrates companies, suppliers, clients, departments (like engineering and shop floor), functions and resources.	System integration and the exchange of data and information in a fast and efficient way both inside and between companies allow productivity gains, transaction costs reduction, use of synergies, greater coordination of value chains and faster development of projects, products and services.	Brettel et al. (2014); Rubmann et al. (2015); Dalenogare et al. (2018); Pérez-Lara et al. (2020); Garrocho et al. (2020)
Industrial Internet of Things (IIoT)	It is a global infrastructure rooted in interoperable information and communications technologies that allow the development of advanced services through a physical and virtual interconnection of objects. In other words, the IIoT is a robust, intuitive and scalable technology that fosters the digital transformation of the world connected by the Internet, providing relevant data to the whole value chain in real time. Smart devices, machines and equipment can communicate and interact with centralized controllers in manufacturing systems.	Autonomous decisions based on pre-configured parameters and on data collected by sensors become possible, resulting in much faster response and adaptation by production systems in real time. Efficiency gains in the use of machines and waste reduction are evident benefits.	Kagermann et al. (2011); Rubmann et al. (2015); Majeed & Rupasinghe (2017); Manavalan & Jayakrishna (2019)

Table 1. Continued…

Technology	Definition	Impacts	References
Cloud Computing	Cloud computing aims to provide information technology services (e.g.: processing, storing and connectivity capacity) on demand and with usage-based payment. This technology allows large amounts of data to be stored in a server network. In addition, it grants access to data from any location, at any time and from different devices and platforms. Connectivity enables instant data transmission.	Cloud computing leads to a reduction in the need for investment in equipment and technological resources because storage space and processing capacity are hired on demand. Gains related to flexibility, agility and adaptability of use and data analysis are also present. This technology also facilitates client-supplier collaboration and communication between different areas in an organization.	Xu (2012); Porter & Heppelmann (2014) Velasquez et al (2018); Hadwer et al. (2021)
Additive Manufacturing	It can be defined as a process of combining materials to make objects using 3D model data (CAD 3D), usually layer-by-layer. Additive manufacturing converts a CAD 3D model into layers. Based on this information, it determines the path (CNC language) and the deposition parameters, which are later processed by four basic components: CNC controller; motion system; power supply; addition material feeding system. This definition is widely applicable to all classes of materials, including metals, ceramics, polymers, compounds and biological systems.	It allows the creation of prototypes and individual components and enables the production of small and customized batches with construction advantages like complexity and lightness. There is also the benefit of production flexibility through a direct transformation of 3D digital models into physical products by using agile and versatile manufacturing machines with no need for specific tools or molds. This decentralized use might reduce costs related to logistics and storage, as well as marginal costs related to production, cycle time and time to market.	Frazier (2014); Rubmann et al. (2015); Weller et al. (2015); Dalenogare et al. (2018)
Autonomous Robots	Autonomous robots can perform non-routine cognitive and manual tasks, which boosts replaceable work profiles and occasionally compensates for workforce shortages in the market. Autonomous robots can also integrate information from multiple sensors and adapt their movement, thus performing different tasks and providing data in real time for decision making.	Studies show the adoption of autonomous robots in different economic activities, such as construction industry, hospitals, hotel business, car part production and food industry. Some of the benefits identified are logistics cost reduction and time saved with collection and shipping of items through the supply chain.	Gray & Davis (2013); Decker et al. (2017); Leurent et al. (2019); Pan & Pan (2019); Hussain et al., (2014); Pillai et al (2021)

Table 1. Continued…

Technology	Definition	Impacts	References
Augmented Reality (AR)	Augmented Reality (AR) is a technology that allows us to overlap virtual elements with the real world in real time. Information and objects overlap with the real world, improving users' perception of reality. This technology combines the real world with the virtual world. It is interactive in real time and registered in 3D. The essential parts to an AR system are electronic devices like AR glasses, cameras, earphones, displays, tablets and projectors, which are used to combine reality with the virtual world. Any type of hardware that interacts with the human senses can be used with AR.	AR technology aims to improve human performance related to various activities like training sessions, maintenance, product development projects, logistics tasks, operation layout, etc. This technology facilitates problem solving through increasing users' perception of reality.	Palmarini et al. (2017); Alcácer & Cruz-Machado (2019)
Cybersecurity	Cybersecurity can be defined as a set of procedures, practices and technologies that aim to detect, prevent, protect and respond to virtual attacks against cyberspace and information systems.	Cybersecurity avoids considerable losses resulting from virtual attacks and/or sensitive data leakage.	Craigen et al. (2014); Piedrahita et al. (2018); Alcácer & Cruz-Machado (2019)

Source: Authors' own elaboration.

2.2 Theories of adoption and diffusion of innovations

The concepts of invention, innovation, adoption and diffusion of technologies are fundamental to this study. Invention can be defined as the development of a new product or process which still has not been introduced to the market. Innovation, in turn, refers to an invention that is put into practice and, therefore, is available on the market. An innovation is an idea, practice, method or product/service perceived as new by an individual or a company on a market (Rogers, 1983; Schumpeter, 1997).

The adoption of technology, which is characterized by its use by a company or individual at a given moment in time, is understood as a separated moment from the innovation process. Adoption results from an individual decision influenced by a set of factors that affect an individual's perception of the expected usefulness of the technology (Sunding & Zilberman, 2001; Vinholis et al., 2015; Carrer et al., 2022). The adoption of an innovation by a group of individuals or companies over time represents the diffusion of the technological innovation. Without diffusion, the socioeconomic impacts of the innovation would be remarkably limited (Schumpeter, 1997; Hall, 2004).

The diffusion of innovations happens when the innovation is clearly better than the product, service or process that was previously available. Diffusion can also feedback the innovation process because through learning, imitation and feedback, the characteristics of the original innovation can be improved (Hall, 2004). Three traditional theoretical approaches have been historically used to explain processes of technological innovation diffusion: (i) epidemic approach, (ii) rank approach and (iii) order effects approach (Bocquet et al., 2007; Foster & Rosenzweig, 2010).

The epidemic approach consists in the diffusion of an innovation as a result of information being spread among individuals. In this approach, an innovation's diffusion speed depends especially on the frequency of contact among potential and actual users, and on the process through which individuals are informed about the new technology (Geroski, 2000). In rank classification, the companies that will likely adopt a new technology are ranked according to their characteristics. The main focus of this approach is on each company's individual decision about the adoption or non-adoption of a new technology. This decision depends on a set of factors that affect the perceived usefulness of the adoption by the company (Foster & Rosenzweig, 2010; Carrer et al., 2019). How an innovation will be adopted depends on each company's characteristics (e.g.: production scale, search for information and established routines) and on the perceived attributes of the technology (e.g.: relative advantage, compatibility, complexity, experimentability and observability).

The third approach, order effects, is based on game theory. The adoption of a new technology depends on the number of previous adopters. For a given implementation cost of the technology, there will be a number of adopters after whom it will not be profitable to adopt it (Karshenas & Stoneman, 1993), which means that an adopter's profit depends on their position in adoption order. Early adopters of a new technology will make greater profits because they were the pioneers (Fudenberg & Tirole, 1985). That being said, adoption is based on strategic interactions among companies: the order companies will adopt the new technology and the number of other possible adopters. Strategic determinants are considered in order to understand why companies that share similar capital characteristics may differ in terms of adoption dates (Reinganum, 1981).

Some authors advocate a technological diffusion model that aggregates the traditional theoretical approaches previously mentioned. Thus, the characteristics of the company and of the innovation, the order of adoption and the epistemic effects of information spread could explain the diffusion of an innovation (Piaralal et al., 2015; Maroufkhani et al., 2020; Kimiagari & Baei, 2022).

In fact, the TOE theoretical model (Technology-Organization-Environment) encompasses elements from different innovation diffusion approaches to explain the determinants of the decisions regarding adoption by companies. This model simultaneously considers three dimensions that influence decisions related to the adoption of an innovation by companies that are part of an industry: (1) perceived characteristics of the technology; (2) structural, strategical and organizational company factors; (3) characteristics of economic, technological, institutional and geographical environments. Because it encompasses aspects of the several dimensions that influence the adoption of innovations, the TOE theoretical model has been used to analyze the adoption of Industry 4.0 digital technologies by companies, including small and mid-size organizations (Ramdani et al., 2013; Lin, 2014; Pan & Pan, 2019; Maroufkhani et al., 2020; Hadwer et al., 2021; Kimiagari & Baei, 2022). This paper follows this path by using variables that represent the three dimensions of the TOE theoretical model to compare adopters and non-adopters of Industry 4.0 technologies.

First, we should consider the characteristics of the technology, such as relative advantage, compatibility, complexity and observability. The perception of these characteristics by a company is a determinant of the decision regarding adopting the innovation or not. For instance, if a company notices that an innovation is compatible with its competences and established internal routines, it tends to adopt the technology faster than a company that does not perceive such compatibility in the innovation (Kimiagari & Baei, 2022; Hadwer et al., 2021).

Secondly, it is assumed that the heterogeneity among organizations is important to determine the adoption of innovations. Internal, structural and organizational characteristics of the company might inhibit or facilitate the adoption of innovations. Therefore, factors like company size, human resources qualification, skills related to the use of physical resources, access to information sources, organizational culture, how relationships with stakeholders are established and adaptation capacity could be determinants of decisions regarding the adoption of innovations (Piaralal et al., 2015; Pan & Pan, 2019; Maroufkhani et al., 2020; Hadwer et al., 2021; Kimiagari & Baei, 2022).

Finally, the characteristics of the environment in which companies are located also influence their decisions about adopting an innovation. Exogenous aspects of the institutional, economic and geographic environments might restrict or facilitate technological diffusion. In this case, some factors should be considered, such as access to public policies, market regulation level, market competition structure, infrastructure conditions and production factors availability (Piaralal et al., 2015; Hadwer et al., 2021).

Figure 1 introduces the TOE theoretical model applied to Industry 4.0 technologies, which supports the empirical analyses in this study.

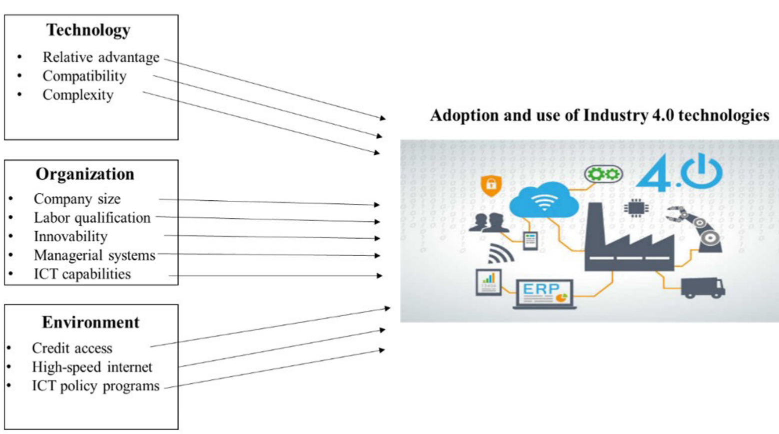

Figure 1. Determinants of Industry 4.0 technology adoption. Source: Authors' own creation.

3 Methodology

The methodology used in this paper encompasses a survey for primary data collection and a subsequent analysis of a sample of São Paulo state companies. First, two key players in the development of Industry 4.0 technology were interviewed: (i) the CEO of one of the biggest Brazilian companies specializing in MES (*Manufacturing*

Execution System), IIoT (*Industrial Internet of Things*) and Industrial Automation solutions; and (ii) the Integration, Information and Business Intelligence (BI) manager of a company that specializes in technological solutions related to smart machines and devices. With those interviews, we aimed to capture general aspects of the technological development and diffusion processes of Industry 4.0 technologies for small and medium-sized companies in São Paulo state. Semi-structured interviews were carried out remotely through Google Meet.

Based on the semi-structured interviews and on literature review, we developed a structured questionnaire that was directed to a sample of companies in the metallurgical sector whose activities involve machining. The questionnaire was designed in order to obtain information on the adoption of Industry 4.0 technologies and to collect variables that are representative of company characteristics, perceptions of Industry 4.0 technologies and institutional and technological environments.

The sample was defined based on a list of 170 companies which operate in the metallurgical sector with machining of parts. The list was obtained from a large cutting tools supplier who has a commercial relationship with the companies. It is important to mention that this was the best possible strategy for our field research because there is no official lists of companies that are registered in this field. Based on the list, 68 companies were contacted by phone and e-mail and agreed to take part in the survey. Nevertheless, only 30 companies responded to the structured questionnaire, which was available online through Google Forms between September and December 2021. The data collected and analyzed refers to fiscal year 2021.

The data from the 30 companies was organized and analyzed through simple descriptive statistics (mean, frequency and standard deviation), *t*-test to compare means and frequencies, and correlation analysis. The descriptive analysis of the data allowed an assessment of adoption of different Industry 4.0 technologies and a comparison between the characteristics of companies that adopt Industry 4.0 technologies and the characteristics of those which do not adopt such technologies. Correlation analysis allowed the calculation and analysis of the correlation coefficients among the variables presented in Table 2 and the different Industry 4.0 technologies adopted by companies. Table 2 contains the variables that were used in the comparative analysis between adopters and non-adopters of Industry 4.0 technologies. The means and frequencies of the variables presented in Table 2 were statistically compared between the groups of companies that adopted or did not adopt 4.0 technologies. There are several hypothesis tests recommended for each case, and Student's *t*-test is one of the most used. This test is recommended when the size of the sample is not large enough to form a normal probability distribution (Scheaffer et al., 2010). This study adopted the *t*-test to compare the means and frequencies of the variables presented in Table 2 for two groups of companies: (i) adopters of Industry 4.0 technologies and (ii) non-adopters of Industry 4.0 technologies.

Considering samples of two distinct populations and a given characteristic/variable, labelled x_1 and x_2, the means and frequencies of the two samples are compared. Mathematically, the methodology assumes that both populations are normal, with a population mean, and a standard deviation. Furthermore, there must be independence between the variables for both populations (Pinheiro et al., 2009). Student's *t*-test originally assumes that the standard deviation is equal for both populations. In this case, Equation 1 is used to obtain Student's *t* (Scheaffer et al., 2010):

Table 2. Variables used in the comparison between adopters and non-adopters of Industry 4.0 technologies.

Variable	Description
1. Organizational characteristics	
Time on the market	Time (in years) the company has been on the market
Number of workers	Total number of staff
Workers' qualification	Likert scale variable (1 – very low; 5 – very high) obtained as a response to "Rate the general level of labor qualification in the company".
Workers in ICT	Binary variable that takes value 1 for companies that have workers specializing in ICT; 0 otherwise
IT consulting	Binary variable equals 1 for companies that hire consulting services in the field of IT; 0 otherwise
Machines with CNC	Number of machines with computer numerical control (CNC) that the company owns
Broadband internet	Binary variable that takes value 1 for companies that have access to broadband internet; 0 otherwise
ERP	Binary variable equals 1 for companies which adopt ERP systems (*Entreprise Resources Planning*); 0 otherwise
MRP	Binary variable equals 1 for companies which adopt MRP systems (*Material Requirement Planning*); 0 otherwise
Tests technologies	Likert scale variable (1 – completely disagree; 5 – completely agree) obtained from the following statement: "The company frequently tests new technologies and organizational practices".
Accesses information	Binary variable equals 1 for companies whose senior management frequently seeks information on production, market, technologies and public policies; 0 otherwise
2. Characteristics of the technological environment	
STI Programs	Binary variable that takes value 1 for companies that participate in cooperation programs with universities, Science and Technology Institutes or agencies that foster research and technological development; 0 otherwise
Credit access	Binary variable equals 1 for companies that frequently access credit to buy machines, equipment and new technologies; 0 otherwise
Knows Câmara 4.0	Binary variable equals 1 for companies which have knowledge of *Câmara Brasileira da Indústria 4.0* or other local or national initiatives for the diffusion of Industry 4.0 technologies; 0 otherwise
3. Perception of 4.0 technologies	
Advantage	Likert scale variable (1 – completely disagree; 5 completely agree) obtained from the following statement: "I understand that 4.0 technologies (e.g.: cloud computing, IIoT and big data) bring economic benefits (cost reduction and/or an increase in profit) to organizations".
Compatibility	Likert scale variable (1 – completely disagree; 5 – completely agree) obtained from the following statement: "I understand that 4.0 technologies (e.g.: cloud computing, IIoT and big data) are compatible with the competencies of my organization".
Complexity	Likert scale variable (1 – completely disagree; 5 – completely agree) obtained from the following statement: "I understand that 4.0 technologies (e.g.: cloud computing, IIoT and big data) are complex and hard to manage".

$$t = \frac{\bar{x}1 - \bar{x}2}{sa.\sqrt{(1/n1)+(1/n2)}} \tag{1}$$

In turn, pooled variance (sa) is obtained by:

$$sa^2 = \frac{(n1-1)^2.s1^2+(n2-1)^2.s2^2}{n1+n2-2} \quad (2)$$

The variables used in Equations 1 and 2 can be defined as: $\overline{x}1$ = mean of variable X in population 1; $\overline{x}2$ = mean of variable X in population 2; $n1$ = number of elements in population 1; $n2$ = number of elements in population 2; $s1 =$ variance of X in population 1; $s2 =$ variance of X in population 2; gl = degrees of freedom of the test statistics.

The standard deviation of the populations might be distinct. In this case, there is not an exact solution method. However, with an adaptation of Equation 1, it is possible to obtain an approximate solution to the problem:

$$t = \frac{\overline{x}1-\overline{x}2}{\sqrt{(s1^2/n1)+(s2^2/n2)}} \quad (3)$$

Equation 3 was adopted to calculate the *t*-test for samples with distinct variances. Moreover, it is necessary to establish the confidence level (α) for the tests, which represents the maximum error probability that is expected of the test result. In this study, we had a confidence level of 10%. Finally, the degrees of freedom must be defined. To do so, Equation 4 is used in case of equal variances, and Equation 5 for different variances:

$$gl = n1 + n2 - 2 \quad (4)$$

$$gl = \frac{[(s1^2/n1)+(s2^2/n2]^2}{[((s1^2/n1)^2/(n1-1))+((s2^2/n2)^2/(n2-1))]} \quad (5)$$

In addition, the Pearson correlation coefficient of the variables was calculated through the following Equation 6:

$$r = \frac{\sum(x1-\overline{x1})(x2-\overline{x2})}{\sqrt{\sum(x1-\overline{x1})^2 \times \sum(x2-\overline{x2})^2}} = \frac{cov(x1,x2)}{\sqrt{var(x1) \times var(x2)}} \quad (6)$$

in which r is the Pearson correlation coefficient, which varies between -1 and 1; x_1 and x_2 are two variables of interest; $\overline{x1}$ and $\overline{x2}$ are the mean values of variables x1 and x2; $cov(x1, x2)$ is the covariance between variables x_1 e x_2; $var(x1)$ is the variance of variable x_1 and $var(x2)$ is the variance of variable x_2. The r coefficient quantifies the linear relationship strength between the two variables (x1 and x2). The closer r is to 1 (-1), the stronger the positive (negative) relationship between variables x_1 and x_2. It is suggested that values of r higher than |0,4| indicate moderate/strong correlation.

4 Results

Figure 2 shows the technologies adopted by companies and the number of adopters of each technology. The technologies adopted by the companies in this study's sample are Cloud Computing (10 companies), Horizontal and Vertical Integration Systems (5 companies), Big Data (4 companies) and Industrial Internet of Things (4 companies). Literature shows that the other technologies (3D Printers, Autonomous Robots and

Augmented Reality) are the least adopted by companies from developing countries (Tortorella et al., 2020). In fact, in the interviews with key players and during the validation of the structured questionnaire, it was possible to notice that said technologies are still far from the reality of small and medium-sized São Paulo state companies in the metallurgical sector that make use of machining processes.

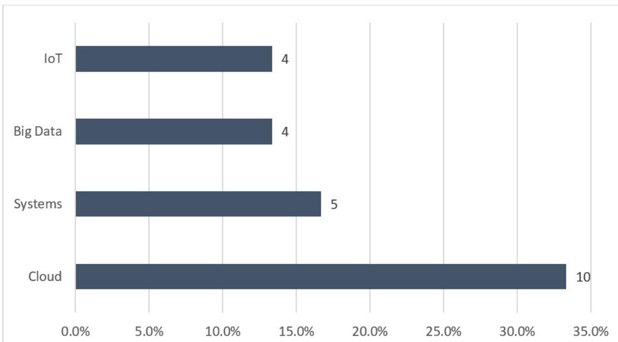

Figure 2. Adoption of Industry 4.0 technologies by the companies in the sample.

It is possible to perceive that adoption – even of a single technology – is still low: 60% of the companies analyzed do not adopt Industry 4.0 technologies. The technology that has the highest adoption rate is Cloud Computing (33.3% of adopters). This technology has relatively low cost – regarding both initial investment and use –, reasonably simple management, and it can be used for different tasks in different production scales. For instance, it can be used to merely add greater security to the company's strategic information or even to increase capacity to integrate, monitor and control several organizational processes. Companies reported cost reduction in terms of equipment, server maintenance and staff as benefits brought by cloud computing.

The second most adopted technology is computerized systems for horizontal and vertical task integration (5 adopters). This technology is important to increase the coordination of managerial systems and processes within a company and also among companies in the value chain. It is crucial to highlight that all these companies also adopted some type of ERP or MRP system, which indicates that they are complementary technologies. When it comes to Big Data and IoT technologies, only 4 companies in the sample adopted them. They are more complex to use, demand higher investment and are only applicable to more specific tasks.

It is important to emphasize that a single company might adopt two or more technologies, and that a larger number of technologies adopted indicates a greater intensity of use of Industry 4.0 technologies. In this sense, two companies in the sample adopted the four technologies, two adopted three technologies (Cloud + Integration Systems + Big Data), one company adopted two technologies (Cloud + IoT) and seven companies adopted just one technology (5 Cloud, 1 Integration Systems and 1 IoT).

Table 3 presents a comparative analysis between the companies that adopt Industry 4.0 technologies and those that do not adopt the technologies. Companies which adopted at least one Industry 4.0 technology were considered adopters. We assume that the adoption of at least one of the investigated technologies indicates that the company is moving towards "philosophy 4.0".

Table 3. Comparison between companies which adopt and those which do not adopt Industry 4.0 technologies.

	Adopters		Non-Adopters		*p*-value
	12 companies		18 companies		
	Mean	S.D.	Mean	S.D.	
Time on the market	19,083	8,229	16,333	8,160	0,189
Number of workers	27,083	20,277	23,889	17,868	0,332
Workers' qualification	3,917	0,900	3,611	0,850	0,181
Workers in ICT**	0,500	0,522	0,111	0,323	0,017
IT consulting***	0,667	0,492	0,167	0,383	0,004
Machines with CNC	6,333	6,372	6,278	5,859	0,490
Broadband Internet*	1,000	0,000	0,889	0,323	0,082
ERP***	0,500	0,522	0,056	0,236	0,008
MRP**	0,333	0,492	0,056	0,236	0,045
Tests technologies	2,833	0,718	2,556	0,984	0,190
Accesses information*	0,917	0,288	0,722	0,461	0,083
STI programs**	0,417	0,515	0,056	0,236	0,020
Credit access	0,750	0,452	0,556	0,511	0,142
Knows Câmara 4.0***	0,667	0,492	0,222	0,428	0,009
Advantage***	4,333	0,887	2,889	1,078	0,000
Compatibility***	4,500	0,674	2,333	1,283	0,000
Complexity	2,583	1,505	2,611	1,037	0,478

*** mean/frequency with a difference that is statistically significant at 1% level; ** mean/frequency with a difference that is statistically significant at 5% level; * mean/frequency with a difference that is statistically significant at 10% level.

The comparative analysis presented in Table 3 allows some relevant remarks. First, it is evidently important to have workers that are qualified in information and communications technology for the adoption and use of Industry 4.0 technologies. Among the companies that adopt the technologies, 50% have staff that specialize in ICT and 66.7% frequently hire IT consulting services. On the other hand, among non-adopters, only 11% have staff specializing in ICT and 16.7% hire IT consulting services. The differences between "Workers in ICT" and "IT consulting" variables for adopters and non-adopters of 4.0 technologies are statistically significant at 2% and 1%, respectively. These results corroborate the literature that shows that the availability of qualified labor to manage and operate digital technologies is one of the main drivers to increase the adoption of such technologies by small and medium-sized companies (Horváth & Szabó, 2019; Stentoft et al., 2021). In this sense, support from senior management to provide staff with training and the existence of good labor qualification programs in digital skills are important to increase the diffusion of Industry 4.0 technologies among small and medium-sized companies (Agostini & Nosella, 2019).

As expected, all companies that adopted 4.0 technologies have broadband internet available in their facilities. Internet availability is fundamental for technologies to be used efficiently. Despite the statistically significant difference in terms of frequencies of 10%, broadband internet access does not seem to be a problem for the companies in the sample, as 89% of non-adopters also have broadband internet available in their facilities.

The differences between the ERP and MPR adoption rates are fairly significant for the two groups. Among companies that adopt Industry 4.0 technologies, 50% also adopt ERP and 33.3% use MRP. Among non-adopters of 4.0 technologies, only 5.6% adopt ERP and MRP. These results reveal some interesting points. Firstly, they reveal that companies which adopt Industry 4.0 technologies have an *a priori* higher intensity of use of managerial technologies. Secondly, they reveal synergies and learning gains in the use of complementary managerial technologies. Thirdly, it is possible to observe that the adoption of more traditional production management technologies is still very incipient among the companies in the sample, especially among those that do not adopt 4.0 technologies.

Therefore, a greater diffusion of Industry 4.0 technologies in small and medium-sized companies in Brazil seems to depend on overcoming barriers related to other managerial technologies that precede Industry 4.0. This result indicates that the small and mid-size companies analyzed lag behind when it comes to the use of managerial technologies. In fact, according to Khanzode et al. (2021), technological lag is one of the two most relevant barriers against the adoption of Industry 4.0 technologies by small and medium-sized companies. In addition, Agostini and Nosella (2019) identified that the previous level of investment in production management resources (ERP and MRP systems, flexible manufacturing system – FMS, CNC machines, etc.) positively affects the intensity of adoption of Industry 4.0 technologies by small and medium-sized companies in Europe. In this sense, it is possible to detect the presence of important complementarities and synergies between the availability of managerial resources and the adoption of Industry 4.0 technologies by small and mid-size companies.

In terms of information search, 91.7% of the companies that adopt Industry 4.0 technologies stated that their senior management often searches for information on technology, production, market and public policies. Among non-adopters, 72.2% stated that their senior management frequently looks for this type of information. This result shows that, in general, the senior management of the analyzed companies has searched for information to subsidize their decision-making process.

Participation in cooperation programs with universities, science and technology institutes or agencies that foster research and technological development is higher among the companies which adopt Industry 4.0 technologies: 41.7% of adopters participate in these programs while only 5.6% of non-adopters participate, and the difference between frequencies is statistically significant at 3%. This result corroborates the importance of partnerships between companies and universities/science and technology institutes for the development and diffusion of Industry 4.0 technologies (Horváth & Szabó, 2019). The companies that participate in this type of program are more connected to the process of scientific and technological development, which results in learning gains and possibilities for fostering technological innovation.

Non-adopters' level of knowledge of *Câmara Brasileira da Indústria 4.0* or other national initiatives for the diffusion of Industry 4.0 technology is considerably low (22.2%). This result corroborates that the non-adoption of the technologies is related to a lack of knowledge of the technologies and of diffusion initiatives. The lack of knowledge of Industry 4.0 technologies and little understanding of the strategical importance of digital technologies were also considered permanent barriers faced by small and medium-sized companies in Romania, the United Kingdom and Denmark (Türkeș et al., 2019; Masood & Sonntag, 2020; Stentoft et al., 2021).

Adopters agree more that the adoption of 4.0 technologies increases profits and/or reduces production costs. Moreover, adopters have a greater perception that 4.0 technologies are compatible with the internal competencies developed in the company. These results corroborate the importance of companies perceiving the economic advantages and compatibilities of Industry 4.0 innovations (Stentoft et al., 2021).

Table 4 introduces an additional analysis of the correlation among the variables of adoption of each of the four Industry 4.0 technologies and the variables representing the TOE model. It is possible to observe that the coefficients of correlation that were calculated corroborate the comparative analyses presented in Table 3. That is to say, availability of qualified labor in ICT, previous adoption of other managerial technologies, search for information and perception of benefits/compatibilities of the technologies are the variables that show the greatest correlation with the adoption of Industry 4.0 technologies by the small and medium-sized companies in the sample.

Table 4. Correlation matrix of the variables of adoption of Industry 4.0 technologies with the variables representing the TOE framework.

	CLOUD	IOT	BIG DATA	SYSTEMS
CLOUD	1	0,352	0,448**	0,448**
IOT	0,352	1	0,354	0,354
BIG DATA	0,448**	0,354	1	0,761
SYSTEMS	0,448**	0,354	0,761***	1
Time on the market	0,196	0,043	0,313	0,424**
Number of workers	0,019	0,083	0,569***	0,569***
Workers' qualification	0,073	0,358**	0,046	0,149
Workers in ICT	0,539***	0,433**	0,543***	0,543***
IT consulting	0,302	0,287	0,552***	0,552***
Machines with CNC	0,029	0,193	0,322	0,322
Broadband internet	0,182	0,101	0,111	0,111
ERP	0,382**	0,433**	0,543***	0,543***
MRP	0,26	0,354	0,523***	0,761***
Tests technologies	0,071	0,234	0,242	0,143
Accesses information	0,584***	0,287	0,192	0,192
STI programs	0,453*	0,253	0,182	-0,027
Accesses credit	0,223	0,084	0,146	0,142
Knows Câmara 4.0	0,585***	0,287	0,192	0,192
Advantage	0,388**	0,331	0,444**	0,447**
Compatibility	0,55***	0,55***	0,381**	0,444**
Complexity	0,101	-0,038	0,36**	-0,038

*** correlation coefficient statistically significant at 1%; ** correlation coefficient statistically significant at 5%.

In summary, the results of this study show that the adoption of 4.0 technologies by the small and medium-sized companies in the sample is related to human resources availability (qualified labor and IT consulting), organizational resources (managerial systems), and also to the perception, by decision-makers, that such technologies result in economic benefits and are compatible with the internal capabilities of the companies. These results are in line with other studies on the adoption of Industry 4.0 technologies by small and medium-sized companies (Agostini & Nosella, 2019; Horváth & Szabó, 2019; Türkeș et al., 2019; Maroufkhani et al, 2020; Khanzode et al., 2021; Stentoft et al., 2021).

5 Conclusion

This paper discussed the adoption of Industry 4.0 technologies by a sample of small and mid-size companies in the metallurgical sector that use machining as part of their operations. Based on a survey conducted with a sample of 30 companies located in São Paulo state, it was possible to make a comparison among the characteristics of adopters and non-adopters of Industry 4.0 technologies. The literature reviewed shows nine technologies that are considered the “pillars” of the Industry 4.0 concept: Big Data, Simulation, Horizontal and Vertical System Integration, Industrial Internet of Things, Cloud Computing, Additive Manufacturing, Autonomous Robots, Augmented Reality and Cybersecurity. The companies in the sample adopted Cloud Computing (10 companies), Horizontal and Vertical Integration Systems (5 companies), Big Data (4 companies) and Industrial Internet of Things (4 companies).

The results of the statistical analyses show the importance of the availability of qualified labor in ICT for the adoption of 4.0 technologies. In addition, it was possible to notice that adopters of Industry 4.0 technologies have a greater intensity of use of managerial resources, measured by the adoption of “preceding” managerial technologies like ERP and MRP. A low level of adoption of ERP and MRP is an indicator of a technological gap in the companies in the sample, especially in non-adopters of 4.0 technologies. Partnerships with research institutes and agencies that foster research have also proved relevant to the adoption of Industry 4.0 technologies. Furthermore, adopters detect more easily economic benefits in 4.0 technologies and their compatibilities with companies’ internal competencies. The empirical results of this study are supported by the TOE theoretical framework and are in line with other studies on the adoption of Industry 4.0 technologies by small and mid-size companies in different countries.

These results are important to suggest paths for public policies and private strategies aiming at a greater diffusion of “4.0 philosophy” among small and mid-size companies in Brazil. We have also detected that the availability of workers with ICT skills, constant search for information, partnerships with research and technological development institutions, previous adoption of other production management technologies (MRP and ERP) and businessmen’s perceptions of 4.0 technologies are factors to be developed in order to increase the diffusion of technologies. Public policies and/or strategies by service providers and companies that develop 4.0 technologies should consider these factors.

Finally, the size of the sample did not allow us to make more robust statistical analyses (e.g.: parametric models of determinants of 4.0 technologies adoption probability), which was the main limitation of this study. Despite our efforts to collect the primary data, it was not possible to obtain a larger sample. Future studies could have a database encompassing a larger number of small and medium-sized companies so that more robust analyses can be performed.

References

Agostini, L., & Nosella, A. (2019). The adoption of Industry 4.0 technologies in SMEs: results of an international study. *Management Decision*, 58(4), 625-643. http://dx.doi.org/10.1108/MD-09-2018-0973.

Alcácer, V., & Cruz-Machado, V. (2019). Scanning the Industry 4.0: a literature review on technologies for manufacturing systems. *Engineering Science and Technology, an International Journal*, 22(3), 899-919. http://dx.doi.org/10.1016/j.jestch.2019.01.006.

Bag, S., Gupta, S., & Kumar, S. (2021). Industry 4.0 adoption and 10R advance manufacturing capabilities for sustainable development. *International Journal of Production Economics*, 231, 107844. http://dx.doi.org/10.1016/j.ijpe.2020.107844.

Bag, S., Wood, L. C., Mangla, S. K., & Luthra, S. (2020). Procurement 4.0 and its implications on business process performance in a circular economy. *Resources, Conservation and Recycling*, 152, 104502. http://dx.doi.org/10.1016/j.resconrec.2019.104502.

Bocquet, R., Brossard, O., & Sabatier, M. (2007). Complementarities in organizational design and the diffusion of information technologies: an empirical analysis. *Research Policy*, 36(3), 367-386. http://dx.doi.org/10.1016/j.respol.2006.12.005.

Brasil. Ministério da Ciência, Tecnologia, Inovações e Comunicações. (2019). *Plano de ação da Câmara Brasileira da Indústria 4.0 do Brasil 2019-2022.* Brasília.

Brettel, M., Friederichsen, N., Keller, M., & Rosenberg, M. (2014). How virtualization, decentralization and network building change the manufacturing landscape: an Industry 4.0 perspective. *International Scholarly and Scientific Research & Innovation*, 8(1), 37-44.

Büchi, G., Cugno, M., & Castagnoli, R. (2020). Smart factory performance and Industry 4.0. *Technological Forecasting and Social Change*, 150, 119790. http://dx.doi.org/10.1016/j.techfore.2019.119790.

Carrer, M. J., Silveira, R. L. F. D., & Souza, H. M. D., Fo. (2019). Factors influencing hedging decision: evidence from Brazilian citrus growers. *The Australian Journal of Agricultural and Resource Economics*, 63(1), 1-19. http://dx.doi.org/10.1111/1467-8489.12282.

Carrer, M. J., Souza, H. M., Fo., Vinholis, M. D. M. B., & Mozambani, C. I. (2022). Precision agriculture adoption and technical efficiency: an analysis of sugarcane farms in Brazil. *Technological Forecasting and Social Change*, 177, 121510. http://dx.doi.org/10.1016/j.techfore.2022.121510.

Craigen, D., Diakun-Thibault, N., & Purse, R. (2014). Defining cybersecurity. *Technology Innovation Management Review*, 4(10), 13-21. http://dx.doi.org/10.22215/timreview/835.

Cruz-Mejía, O., Márquez, A., & Monsreal-Barrera, M. M. (2019). Product delivery and simulation for Industry 4.0. In M. Gunal (Ed.), *Simulation for Industry 4.0* (pp. 81-95). Cham: Springer. http://dx.doi.org/10.1007/978-3-030-04137-3_5.

Dalenogare, L. S., Benitez, G. B., Ayala, N. F., & Frank, A. G. (2018). The expected contribution of Industry 4.0 technologies for industrial performance. *International Journal of Production Economics*, 204, 383-394. http://dx.doi.org/10.1016/j.ijpe.2018.08.019.

Decker, M., Fischer, M., & Ott, I. (2017). Service Robotics and Human Labor: A first technology assessment of substitution and cooperation. *Robotics and Autonomous Systems*, 87, 348-354. http://dx.doi.org/10.1016/j.robot.2016.09.017.

Drath, R., & Horch, A. (2014). Industrie 4.0: hit or hype? [Industry forum]. *IEEE Industrial Electronics Magazine*, 8(2), 56-58. http://dx.doi.org/10.1109/MIE.2014.2312079.

Foster, A. D., & Rosenzweig, M. R. (2010). Microeconomics of technology adoption. *Annual Review of Economics*, 2(1), 395-424. http://dx.doi.org/10.1146/annurev.economics.102308.124433. PMid:24386501.

Frank, A. G., Dalenogare, L. S., & Ayala, N. F. (2019). Industry 4.0 technologies: implementation patterns in manufacturing companies. *International Journal of Production Economics*, 210, 15-26. http://dx.doi.org/10.1016/j.ijpe.2019.01.004.

Frazier, W. E. (2014). Metal additive manufacturing: a review. *Journal of Materials Engineering and Performance*, 23(6), 1917-1928. http://dx.doi.org/10.1007/s11665-014-0958-z.

Fudenberg, D., & Tirole, J. (1985). Preemption and rent equalization in the adoption of new technology. *The Review of Economic Studies*, 52(3), 383-401. http://dx.doi.org/10.2307/2297660.

Garrocho, C. T. B., Silva, M. C., Ferreira, C. M. S., Cunha Cavalcanti, C. F. M., & Oliveira, R. A. R. (2020). Real-time systems implications in the blockchain-based vertical integration of industry 4.0. *Computer*, 53(9), 46-55. http://dx.doi.org/10.1109/MC.2020.3002686.

Geroski, P. A. (2000). Models of technology diffusion. *Research Policy*, 29(4), 603-625. http://dx.doi.org/10.1016/S0048-7333(99)00092-X.

Gray, J. O., & Davis, S. T. (2013). Robotics in the food industry: an introduction. In D. G. Caldwell (Ed.), *Robotics and automation in the food industry* (pp. 21-35). Cambridge: Woodhead Publishing. http://dx.doi.org/10.1533/9780857095763.1.21.

Gunal, M. M. (2019). *Simulation for Industry 4.0.* Basel: Springer Nature. http://dx.doi.org/10.1007/978-3-030-04137-3.

Hadwer, A. A., Tavana, M., Gillis, D., & Rezania, D. (2021). A systematic review of organizational factors impacting cloud-based technology adoption using Technology-organization-environment framework. *Internet of Things*, 15, 100407. http://dx.doi.org/10.1016/j.iot.2021.100407.

Hall, B. (2004). Innovation and diffusion. In J. Fagerberg & D. C. Mowery (Eds.), *The Oxford handbook of innovation*. Oxford: Oxford University Press. http://dx.doi.org/10.3386/w10212.

Hiba, J. H., Shnain, A. H., Hadishaheed, S., & Ahmad, A. H. (2015). Big data and five v's characteristics. *International Journal of Advances in Electronics and Computer Science*, 2(1), 16-23.

Horváth, D., & Szabó, R. Z. (2019). Driving forces and barriers of Industry 4.0: do multinational and small and medium-sized companies have equal opportunities? *Technological Forecasting and Social Change*, 146, 119-132. http://dx.doi.org/10.1016/j.techfore.2019.05.021.

Hussain, A., Malik, A., Halim, M. U., & Ali, A. M. (2014). The use of robotics in surgery: a review. *International Journal of Clinical Practice*, 68(11), 1376-1382. http://dx.doi.org/10.1111/ijcp.12492. PMid:25283250.

Kagermann, H., Wolf-Dieter, L., & Wolfgang, W. (2011). *Industrie 4.0: Mitdem Internet der Dinge auf dem Weg zur 4. industriellen Revolution.* Retrieved in 2021, August 15, from https://www.ingenieur.de/technik/fachbereiche/produktion/industrie-40-mit-internet-dinge-weg-4-industriellen-revolution/

Karshenas, M., & Stoneman, P. L. (1993). Rank, stock, order, and epidemic effects in the diffusion of new process technologies: an empirical model. *The RAND Journal of Economics*, 24(4), 503-528. http://dx.doi.org/10.2307/2555742.

Khanzode, A. G., Sarma, P. R. S., Mangla, S. K., & Yuan, H. (2021). Modeling the Industry 4.0 adoption for sustainable production in Micro, Small & Medium Enterprises. *Journal of Cleaner Production*, 279, 123489. http://dx.doi.org/10.1016/j.jclepro.2020.123489.

Kimiagari, S., & Baei, F. (2022). Promoting e-banking actual usage: mix of technology acceptance model and technology-organisation-environment framework. *Enterprise Information Systems*, 16(8-9), 1894356. http://dx.doi.org/10.1080/17517575.2021.1894356.

Leurent, H., Betti, F., Narayan, J., de Boer, E., Widmer, A., Diaz, D. H., George, K., Marya, V., Schmitz, C., Kelly, R., Miremadi, M., Niculescu, D., & Hou, F. (2019). *Fourth Industrial revolution beacons of technology and innovation in manufacturing* (White Paper). Geneva: World Economic Forum. Retrieved in 2020, August 26, from http://www3.weforum.org/docs/WEF_4IR_Beacons_of_Technology_and_Innovation_in_Manufacturing_report_2019.pdf

Lin, H. F. (2014). Understanding the determinants of electronic supply chain management system adoption: using the technology–organization–environment framework. *Technological Forecasting and Social Change*, 86, 80-92. http://dx.doi.org/10.1016/j.techfore.2013.09.001.

Lu, Y. (2017). Industry 4.0: a survey on technologies, applications and open research issues. *Journal of Industrial Information Integration*, 6, 1-10. http://dx.doi.org/10.1016/j.jii.2017.04.005.

Majeed, A. A., & Rupasinghe, T. D. (2017). Internet of Things (IoT) embedded future supply chains for industry 4.0: an assessment from an ERP-based fashion apparel and footwear industry. Int. *The Journal of Supply Chain Management*, 6(1), 25-40.

Manavalan, E., & Jayakrishna, K. (2019). A review of Internet of Things (IoT) embedded sustainable supply chain for industry 4.0 requirements. *Computers & Industrial Engineering*, 127, 925-953. http://dx.doi.org/10.1016/j.cie.2018.11.030.

Maroufkhani, P., Tseng, M. L., Iranmanesh, M., Ismail, W. K. W., & Khalid, H. (2020). Big data analytics adoption: determinants and performances among small to medium-sized enterprises. *International Journal of Information Management*, 54, 102190. http://dx.doi.org/10.1016/j.ijinfomgt.2020.102190.

Masood, T., & Sonntag, P. (2020). Industry 4.0: adoption challenges and benefits for SMEs. *Computers in Industry*, 121, 103261. http://dx.doi.org/10.1016/j.compind.2020.103261.

McAfee, A., & Brynjolfsson, E. (2012). Big data: the management revolution. *Harvard Business Review*, 90(10), 60-68. PMid:23074865.

Palmarini, R., Erkoyuncu, J. A., & Roy, R. (2017). An innovate process to select Augmented Reality (AR) technology for maintenance. *Procedia CIRP*, 59, 23-28. http://dx.doi.org/10.1016/j.procir.2016.10.001.

Pan, M., & Pan, W. (2019). Determinants of adoption of robotics in precast concrete production for buildings. *Journal of Management Engineering*, 35(5), 05019007. http://dx.doi.org/10.1061/(ASCE)ME.1943-5479.0000706.

Pérez-Lara, M., Saucedo-Martínez, J. A., Marmolejo-Saucedo, J. A., Salais-Fierro, T. E., & Vasant, P. (2020). Vertical and horizontal integration systems in Industry 4.0. *Wireless Networks*, 26(7), 4767-4775. http://dx.doi.org/10.1007/s11276-018-1873-2.

Piaralal, S. K., Nair, S. R., Yahya, N., & Karim, J. A. (2015). An integrated model of thelikelihood and extent of adoption of green practices in small and medium sized logistics firms. *American Journal of Economics*, 5, 251-258.

Piedrahita, A. F. M., Gaur, V., Giraldo, J., Cardenas, A. A., & Rueda, S. J. (2018). Virtual incident response functions in control systems. *Computer Networks*, 135, 147-159. http://dx.doi.org/10.1016/j.comnet.2018.01.040.

Pillai, R., Sivathanu, B., Mariani, M., Rana, N. P., Yang, B., & Dwivedi, Y. K. (2021). Adoption of AI-empowered industrial robots in auto component manufacturing companies. *Production Planning and Control*, 33(16), 1517-1533. http://dx.doi.org/10.1080/09537287.2021.1882689.

Pinheiro, A., Sen, P. K., & Pinheiro, H. P. (2009). Decomposability of high-dimensional diversity measures: quasi U-statistics, martingales and non-standard asymptotics. *Journal of Multivariate Analysis*, 100(8), 1645-1656. http://dx.doi.org/10.1016/j.jmva.2009.01.007.

Porter, M., & Heppelmann, J. (2014). How smart, connected products are transforming competition. *Harvard Business Review*, 92, 64-88.

Raguseo, E. (2018). Big data technologies: an empirical investigation on their adoption, benefits and risks for companies. *International Journal of Information Management*, 38(1), 187-195. http://dx.doi.org/10.1016/j.ijinfomgt.2017.07.008.

Raj, A., Dwivedi, G., Sharma, A., Jabbour, A. B., & Rajak, S. (2020). Barriers to the adoption of Industry 4.0 technologies in the manufacturing sector: an inter-country comparative perspective. *International Journal of Production Economics*, 224, 107546. http://dx.doi.org/10.1016/j.ijpe.2019.107546.

Ramdani, B., Chevers, D., & Williams, D. A. (2013). SMEs’ adoption of enterprise applications: a technology-organisation-environment model. *Journal of Small Business and Enterprise Development*, 20(4), 735-753. http://dx.doi.org/10.1108/JSBED-12-2011-0035.

Reinganum, J. F. (1981). Market structure and the diffusion of new technology. *The Bell Journal of Economics*, 12(2), 618-624. http://dx.doi.org/10.2307/3003576.

Reischauer, G. (2018). Industry 4.0 as policy-driven discourse to institutionalize innovation systems in manufacturing. *Technological Forecasting and Social Change*, 132, 26-33. http://dx.doi.org/10.1016/j.techfore.2018.02.012.

Roblek, V., Mesko, M., & Krapez, A. (2016). A complex view of industry 4.0. *SAGE Open*, 6(2). http://dx.doi.org/10.1177/2158244016653987.

Rogers, E. M. (1983). *Diffusion of innovations* (3rd ed.). New York: The Free Press.

Rubmann, M., Lorenz, M., Gerbert, P., Waldner, M., Justus, J., Engel, P., & Harnisch, M. (2015). Industry 4.0: the future of productivity and growth in manufacturing industries. *Boston Consulting Group*, 9(1), 54-89.

Scheaffer, R. L., Mulekar, M. S., & McClave, J. T. (2010). *Probability and statistics for engineers.* Boston: Cengage Learning.

Schumpeter, J. (1997). *A teoria do Desenvolvimento Econômico: uma investigação sobre os lucros, capital, crédito, juro e o ciclo econômico.* São Paulo: Nova Cultural.

Sindicato da Indústria de Produtos de Cacau, Chocolates, Balas e Derivados do Estado de São Paulo – SICAB. (2018, 7 de maio). *Fiesp identifica desafios da Indústria 4.0 no Brasil e apresenta propostas.* Retrieved in 2020, August 26, from https://www.fiesp.com.br/sicab/noticias/fiesp-identifica-desafios-da-industria-4-0-no-brasil-e-apresenta-propostas

Sousa Jabbour, A. B. L., Jabbour, C. J. C., Foropon, C., & Godinho, M., Fo. (2018). When titans meet: can industry 4.0 revolutionise the environmentally-sustainable manufacturing wave? The role of critical success factors. *Technological Forecasting and Social Change*, 132, 18-25. http://dx.doi.org/10.1016/j.techfore.2018.01.017.

Stentoft, J., Adsbøll Wickstrøm, K., Philipsen, K., & Haug, A. (2021). Drivers and barriers for Industry 4.0 readiness and practice: empirical evidence from small and medium-sized manufacturers. *Production Planning and Control*, 32(10), 811-828. http://dx.doi.org/10.1080/09537287.2020.1768318.

Sunding, D., & Zilberman, D. (2001). The agricultural innovation process: research and technology adoption in a changing agricultural sector. *Handbook of Agricultural Economics*, 1, 207-261.

Taştan, H., & Gönel, F. (2020). ICT labor, software usage, and productivity: firm-level evidence from Turkey. *Journal of Productivity Analysis*, 53(2), 265-285. http://dx.doi.org/10.1007/s11123-020-00573-x.

Tortorella, G. L., Vergara, A. M. C., Garza-Reyes, J. A., & Sawhney, R. (2020). Organizational learning paths based upon industry 4.0 adoption: an empirical study with Brazilian manufacturers. *International Journal of Production Economics*, 219, 284-294. http://dx.doi.org/10.1016/j.ijpe.2019.06.023.

Türkeș, M. C., Oncioiu, I., Aslam, H. D., Marin-Pantelescu, A., Topor, D. I., & Căpușneanu, S. (2019). Drivers and barriers in using industry 4.0: a perspective of SMEs in Romania. *Processes (Basel, Switzerland)*, 7(3), 153. http://dx.doi.org/10.3390/pr7030153.

Velasquez, N., Estevez, E., & Pesado, P. (2018). Cloud computing, big data and the industry 4.0 reference architectures. *Journal of Computer Science and Technology*, 18(3), e29. http://dx.doi.org/10.24215/16666038.18.e29.

Vinholis, M. D. M. B., Souza, H. M. D., Fo., Carrer, M. J., & Chaddad, F. R. (2015). Determinants of recognition of TRACES certification as valuable opportunity at the farm level in São Paulo, Brazil. *Production*, 26(1), 78-90. http://dx.doi.org/10.1590/0103-6513.146513.

Wamba, S. F., Akter, S., Edwards, A. J., Chopin, G., & Gnanzou, D. (2014). How 'big data' can make big impact: findings from a systematic review and a longitudinal case study. *International Journal of Production Economics*. http://dx.doi.org/10.1016/j.ijpe.2014.12.031.

Wang, S., Wan, J., Zhang, D., Li, D., & Zhang, C. (2016). Towards smart factory for industry 4.0: a self-organized multi-agent system with big data-based feedback and coordination. *Computer Networks*, 101, 158-168. http://dx.doi.org/10.1016/j.comnet.2015.12.017.

Wang, Y., Kung, L., & Byrd, T. A. (2018). Big data analytics: understanding its capabilities and potential benefits for healthcare organizations. *Technological Forecasting and Social Change*, 126, 3-13. http://dx.doi.org/10.1016/j.techfore.2015.12.019.

Weller, C., Kleer, R., & Piller, F. T. (2015). Economic implications of 3D printing: market structure models in light of additive manufacturing revisited. *International Journal of Production Economics*, 164, 43-56. http://dx.doi.org/10.1016/j.ijpe.2015.02.020.

Xu, X. (2012). From cloud computing to cloud manufacturing. *Robotics and Computer-integrated Manufacturing*, 28(1), 75-86. http://dx.doi.org/10.1016/j.rcim.2011.07.002.

Yin, Y., Stecke, K. E., & Li, D. (2017). The evolution of production systems from industry 2.0 through industry 4.0. *International Journal of Production Research*, 7543, 1-14.

Zezulka, F., Marcon, P., Vesely, I., & Sajdl, O. (2016). Industry 4.0: an introduction in the phenomenon. *IFAC-PapersOnLine*, 49(25), 8-12. http://dx.doi.org/10.1016/j.ifacol.2016.12.002.