UNIVERSIDADE FEDERAL DE SÃO CARLOS
CENTRO DE CIÊNCIAS EXATAS E TECNOLOGIA
PROGRAMA DE PÓS-GRADUAÇÃO EM ENGENHARIA DE PRODUÇÃO

DANIELE DOS REIS PEREIRA MAIA

SIX SIGMA AND BIG DATA IN THE INDUSTRY 4.0 CONTEXT: SYSTEMATIC LITERATURE REVIEW AND SURVEY ON BRAZILIAN MANUFACTURING COMPANIES

SÃO CARLOS-SP
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Texto de Defesa apresentado ao Programa de Pós-Graduação em Engenharia de Produção da Universidade Federal de São Carlos (UFSCar), como parte dos requisitos para obtenção do título de mestre em Engenharia de Produção.

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RESUMO

O desenvolvimento de processos interconectados, digitalizados, autônomos e integrados em diferentes partes dos sistemas de produção tem se apoiado nos avanços das tecnológicos da Indústria 4.0. A Indústria 4.0 engloba um amplo conjunto de tecnologias, dentre elas, estão as tecnologias que suportam a geração e análise de grandes volumes de dados em tempo real, apoiados por tecnologias como Big Data, Big Data Analytics (BDA) e Internet das coisas (IoT), que dão suporte à busca por melhorias operacionais como fluxos otimizados e identificação de anomalias em tempo real. Objetivos semelhantes são compartilhadas por metodologias de melhoria operacional, como Seis Sigma (SS) e Lean Seis Sigma (LSS), que durante as últimas 3 décadas desempenham um papel importante no controle e melhoria da dos processos seguindo o método estruturado DMAIC e ferramentas e técnicas para análise de dados. Os avanços tecnológicos provenientes das tecnologias da Indústria 4.0 podem apoiar e ampliar os recursos da metodologia SS, possibilitando atingir outros patamares de desempenho operacional. Para identificar as principais tecnologias da Indústria 4.0 que podem ser integradas com a metodologia SS, as principais relações e benefícios e as direções futuras neste campo de estudo, foi realizada uma Revisão Sistemática da Literatura considerando as bases de dados Web of Science e Scopus. Como resultado foram identificadas que as tecnologias que mais apoiam o SS são Big Data, BDA e IoT e que as relações mostram que estas tecnologias suportam positivamente a análise de dados e a melhor tomada de decisões nos projetos de melhoria. Consideradas as evidências da relação da metodologia Seis Sigma com o BDA, foi desenvolvida a proposição de hipóteses e de um modelo teórico com o objetivo de investigar por meio de uma Survey as relações entre as práticas de BDA, SS e desempenho da qualidade e do negócio. A pesquisa foi realizada com especialistas SS de diversas empresas de manufatura brasileiras, em um total de 171 respondentes. O modelo proposto e as hipóteses foram confirmadas por meio da técnica PLS-SEM, mostrando que o BDA impacta positivamente as práticas SS e quando integradas, tem maior impacto na melhoria do desempenho da qualidade e do negócio.

Palavras-Chave: Seis Sigma, Lean Seis Sigma, DMAIC, Big Data, Desempenho.

ABSTRACT

The development of interconnected, digitized, autonomous and integrated processes in different parts of production systems has been supported by technological advances in Industry 4.0. Industry 4.0 encompasses a wide range of technologies, among which are technologies that support the generation and analysis of large volumes of data in real time, supported by technologies such as Big Data, Big Data Analytics (BDA) and Internet of Things (IoT), which support the search for operational improvements such as optimized flows and real-time anomaly identification. Similar goals are shared by operational improvement methodologies such as Six Sigma (SS) and Lean Six Sigma (LSS), which over the past 3 decades play an important role in process control and improvement following the DMAIC structured method and tools and techniques for data analysis. Technological advances from Industry 4.0 technologies can support and expand the resources of the SS methodology, making it possible to reach other levels of operational performance. To identify the main technologies of Industry 4.0 that can be integrated with the SS methodology, the main relationships and benefits and the future in this field of study, a Systematic Literature Review was carried out considering the Web of Science and Scopus databases. As a result, it was identified that the technologies that most support SS are Big Data, BDA and IoT and that the relationships presented that these technologies positively support data analysis and better decision-making in improvement projects. Considering the evidence of the relationship between the Six Sigma methodology and the BDA, the proposition of hypotheses and a theoretical model were developed with the aim of investigating through a survey of relationships between the practices of BDA, SS and quality and business performance. A survey was carried out with SS specialists from several Brazilian manufacturing companies, in a total of 171 founders. The proposed model and hypotheses were confirmed using the PLS-SEM technique, showing that the BDA positively impacts SS practices and when integrated, it has a greater impact on improving quality and business performance.

Keywords: Six Sigma, lean Six Sigma, DMAIC, Big Data, Performance.

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LISTA DE ABREVISTURAS E SIGLAS

AI - Artificial intelligence

BD - Big Data

BDA - Big Data Analytics

CC - Cloud Computing

CI - Continuous Improvement

CPS - Sistema Ciberfísico

CRISP-DM - Cross Industry Standard Process for Data Mining

EV - Self-driving

I4.0 - Industry 4.0

IIoT - Internet das Coisas (IoT) nas indústrias

IoT - Internet das Coisas

LSS - Lean Six Sigma

M2M - Machine to Machine

PLS- SME- Partial Least Square – Structural Equation Modeling

RFID - Radio Frequency Identification

SLR - Systematic Review of the Literature

SS - Six Sigma

TI - Information Technology

WSN - Wireless Sensor Network

SUMÁRIO

1. INTRODUCTION

This first chapter contextualizes the theme, specifies the objectives and justifies the importance of the study. Likewise, it discusses the objectives and research questions, synthesis of the methods and techniques used and the structure of the work.

1.1 CONTEXTUALIZATION AND MOTIVATION

Globalization and new technologies have significantly influenced the competitiveness of manufacturing companies (IYEDE; FALLON; DONNELLAN, 2018). Due to the rapid evolution of digital information, several organizations have sought new types of strategies to improve the efficiency of operations and increase their competitive advantage over competitors (FLOR VALLEJO *et al.*, 2020).

For decades, continuous improvement (CI) was considered a standout strategy for the success of organizations (ANTONY; SNEE; HOERL, 2017). Several business companies around the world have incorporated approaches such as Six Sigma (SS) and Lean Six Sigma (LSS) (SALAH; CARRETERO; RAHIM, 2010; ALBLIWI; ANTONY; LIM, 2015; ANTONY; GUPTA, 2019; FLOR VALLEJO *et al.*, 2020). The SS approach, plays an important role in reducing process variability and eliminating waste following the highly structured and disciplined DMAIC method, and using statistical tools and techniques for data analysis (BAÑUELAS; ANTONY, 2003; BHUIYAN; BAGHEL, 2005; TANG et *al.*, 2007; SHAH; CHANDRASEKARAN; LINDERMAN, 2008; NICOLETTI, 2013; ANTONY *et al.*, 2019). Lean is essential for -the elimination of waste and processes non-value-added activities for customers (SONY, 2018). The joining of the two approaches, results in LSS, which meets the growing organizational needs in CI processes encompassing the robustness of a problem solving systematic approach with the speed to generate value stream flows (ANTONY *et al.*, 2018). Considering the importance of SS as an improvement approach focused on reducing variation in organizational processes by using improvement specialists, a structured method, and performance metrics with the aim of achieving strategic objectives (SCHROEDER *et al.*, 2009; LAMINE; LAKHAL, 2018; SCHMIDT et al., 2018), and as LSS includes the elements of SS, this research encompasses SS and LSS, similar to what happens with other studies (e.g., Kregel *et al.*, 2020).

Another strategic phenomenon that has been adopted by companies to face the challenges of process improvement and competitiveness in dynamic scenarios, concerns the approach of Industry 4.0 (LU, 2017). Industry 4.0 (I4.0) is composed of continuous innovation and technological development (DURANA *et al.,* 2019). I4.0 encompass several information technologies such as 3D printing, Cyber Physical Systems (CPS), Internet of Things (IoT), Cloud Computing, mobile devices, Big Data and others (ALMADA-LOBO, 2015). These technologies are incorporated into manufacturing, products, supply chain and services (FRANK; DALENOGARE; AYALA, 2019).

With the accelerated advancement of the use of these technologies, it is expected that the amount of data coming, for example, from devices related to the IoT and CPS will grow exponentially and reach the volume of large data sets, called "Big Data" (SIVARAJAH *et al.,* 2017; HE; WANG, 2018; MA *et al.,* 2020). Big Data can be combined with a set of tools for analysis, detection of failures or critical situations and efficient continuous improvement, allowing for increased knowledge for decision-making (GÖLZER; FRITZSCHE, 2017). In order to have conditions for the analysis of Big Data, it is necessary to develop Big Data Analytics capability, which includes infrastructure and techniques to manage, process and analyze Big Data (HARSH; ACHARYA; CHAUDHARY, 2018; RIALTI *et al.,* 2019).

In the context of CI, this trend would certainly represent opportunities for better use of existing resources (GIANNETTI; RANSING, 2016). Technological advances could overcome the challenges currently faced by SS, such as the lack of data and the difficulty in collecting data to improve and reach other levels of operational performance (ROSIN *et al.,* 2020; DALENOGARE *et al.,* 2018; FACORACHIAN; KAZEMI, 2018).

The main reasons and gaps for carrying out the study are: i) there is a need for studies of the impacts on SS caused by Industry 4.0 technologies and ii) it is relevant to analyze which technologies support SS and how they can be integrated into this methodology (ANTONY *et al.,* 2019; ANTONY; SONY, 2019; SAIDI; SOULHI, 2018; NICOLETTI, 2014, 2015; GIANNETTI; RANSING 2016; CHIARINI; KUMAR, 2020; GIJO *et al.,* 2021). Thus, considering the applicability and possible benefits of SS in the context of Industry 4.0, the first objective of this research was to identify and compile, through a Systematic Literature Review (RSL), which I4.0 technologies can be integrated with SS, what are the main relationships and benefits, and the future directions in this field of study.

Considering the strong evidence obtained through the SLR that the relationship between Big Data/BDA and SS is promising and can generate potential benefits through more structured improvements and better decision-making (e.g., YADAV; SHANKAR; SINGH, 2020; BELHADI *et al.,* 2020; GUPTA; MODGIL; GUASEKARAN 2020; PARK; DHALGAARD-PARK; KIM, 2020; TAY; LOH, 2021), the second objective is to empirically investigate, through a survey, the relationships between BDA capability,SS practices, and Quality Performance and Business Performance in manufacturing companies in Brazil.

1.2 RESEARCH PURPOSE

To achieve the research objectives, two studies were conducted and integrated. The first used an SLR method with the aim of identifying the main relationships between SS and I4.0 technologies. Based on the SLR results, was evidenced the need to further study between Big Data/BDA and SS. The SLR also helped in the proposition of a conceptual model, used in the subsequent empirical study, which through a survey, verify the relationships between BDA and SS in a manufacturing context. Table 1.1 shows these objectives and how (research method) they are addressed in this study.

Table 1.1 - Specific objectives

Research objective	**Dissertation Chapter**	**Method**
Specific objective 1 Consolidate existing knowledge in the literature to identify the main I4.0 technologies that can be integrated with SS, the main relationships and benefits between SS and I4.0 technologies, and the future directions in this field of study	2. Industry 4.0 and Six Sigma technologies: a systematic review of the Literature	Systematic Literature Review
Specific objective 2 Investigate the relationships between BDA capability, SS practices, Quality Performance and Business Performance in manufacturing companies in Brazil.	3. Six Sigma, Big Data Analytics and Performance: an empirical study of Brazilian manufacturing companies	Survey

Source: Prepared by the author

1.3 RESEARCH METHOD

The research method is how to do science, it considers the direction of adopted procedures and their tools (DEMO, 1985). As well as the systematic performance of steps guided by theoretical knowledge to understand the correlations and aspects of a given phenomenon (GOLDENBERG, 2004).

Method selection is an important decision for conducting the research process. (FLEURY *et al.*, 2012). This choice depends on several factors, such as the nature of the research problem, ease of access to data, resources, among others (MARCONI; LAKATOS, 2003; CAUCHICK MIGUEL *et al.*, 2012). Most of the time, a combination of two or more methods is required (MARCONI; LAKATOS, 2003). This research adopts the format of articles, and for this reason, different methods will be used to achieve the proposed objectives, a Systematic Literature Review and a Survey.

Literature review is a fundamental tool to manage the diversity of knowledge, the researcher assesses to the relevant intellectual territory in order to develop the existing knowledge base and identify research questions (TRANFIELD; DENYER; SMART, 2003). For scholars, systematic review increases methodological rigor directed and outlined by a set of principles and a restricted protocol (BRINER; DENYER, 2012). It differs from traditional narrative reviews because of the rigor of the replicable research process, selected by explicit criteria and analyzed by full, unbiased reviews of the literature, articulating data in an analogous way to legitimate evidence of the results (COOK *et al.*, 1997). Systematic reviews are important to support the identification of a research topic and for the construction of theoretical concepts (WEBSTER; WATSON, 2002; ROWLEY; SLACK, 2004).

The results found through the SLR were used to develop the theoretical model, which will be validated and measured through a Survey. Survey is considered one of the most important measurement methods in empirical research, its features include implementation of interviews, questionnaires and measurement procedures (TROCHIM, 2015).

It is classified as a quantitative method for having important systematic conditions, such as standardized information about the element under study, well-structured and predefined questions; and normally consisting of information collected (from a large sample) sufficient for statistical analysis(PINSONNEAULT; KRAEMER, 1993).

It can be applied to three different functions, it depends on its purpose, (PINSONNEAULT; KRAEMER, 1993; FORZA, 2002):

- Exploratory research: its aim is to identify the specificity and preceding concepts of a phenomenon to provide complete information content and definition of concepts to be measured (PINSONNEAULT; KRAEMER, 1993; FORZA, 2002).

- Description research: it is about understanding the relevance of a certain phenomenon (FORZA, 2002). It only describes what exists and makes comparisons of the distribution of the phenomenon between subgroups of a population (PINSONNEAULT; KRAEMER, 1993).
- Explanation research: its objective is to test and validate the concepts involved in relation to the phenomenon (PINSONNEAULT; KRAEMER, 1993; FORZA, 2002). This occurs when the knowledge of the phenomenon has already been combined and the theoretical condition as concepts, models and hypotheses are established (FORZA, 2002).

Regarding the type of survey, the Survey can be classified as transversal or longitudinal, this depends on the explicit attention to the dimension of time (PINSONNEAULT; KRAEMER, 1993; BRYMAN, 2012). When the objective is to characterize and test the subset of the sample in a single time, the transversal is the most appropriate (PINSONNEAULT; KRAEMER, 1993). The transversal involves collecting data (usually much more than one case) but at a single point of time, to identify the relationship of two or more variables (BRYMAN, 2012). On the other hand, when the objective is to investigate the variation of the process (understanding and consequences of a given phenomenon) over time, the most appropriate is the longitudinal (PINSONNEAULT; KRAEMER, 1993). The longitudinal survey makes it possible to analyze the evolution of variables (BRYMAN, 2012).

The type of Survey considered in this study is classified as transversal, since the survey intends to collect data at a single moment in time to identify the relationship of two or more variables and define the concepts to be measured. It can be considered as explanation research, as it aims test and validate the concepts involved in relation to the phenomenon.

The hypotheses will be analyzed using the technique of Structural Equation Modeling using Partial Least Squares (Partial Least Square - Structural Equation Modeling - PLS-SEM). The technique is considered the evolution of traditional statistical methods for specific set analysis in hypothetical relationships (HAIR *et al.,* 2016; HAIR *et al.,* 2017). Its objective is to develop new theories and confirm existing ones (REINARTZ; HAENLEIN; HENSELER, 2009; HAIR *et al.,* 2016).

The technique uses the maximum likelihood algorithm, without making great demands on data distribution, sample size and informative indicators (HAIR *et al.*, 2014). They are able to achieve meaningful solutions even in smaller sample sizes, in numerous constructs or non-normal data distributions, and in more complex theoretical models (such as multiple items), which further enhances the measurement and development of structural theory (HAIR *et al.*, 2017).

1.4 WORK STRUCTURE

Chapter 1 contextualizes the theme of the dissertation, objectives, research methods and work structure. Chapter 2 presents a SLR on Industry 4.0 technologies and Six Sigma. Chapter 3 presents a quantitative study based in a conceptual model, to verify the relationship between BDA, SS, the relationships between BDA, SS, Quality Performance and Business Performance in manufacturing companies in Brazil. Chapter 4 is the conclusion of this research.

2 TECHNOLOGIES OF I4.0 AND SIX SIGMA: A SYSTEMATIC LITERATURE REVIEW

The production processes have been supported by technological advances related to the technologies of Industry 4.0 (I4.0). In this scenario, process improvement approaches, such as Six Sigma (SS), are necessary and useful to maximize the effects of the introduction of such technologies and can be helped by them. There is evidence in the literature that there are potential connections between I4.0 technologies and SS, but it is not clear what the technologies are, how the technologies can be incorporated into SS, what benefits generated. This study aims to elucidate these issues through a Systematic Literature Review, which also identified the main authors, articles, journals and trends in the use of I4.0 technologies by this improvement approach. The main findings show that it is possible and beneficial to integrate Six Sigma with I4.0 technologies. We identified that the two technologies with the greatest connection to SS are Big Data (BD) and Internet of Things (IoT). These technologies, respectively, make real-time information and a large amount of data available for analysis. When incorporated into SS projects, they result in better operational performance such as increased productivity, efficiency and cost reduction. Integration into the SS program enables better decision making and new program paradigm, with the application of more advanced statistical analysis and techniques. The SLR findings helps future researchers interested in the topic, additionally, the presentation of how I4.0 can support SS helps practitioners in managing improvement projects with the use of technological resources.

Keywords: Six Sigma, DMAIC, I4.0, Big Data Analytics, IoT

2.1 Introduction

Six Sigma (SS) is a business improvement strategy that seeks to find and eliminate causes of defects, achieving better products and services by focusing on outputs which are critical to the customers (Snee, 2010; Antony et. al, 2017). The implementation of SS has been a successful strategy to improve operational efficiency, productivity and reduce costs (Linderman et al., 2003; Schroeder et al., 2008). SS is applied to reduce variation in processes, using the DMAIC structured method for problem solving and statistically based problem-solving tools, which collect and delivers data to drive solutions (Snee & Hoerl, 2007; Schroeder et al., 2008).

SS is known for its data-driven approach to achieve process improvement through the application of the DMAIC (Antony et al., 2018). The success of SS projects depends on the correct completion of each of the DMAIC phases, the use of appropriate tools, as well as on the availability of data (Snee, 2010). To achieve results through the SS projects, data are needed to identify problems and Critical to Quality (CTQ) parameters and to analyze the causes and propose action plans, especially when the nature of the problem is not clear (De Mast & Lokkerbol, 2012). The importance of the data is similar for Lean Six Sigma (LSS), which is the integration of the consecrated Lean system with the efficient Six Sigma improvement methodology (Drohoremetski et al., 2014). LSS professionals are constantly improving data analysis, which involves collection, refinement and statistical analysis, to better identify performance variables relevant to customers, showing the importance of data for improvement projects and goals (Stojanovic et al., 2015; Stojanovic & Milenovic, 2018).

Organizations are incorporating several technologies in productive systems, that increase the amount of data available, control over processes and sees operations as a comprehensive system (Saucedo-Martínez et al., 2018). These set of technologies have been termed as Industry 4.0 (I4.0) and is supported by technologies such as 3D Printing, Internet of Things (IoT), Cloud Computing (CC), Artificial Intelligence (AI), Big Data, Cyber-Physical Systems (CPS), among others (Almada-Lobo, 2015). In the context of Continuous Improvement (CI) programs, such as SS, the incorporation of technologies in the processes represents an imminent opportunity to leverage existing resources (Giannetti & Ransing, 2016). The technologies allows to integrate sensors, smart devices and information systems to share and cross data in real time, supporting changes and decision-making (Xu et al., 2018).

Some authors have addressed the need and advantages of incorporating I4.0 technologies in SS projects (Tay & Loh, 2021; Gijo et al., 2021; Chiarini & kumar, 2021). Technological advances could overcome the most common challenges currently faced by improvement projects, related to reliability in data collection, lack of current data and enough data for analysis (Albliwi et al., 2014). Most of the LSS tools are based on data integrity, and can have better results if real-time data is used (Arcidiacono & Pieroni, 2018). Large volumes of real-time data meet the growing organizational needs for CI, involving robustness and speed to generate optimized flows and detect anomalies in real time (Antony et al., 2018; Stojanovic et al., 2015). This use make it possible to reach higher levels of operational performance (Rosin et al., 2020; Dalenogare et al., 2018; Fatorachian & Kazemi, 2018).

On the other hand, due to the growing amount of data generated by the use of technologies such as IoT and CPS, the production systems are being transformed into more complex systems (Saidi & Soulhi, 2018; Eleftheriadis & Myklebust, 2016a; Eleftheriadis & Myklebust, 2016b), bringing new challenges to improvement projects. Stojanovic et al., (2015) and Stojanovic & Milenovic (2018) also reinforce that a current limitation is the complexity in dealing with large data sets generated by the current systems.

In this sense, the main gaps in the relationship between I4.0 technologies and SS identified in the literature include: i) there are doubts about the possibility and impacts of extending the SS principles for process improvements in the I4.0 context (Saidi & Soulhi, 2018; Antony et al., 2019; Antony & Sony, 2019; Chiarini & Kumar, 2020; Gijo et al., 2021), ii) there is lack of information about the impact of implementing I4.0 and different information technologies within the context of SS, on organizational performance indicators (Yadav et al., 2020; Chiarini & Kumar, 2020; Farrukh et al., 2020; Tay & Loh, 2021; Yadav et al., 2021), iii) several authors suggest carrying out studies that investigate the integration of the Big Data technology in SS projects (e.g., Belhadi et al., 2020; Antony et al., 2019; Antony & Sony, 2019), since statistical methods, such as Six Sigma could help to adequately use and control variation in Big Data sets (Laux et al., 2017), Big Data Analytics integrated to LSS could help in strategic direction addressing influences from the external environment (Gupta et al., 2020) and the integration of Big Data in DMAIC can help advance practice for process improvement and innovation (Fogarty, 2015).

Considering the applicability and potential benefits of SS in the context of I4.0, the objective of this study is to answer, through a Systematic Literature Review (SLR), the following research questions:

RQ1: Which I4.0 technologies can be integrated with SS?

RQ2: What are the relationships between I4.0 technologies and SS and its benefits?

RQ3: How can i4.0 technologies con be incorporated into DMAIC?

RQ4: What are the trends and future directions in this field of study?

To achieve the proposed objective, the article is structured as follows, section 2 presents a brief literature review to conceptualize SS, LSS and I4.0 technologies. Section 3 details the SLR steps adopted in this study. Section 4 shows the results of the study and, finally, section 5 shows the conclusion, academic and managerial implications.

2.2 Literature Review

2.2.1 *Six Sigma and Lean Six Sigma*

The SS was developed at Motorola by an Engineer Bill Smith in the middle 1980s and broadcast by Jack Welch of General Electric in the 1990s (Snee, 2010; Pepper & Spedding, 2010). Since its origin, it is considered one of the most powerful process improvement strategies, being applied by numerous manufacturing and service organizations in several countries (Antony et al., 2019), such as, Bank of America, Amazon and McKesson Corporation (Fogarty, 2015).

SS follows a structured method to solve problems and eliminate the root cause of the problems (Antony et. al., 2017), the DMAIC method is a cycle to implement improvement projects, which follows the phases: Define, Measure, Analyze, Improve and Control (Fogarty, 2015). DMAIC allows SS to be a systematic and structured approach, used to improve performance and achieve low levels of process variability (Snee, 2010). For the effective application of DMAIC, it uses data and statistical analysis to identify defects in products or processes, and to reduce variability to levels close to zero (Oktadini & Surendro, 2014; Nicoletti, 2013; Antony et al., 2019). It is considered a disciplined and highly quantitative management strategy, with the aim of increasing the profitability of companies, by reducing variability, improving products and processes and increasing customer satisfaction (Antony & Banuelas, 2002).

LSS is a process improvement approach derived from SS, which can be defined by the combination of the SS methodology and the Lean system (Pepper & Spedding, 2010). This combination has been highlighted by several researchers in recent years (Antony et al., 2018) and have been applied by several industries around the world (Salah et al., 2010). The LSS combines the strengths of the SS, mainly the systematic and structured view for solving problems, the robust application of techniques and tools, with the speed of development of Lean projects (Antony et al., 2018), in addition to the Lean focus on eliminating activities that do not add value to the process (Hines et al., 2004). LSS tools need data to identify problems in detail, and it performs best when based when there is integrity, abundance of data and it is obtained in real time (Arcidiacono & Pieroni, 2018).

However, in a scenario of large data volume, the need for data mining and analysis, new knowledge and skills should be developed to analyze the behavior of the process and model the complex relationships of data inputs and outputs (Giannetti, 2017), which is a challenge for SS projects. Other consequences are that intelligent materials and equipment and predictive measures in systems will require new analytical tools in conjunction with existing CI ones (Antony et al., 2019).

2.2.2 *Industry 4.0*

The term I4.0 was introduced during the Hannover Fair in 2011 and announced in 2013 as a German strategic initiative (Xu et al., 2018), used to conceptualize the "smart factory" (Cohen et al., 2017; Antony & Sony, 2019). I4.0 makes a factory be smart by applying advanced information systems and technologies (Arcidiacono & Pieroni, 2018; Laudante, 2017).

There is still no single definition of I4.0, as well as the technologies that fall under the concept (Götz & Jankowska, 2017; Rosin et al., 2020). According to Moeuf et al. (2018) recent studies have identified more than 100 different definitions of I4.0. However, the meaning of the term 4.0 is often associated with technologies. Hermann et al. (2016), for example, define I4.0 as a collective term for technologies and concepts in the value chain. The main technologies that enable smart manufacturing systems in the context of I4.0 include: Big Data and Big Data Analytics, Simulation of autonomous or collaborative Robots (Robots), Machine to Machine communication, Internet of things (IoT), Industrial Internet of Things (IIoT), Internet of Services (IoS), Cyber Security, Cloud Computing (CC), Artificial Intelligence (AI), 3D Additive Production, Augmented Reality and Cyber-Physical Systems (CPS) (e.g., Rüssmann, 2015; Götz & Jankowska, 2017; Moeuf et al., 2018; Zheng et al., 2018; Rosin et al., 2020).

The main guideline of I4.0 is the profound transformation of processes, made possible by the fusion of the virtual and real world, using digitization, automation and robotics in manufacturing (Götz & Jankowska, 2017). Its scope is marked by the possibility of managing CPS using IoT, cloud computing and Big Data, interconnected in different parts of production systems, making them intelligent (Cohen et al., 2017; Fatorachian & Kazemi, 2018). The result of the introduction of these technologies can be summarized as an integrated, suitable, optimized, service-oriented, interoperable and high-tech manufacturing process (Lu, 2017), or even fully automated production (Antony & Sony, 2019). I4.0 encompasses a wide range of interdisciplinary technologies with different levels of maturity that facilitate the digitization, automation, integration of processes along the value chains (Götz & Jankowska, 2017).

The use of interconnected and pervasive technologies generate innovations and solve problems related to human-machine interaction in complex industrial environments (Laudante, 2017). The results extend in terms of flexibility, resource efficiency, broad integration, interoperability (Fatorachian & Kazemi, 2018), better capacity, effectiveness (Mubarok & Arriaga, 2020) and operational performance of manufacturing processes (Dalenogare et al., 2018; Fatorachian & Kazemi, 2018; Rosin et al., 2020).

Technologies play different roles and impact production systems in different ways. The use of IoT, AI and Big Data is the main responsible for the speed of the information flow in all phases of the production system (Park et al., 2020). These three technologies are currently leading the transformation to achieve the vision of smart manufacturing (Mubarok & Arriaga, 2020). Their use impacts the quality and quantity of available data (Park et al., 2020). The IoT, for example, can be incorporated into various manufacturing resources, allowing them to interact and communicate intelligently, enabling the capture and collection of production data in real time (Zheng et al., 2018). This Big Data generates useful information and knowledge to support decision-making driven by Big Data Analytics (Zheng et al., 2018).

IoT and Big Data are presented by several authors in the literature as potential technologies for integration with SS (e.g., Laux et al.; 2017, Park et al., 2020; Yadav et al., 2020; Gupta et al., 2020; Belhadi et al., 2020; Clancy et al., 2021; Tay & Loh 2021) and, for this reason, they will be detailed in the next topics.

2.2.2.1 *Internet of Things*

IoT started with a simple goal of connecting any independent device to the internet and converting it into an intelligent device using sensors, chips and software (Kandasamy et al., 2020). Kevin Ashton in 1999 suggested the term “IoT”, in which the Internet would be the connectivity center for all smart devices (Fatorachian & Kazemi, 2018). A similar term is IIoT, which means the IoT applications in industries (Jayaram, 2016). IoT currently supports several smart industrial applications, such as smart manufacturing and transportation (Singh et al., 2020). The use of IoT defines a global network of interconnected services and intelligent objects that support human activities, through its sensors, computing and communication resources (Lemoine et al., 2020).

IoT combines business intelligence with process workflow management, helping to integrate different value-added processes, through information and data (Sanders et al., 2016). The volume of data allows the decentralization of analysis and decision-making and responses in real time in critical and urgent situations (Rüssmann, 2015; Lemoine et al., 2020). IoT has a crucial role in controlling the quality of processes and services (Lemoine et al., 2020), in predictive maintenance, environmentally friendly manufacturing, product quality and efficiency in energy use (Ghobakhloo, 2018).

2.2.2.2 *Big Data*

With the accelerated advance in the use of information and communication technologies such as Internet of Things and Cyber-Physical Systems, the amount of data is increasing exponentially, producing so-called Big Data (Sivarajah et al., 2017; He & Wang, 2018). Big Data is the term referring to large data sets (Lavalle et al., 2011; Harsh et al., 2018; Karnjanasomwong & Thawesaengskulthai, 2019), and it includes both structured and unstructured data (Karnjanasomwong & Thawesaengskulthai, 2019).

Big Data was originally characterized by 3Vs (Volume, Variety and Veracity), and it was extended over the years into 7Vs: i) volume, deals with the size or large amount of data collected; ii) velocity, it is the rate of data generation, stored and processed; iii) variety, refers to the projected hierarchy of data sets (structured, semi-structured and unstructured) produced from various sources; iv) veracity, it is the uncertainty due to deficiency and inconsistency in the data; v) value, refers to the value of the extracted data, the information and insights the data provides; vi) variability, refers to the variation in data flow rates; and vii) visualization, shows the relationships within a wide range of complex data (Faroukhi et al., 2020).

Big Data sets include a large volume of historical data and can count on real-time data update (Rüssmann, 2015; Nicoletti, 2017; Faroukhi et al., 2020). This makes it possible descriptive, predictive and prescriptive analyzes (Chen et al., 2012). According to Jensen (2020), descriptive analysis is related to a retrospective view of the data, involving statistics and panels with historical data trends; predictive analysis is based on models to determine variables that impact outputs, and also on predictions of how models represent reality; and prescriptive analysis goes a step further in identifying proactive actions, such as making decisions based on predictions.

However, given the dissemination of large amounts of data, it was necessary to develop data management capabilities, infrastructure and processing and analysis techniques to deal with the Big Data, this set of features is called Big Data Analytics (BDA) (Harsh et al., 2018; Rialti et al., 2019). BDA support each "V" in an essential way (Faroukhi et al., 2020). BDA development involves technical, organizational and human capabilities, such as the development of an infrastructure for BDA (tools, physical infrastructure and software systems), management skills to understand the outputs of the BDA and their importance, technical skills (to collect , store, process and analyze data), the development of data-based decision making capabilities in all employees, among others (Belhadi et al., 2020). Literature states that BDA is created by combining three groups of strategic resources: i) physical resources – in the form of infrastructure, software systems, IT, and technologies; ii) organizational resources – in the form of operational management practices and skills; and iii) human resources – in the form of technical skills, or analytical knowledge (Wamba et al., 2017; Rialti et al., 2019; Belhadi et al., 2020).

The capabilities of BDA infrastructures are established by the same theoretical foundation as the information system set (Rialti et al., 2019), however, due to their technical characteristics of BDA, (for example, applications, hardware, data and networks) (Wamba et al., 2017), they present better operational performance than traditional systems, which are fundamental for decision making, control and analysis of processes and others (Rialti et al., 2019). BDA capabilities in management skills are related to organizational operations practices (Rialti et al., 2019). Skills, whether they are managerial or technical skills, and the dimension of organizational learning, are considered fundamental and complementary resources for building BDA capabilities (Dubey et al., 2019). The managerial and technical skills reflect on organizational learning and on decision-making culture based on implementation skills and data analysis, which are key factors for competitive advantage. Organizational learning deals with issues related to social and environmental sustainability (Dubey et al., 2019). Finally, the dimension of data-based decision-making capabilities is related to the ability of a company to make decisions based on Big Data (Dubey et al., 2019; Shamim et al., 2019; Belhadi et al., 2020).

2.3 Research Method

SLR is able to introduce a solid basis for research, enabling the development of theories and the identification of the state of the art of literature on a current topic (Webster & Watson, 2002). SLR consists of mapping and evaluating existing studies, in addition to specifying a research question to expand knowledge (Tranfield et al., 2003). SLR is characterized by being systematic, transparent, and replicable (Cooper, 1988). Its objective is to investigate a large number of studies and, at the same time, not to favor only those aligned with the researchers' point of view (Badger et al., 2000).

However, the value of a review depends on the steps taken, the studies found and the clarity of the reports (Moher et al., 2009). The definition of a detailed research protocol, explaining the objective of the research and the data sources used, as well as the adopted procedures are essential to reach a transparent process, and to avoid biased conclusions throughout it (Biolchini et al., 2005; Sutherland, 2004).

2.3.1 *Research steps*

The RSL guidelines contain three phases: planning the review, conducting the review and reporting the review (Tranfield et al., 2003). Each phase has several associated steps, the planning includes specifying the research questions and developing the review protocol. Conducting the review include the selection of studies, data extraction and synthesis. Finally, the steps associated with the review report are mainly related to the analysis, presentation and interpretation of results (Tranfield et al., 2003; Moreno-Montes et al., 2015). The results are reported using two approaches, descriptive and thematic, the first includes graphs and quantitative description of the results; and the second, intends to identify and compile the main characteristics of elected studies according to the research questions (Tranfield et al., 2003).

Covering the planning phase and the elaboration of research protocol, the research strategy must provide effective solutions to a set of issues (Zhang et al., 2011; Moreno-Montes et al., 2015): i) what will be searched, time interval will be considered, what form of search (search string) and sources; ii) which approach will be used in search and selection; iii) what are the criteria to be used for the selection of studies. These questions are answered in the following sections, showing the research protocol.

2.3.1.1 Planning the review

2.3.1.2 *Search string, database and time interval*

The first step of the protocol and definition of the search string was related to the definition of the research questions, presented in the Introduction of this paper. The two main terms related to the research questions for the search string are I4.0 and Six Sigma, however, other keywords can be useful for finding related studies, mainly for I4.0, which has several definitions. For the selection of search string keywords, two approaches were adopted: an analysis of the terms used in previous studies that perform SLR in the themes and the most frequent terms on I4.0 and Six Sigma research using Vosviewer software. For frequency analysis, searches were made in the Scopus and Web of Science databases to identify journal papers with the terms I4.0 or Six Sigma in the title, keywords and abstract. After duplication, the software provided a list of the most frequent keywords related to Six Sigma and I4.0 Table 2.1.

Table 2.1 - Keywords related to Six Sigma and I4.0.

Six Sigma		**I4.0**	
Key words	**occurrences**	**Key words**	**occurrences**
Six Sigma	1092	I4.0	1241
Work simplification	337	Internet of things	416
Total Quality Management	281	Embedded systems	347
Lean	270	Manufacture	323
Article	265	Industrial revolutions	276
Lean Six Sigma	258	Cyber physical system	188
Human	214	Big Data	185
DMAIC	207	Automation	158
Process engineering	197	Industrial research	142
Quality control	189	Artificial intelligence	137

For the search string, some keywords were not used because they are too generic (article, human, manufacture, industrial research and automation). The terms “lean” and “total quality management” were not included since they represent other CI approaches which are not the focus of the research. The terms "work simplification", "process engineering", "quality control" (associated with Six Sigma) and “artificial intelligence"(associated with I4.0) were included in a test string. However, after reading the titles and abstracts, it was found that the articles were not related to the theme of SLR.

Vosviewer also made it possible to identify other spelling forms of the main terms found for the elaboration of the search string itself. The search string is shown in Table 2.2.

Table 2.2 - Search string.

Theme	Related terms	Source
Six Sigma	("Six Sigma" OR ”Six-Sigma" OR "Six Sigma methodology" OR "Six Sigma methods" OR "Lean Six Sigma" OR "lss" OR "lean and Six Sigma" OR "Lean Six Sigma (lss)" OR "DMAIC" OR "dmaic methodology"))	Vosviewer
Connector	**AND**	
I4.0	"I4.0" OR"Embedded systems" OR "industrial revolutions" OR"cyber physical system "OR" cyber physical systems (cps) "OR" cyber-physical systems (cps) "OR" cyber physicals "OR" cyber-physical system (cps) "OR"Big Data " OR	Vosviewer
	"Internet of things" OR "internet of things (iot)" OR "internet of thing (iot)" OR "iiot" OR "iot" OR	Buer et al. (2018)
	"Industrie 4.0" OR "the fourth industrial revolution" OR "the 4th industrial revolution" OR "smart manufacturing" OR "Smart production" OR "smart factory" OR "smart factories" OR "Cyber physical production system" OR "industrial internet" OR "Big Data" OR "digitalization" OR "digitization" OR "digitalization" OR "digitisation" OR	Buer et al. (2018); Liao et al. (2017)
	"Cloud computing"	Gobbo et al. (2018)

The databases considered were Scopus and Web of Science, due to their scope and relevance to the research area (Aghaei Chadegani et al., 2013) and number of international journals indexed related to the themes. Regarding the time interval used for searches, no time cut was made, all articles until early august (2021) were observed. This choice was made to try to reach the widest possible range. There was also no choice of area or subject of knowledge, all results were considered in a first analysis.

2.3.1.3 *Search and selection*

Given that the themes have a wide domain, an automated search, which uses search strings to retrieve results from sources, such as digital libraries and databases (Zhang et al., 2011), was used for the identification of initial results. With the automated search in title, abstract and keywords, 302 general documents were found in the selected databases. The selection criteria are adapted from Liao et al. (2017) and are presented in Table 2.3. The main criteria are related to access to the full article, the text being written in English, being a conference or journal article, and presenting relationships between SS/LSS and I4.0. Conference articles were considered for review because the subject is recent, and these sources have a faster time to publication.

Table 2.3 - Exclusion and inclusion criteria

Topic	Inclusion Criteria	Exclusion Criteria	Code
Duplication	Do not be a duplicate document	Be a duplicate document	DD
Access	Document to be available	Document not available	DA
Source	Document is a journal or conference article	Document is not a journal or conference article (e.g., book, book chapter, editorial)	DS
Language	Document is in English	Document is not in English	DL
Time	Published in any period	-	DTI
Theme	The document is related to SS and I4.0	The document is not related to SS and I4.0 Document relates only to SS or LSS theme Document relates only to I4.0 theme	DTH
Focus	Document explicitly related SS/LSS and I4.0 or its technologies	SS/LSS or I4.0 (or its technologies) used only in keywords or as an expression Document is not related to the SS/LSS as a CI approach The document does not present explicit relationships between SS and I4.0 The text addresses only I4.O technologies or SS	DF

* Source: Adapted Liao et al. (2017)

2.3.1.4 *Conducting the review*

The research protocol adopted in the selection and conducting review phase was adapted from the PRISMA model, proposed by Moher et al. (2009). The PRISMA flowchart is composed of four steps: Identification, Screening, Eligibility and Inclusion. The results of each stage are shown in Figure 2.1. The codes of Table 2.3 were used in Figure 2.1 to present the reasons for the exclusion of documents as indicated by (Moher et al., 2009).

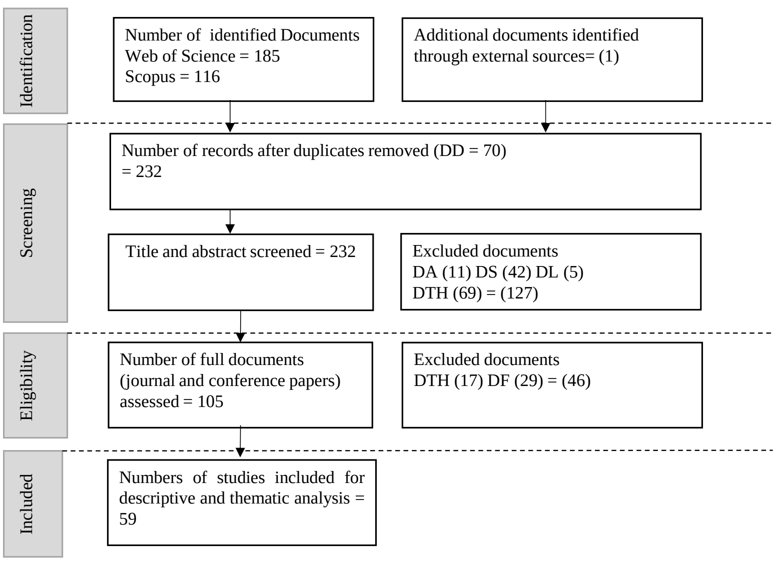

Figure 2.1 - Steps for conducting SL/ Adapted Moher *et al.* (2009)

The identification step was performed through automated search, as already presented, the screening and eligibility steps were performed by two researchers individually based on the inclusion and exclusion criteria. Researchers have both academic and practical experience. When the opinion was different between the two researchers, the document was kept for the next step, after reading it completely, there were no doubts about the classification. In total 59 documents were included for data analysis.

2.3.1.5 *Reporting the review*

The collected data were initially analyzed using a descriptive approach. This analysis observed characteristics of the documents such as: i) distribution of studies over time; ii) type of document (journal or conference); iii) main sources of publication and iv) relevance of the document considering the number of citations. The thematic approach was used to answer the research questions, for this, NVivo and QDA Miner were used for contend analysis. A codebook was created to classify the information, this was based on the main articles on the topic identified in previous reading of the literature.

2.4 Data analysis

2.4.1 *Descriptive Analysis*

The first analysis is about the evolution of publications that correlates I4.0 and SS over time. Figure 2.2 illustrates that there is a growing trend for publications on the topic. Despite some fluctuations, the data show that interest in the topic by researchers has been growing. The data also show that the oldest article found dates from 2013, showing the topicality of the topic. As I4.0 become more evident and applied by organizations, research on the relationship with SS increases.

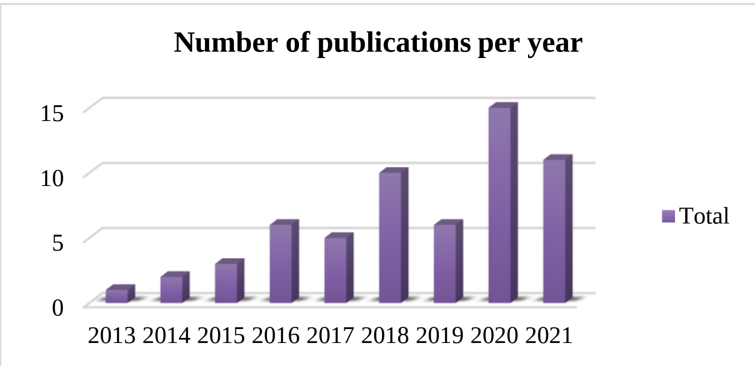

Figure 2.2 - Number of publications per year

The classification of articles by type of documents shows that most of them are composed of Journal articles (39), however, a considerable portion of the articles come from Conferences (20), as presented in Figure 2.3.

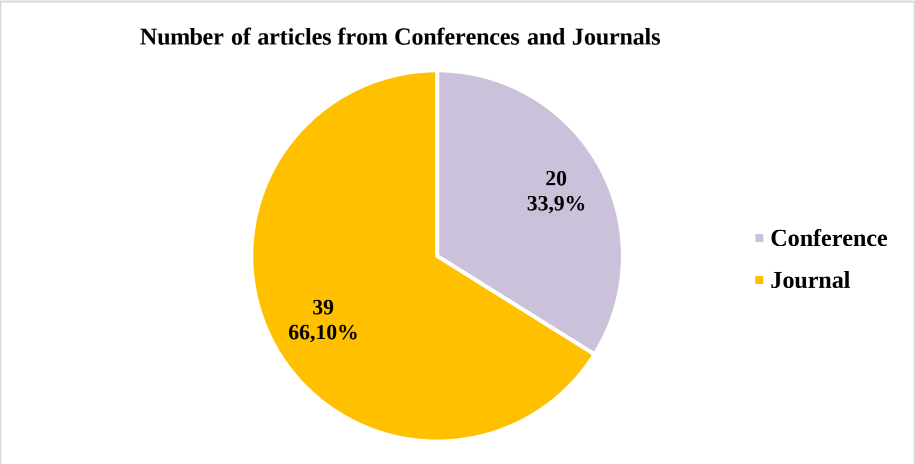

Figure 2.3 - Articles from Conferences and Journals

Regarding the main sources of publication, there is little concentration of articles in a single journal or conference, which shows that the topic is of interest from several sources of publication. The only journals with more than one publication on the topic are The TQM Journal and International Journal of Lean Six Sigma (Appendix B), all with two papers each.

For the analysis of the most relevant articles, considering the number of citations, Scopus and Web of Science was used to survey the number of citations. The results can be seen in Figure 2.4. However, it can be emphasized that the articles are recent, still not allowing a deeper comparative analysis between the selected articles.

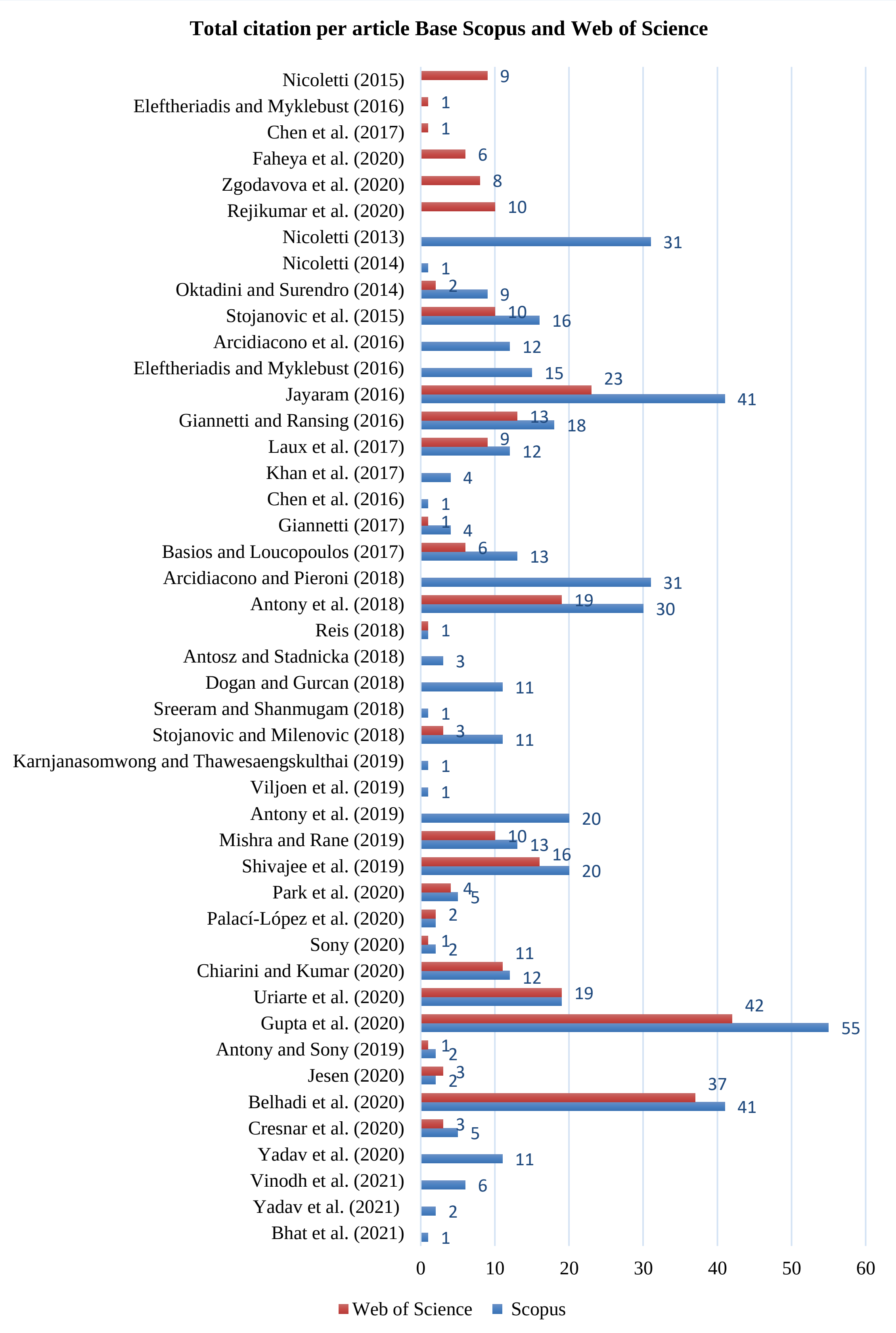

Figure 2.4 - Total citation per article Base Scopus and Web of Science

2.4.2 ***Thematic Analysis***

The thematic analysis aimed to answer the research questions, for that, a content analysis in the full manuscript was applied coding the I4.0 technologies and the relationships with SS. The content analysis allows the measurement of the occurrence of the main technologies and relationships. The documents included in the SLR, their objectives, technology and Methods are presented in Appendix A.

2.4.2.1 *Main technologies*

To answer the first research question, the elected documents were read and codified, to identify the main technologies that can be combined with the SS/LSS approach. The same document can be related to more than one technology in (Appendix A) SLR shows that the main technology that is related to SS is Big Data. This technology provides large datasets and assists in developing and conducting SS projects, which is a data-driven approach. The second main technology related to SS is the IoT, which allows, through sensors, the control, and data of what is happening in the production system in real time. Artificial intelligence, Cyber-Physical Systems and Cloud Computing appear as the next technologies cited as integration possibilities with SS. Both allow for a faster and more continuous flow of data, helping SS in problem solving and decision making.

The vast majority of papers show that I4.0 technologies are positively related to SS, indicating a positive and beneficial view of integration. Figure 2.5, based on the results of Nvivo and Qda Miner, shows which technologies are associated with SS and the intensity of this relationship, based on the number of articles that mention the relationship.

IoT and Big Data were identified as the main technologies related to SS and with the greatest potential for integration with SS into LSS. The results showed that few studies indicate combination with some specific I4.0 technologies (e.g., Drones, Cloud Computing, Augmented Reality, Blockchain, Digitization, Machine to Machine communication). These relationships may not be so evident in the literature due to the fact that I4.0 technologies are at the beginning of their insertion in companies. Another reason can come from the central theme of the SS being the projects to improve and reduce variability, being stimulated, in the first instance, by the provision of data and communication technologies.

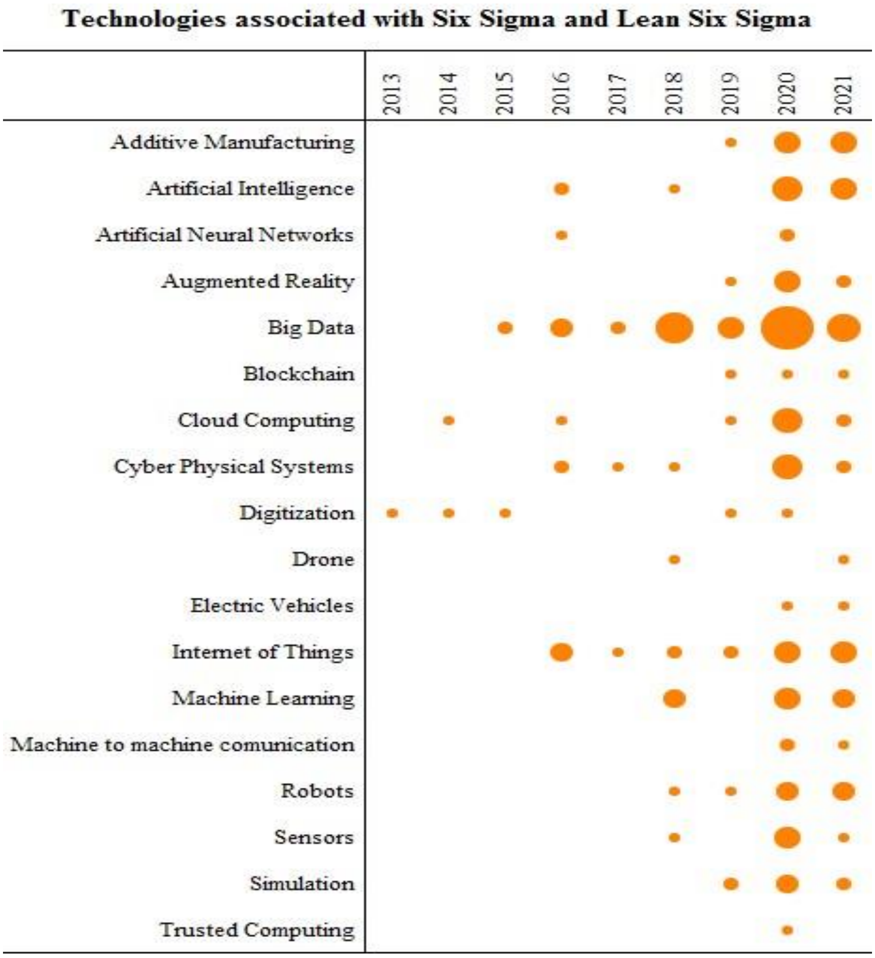

Figure 2.5 - Main Technologies integrated with Six Sigma

Figure 2.6 specifically points to the number of articles in percentage that mention this relationship identified in the literature.

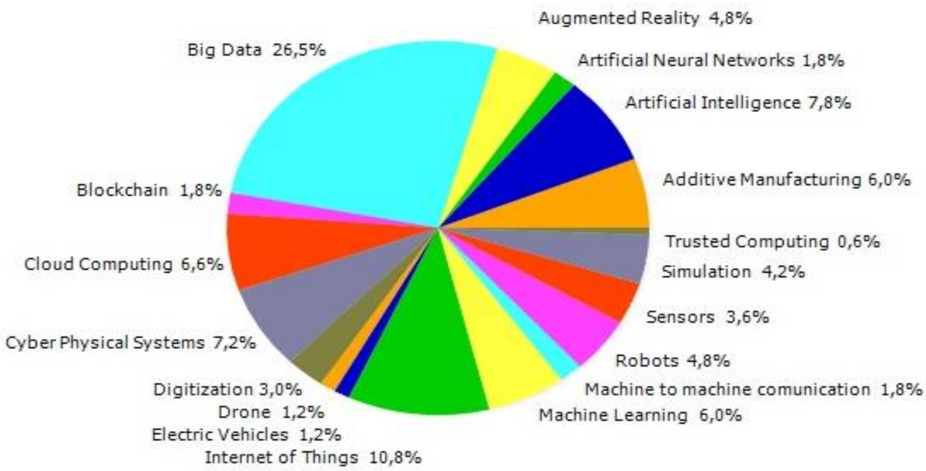

Figure 2.6 - List of SS and LSS and I4.0 technologies

2.4.2.2 *Integration and impacts*

This section describes the main results found in the literature on the integration of SS and I4.0 technologies. It will be divided into an analysis of technologies in general, including authors who only point out the relationship with I4.0 and not a specific technology and a more detailed analysis in relation to Big Data/Big Data Analytics and IoT, as these are the main relationships highlighted in the literature.

2.4.2.2.1 *I4.0 and SS*

The industrial processes under the I4.0 are strongly concentrated in the technology, interconnectivity and automation, which totally changes the concept of process worked by the SS (Saidi & Soulhi, 2018). These changes include the great difficulty in keeping the manufacturing process variability within the tolerance limits in complex operations with several processes and large number of variables (Giannetti & Ransing, 2016). The main traditional SS statistical tools and analysis techniques are not adapted to the characteristics of the complex I4.0 environment (Giannetti & Ransing, 2016; Saidi & Soulhi, 2018). The processes are not isolated, the SS should take into account the different interactions that may occur due to the connectivity between equipment (Saidi & Soulhi, 2018). According to the authors, SS is unable to predict the evolution of large groups of data and handle to multidimensional capability generated by cases of mixtures of normal distributions characterized by complex systems. However, SS and DMAIC will be able to support projects in the context of I4.0, not with the use of basic tools (such as scattering and visual graphics), but with the use of more advanced tools (such as methods based on latent variables, principal components and partial square data) (Palací-López et al., 2020). Possibly, the joint use of other techniques and approaches with SS will be necessary in the context of industry 4.0 (Adrita et al., 2021). In addition, speed will be crucial for quality management in the context of I4.0, it is required for the LSS to meet this speed, that the company adopts Big Data, IoT and AI to the processes, allowing for greater speed in the program's activities (Park et al., 2020).

To analyze the behavior of the processes, intelligent predictive measures will be required in conjunction with the SS, this can be achieved through the use of I4.0 technologies (Antony et al., 2019; Giannetti, 2017).

Oktadini and Surendro (2014), Basios and Loucopoulos (2017), Sreeram and Shanmugam (2018) and Sony (2020) used the DMAIC method under a strategic perspective to drive new business opportunities in technologies coming from I4.0 and to improve the performance of the insertion of these technologies. Oktadini and Surendro (2014) showed that DMAIC improved quality of CC service level agreement by eliminating non-value added steps, making a great combination for improving the quality of Information Technology service delivery and support. Basios and Loucopoulos (2017) used the DMAIC method to identify, analyze and improve inefficient operational processes, and drive new business opportunities in relation to CPS. SS in the context of I4.0 has also used structured design methodology allowing, the development of applications using systems concepts for the design of human-robotic systems, which encapsulates an Internet of Things (IoT) based environment (Sreeram & Shanmugam, 2018). Sony (2020) explored the design of the CPS architecture based on LSS principles. The DMAIC process implemented in each phase of the CPS system configuration demonstrated several benefits, such as reduction of variation, reduction of wasted resources and data collection costs, contribution to CPS configuration projects in self-configuration, self-regulation and automatic optimization, and subsequent expansion of the design of new products and services (Sony, 2020).

In this way, the use of SS is positively associated with the readiness to implement Industry 4.0 (Cresnar et al., 2020). According to the authors, the use of I4.0 technologies together with SS can positively impact the performance of quality and business processes (e.g., Chen et al., 2017; Gijo, 2021; Yadav et al., 2020; Yadav et al., 2021; Tay & Loh 2021).

Yadav et al. (2020), in their study, highlighted the impacts of I4.0 on LSS, in various performance indicators (e.g., productivity, rejections, profitability, delivery performance, Lead time and, Market). Table 2.4 shows the main relationships with I4.0 and the main benefits. The relationships with specific technologies will be presented in separate sections, starting with Big Data and IoT, which were the most mentioned in the SLR.

Table 2.4 – Relationships between I4.0 and SS/LSS

Relationship	Description	Authors
I4.0 technologies supporting SS	I4.0 technologies support intelligent predictive measures, that will be required in SS analysis	Giannetti (2017); Antony et al. (2019) and Chiarini and Kumar (2020)
	Extends toolkits for LSS contributing to process improvements	Tay and Loh (2021)

Table 2.4 – Relationships between I4.0 and SS/LSS (Continue)

I.40 context making changes in SS and DMAIC	SS and DMAIC more efficient decision-making and problem-solving capabilities by incorporating latent variable-based techniques, (e.g., principal component analysis and partial least squares regression) leading to multivariate Six Sigma	Palací-López et al. (2020)
SS and DMAIC projects in the context of I4.0 for better performance of I4.0 technologies	DMAIC method used to drive new business opportunities in technologies coming from I4.0 and to improve the performance of the insertion of technologies (e.g., CC, CPS, Simulation, robotic systems).	Oktadini and Surendro (2014); Basios and Loucopoulos (2017); Sreeram and Shanmugam (2018); Antosz and Stadnicka, (2018); Sony (2020) and Bhat et al. (2021)
I4.0 and SS technologies for better organizational performance	Improvement in productivity, lead time, quality performance, profitability, customer satisfaction, delivery performance, sales turnover, and market share	Yadav et al. (2020) and Tay and Loh (2021)
	Better product development cycle time and product reliability	Gijo et al. (2021)
	Cost, reliability and speed parameters	Viljoen et al. (2019)
I4.0 incompatible with SS	SS works in a more isolated way, without taking into account interactions, interconnections and automation	Saidi and Soulhi (2018)
	The traditional SS statistical toolkit, mainly focused on classical statistical techniques, is not adapted to the characteristics of the complex I4.0 environment	Giannetti and Ransing, (2016); Saidi and Soulhi (2018) and Palací-López et al. (2020)
	SS has limitations in the context of Industry 4.0, requiring the combined use of other techniques and approaches	Adrita et al. (2021)

2.4.2.2.2 *Big Data and Six Sigma*

According to Giannetti and Ransing (2016), the large amount of data can revolutionize the availability of resources for creating new knowledge about processes and decision making. Big Data is a resource for the innovation of LSS paradigm, due to the importance of data quality for conducting LSS projects (Park et al., 2020). Gupta et al. (2020) reinforce that volume is the most important factor for the integration between Big Data and SS, due to the dependence on data that LSS initiatives have. However, when data achieves features such as speed (data generation and transmission) and variety (diversity), they allow the application of LSS activities at an accelerated pace, with precision and information quality (Gupta et al., 2020).

Arcidiacono and Pieroni (2018), Park et al. (2020) and Fogarty (2015) believe in a new paradigm for LSS, marked by more advanced data analysis and projects with broader and more comprehensive scope and observations. Considering that Green Belts and Black Belts training are composed of exploratory, advanced and descriptive data analysis, the use of Big Data makes training more intuitive, as well as improvement projects benefit from the availability and accumulation of information (Fogarty, 2015).

In addition, LSS can accelerate the process of extracting Big Data insights (Fogarty, 2015; Arcidiacono & Pieroni, 2018). The analysis power increases and allow to expand the descriptive and predictive analyzes and identify the root causes that generate variations, enhancing the performance of LSS (Arcidiacono & Pieroni, 2018). BDA are responsible for the structure, skills and for the best extraction of insight about processes with Big Data (Antony & Sony, 2019; Dogan & Gurcan, 2018). BDA offer resources to expand and complete the SS structure and it does not have the purpose or function of replacing it (Fahey et al., 2020, Antony & Sony, 2019; Dogan & Gurcan, 2018). It accelerate the resolution of complex problems and the use of visual analysis (e.g., graphics, charts) of the process, and the SS provides structure for these insights to be introduced to the production process (Fahey et al., 2020), increasing the ability to deal with improvement and LSS implementation goals (Belhadi et al., 2020).

The integrated SS and BDA approaches are mutually reinforcing, strengthening the improvement system and intensifying statistical analysis (Stojanovic et al., 2015; Laux et al., 2017; Stojanovic & Milenovic, 2018; Bhat et al., 2021). The DMAIC approach can guide the analysis of problems using Big Data, since it enables the structuring of complex problems, observing of entire process systems, optimizing of data extraction, categorization and classification, consolidation solutions in terms of data analysis (Arcidiacono et al., 2016; Laux et al., 2017). While BDA enhances strategic knowledge and leverages SS statistical analysis (Laux et al., 2017). Therefore, the integration of approaches would establish an advanced and efficient improvement system (Laux et al., 2017). This integration increase statistical control of the process (Stojanovic et al., 2015; Bhat et al., 2021) understanding the process behavior and elimination of anomalies and its causes (Stojanovic & Milenovic, 2018; Bhat et al., 2021).

Several studies show the result of integrating Big Data into DMAIC, showing results as greater reliability of the product (Karnjanasomwong & Thawesaengskulthai, 2019), identification, prevention, and correction of supply chain errors (Chen et al., 2017) and aid in stratification and capability analysis, identification of root causes, reduction of defects, increased reliability of the production line and supply chain and cost reduction (Mishra & Rane, 2019). Reis (2018) recommends using it for exploratory studies, online and offline process monitoring, predictive modeling, and diagnostic and troubleshooting activities.

In relation to the benefits achieved by the integration, the empirical study carried out by Belhadi et al. (2020) showed that BDA resources have a positive and direct impact on LSS efforts. One of the main points identified is the contribution to decision making that Big Data can provided in the SS/LSS context (Gupta et al., 2020; Dogan & Gurcan, 2018). There are empirical evidences of the results of the integration in health sector, as the improvement of the service process and quality of patient experience and reduction in the use of human and material resources (Arcidiacono & Pieroni, 2018). The integration also favor the improvement of manufacturing processes, resulting better delivery time and production quality (Dogan & Gurcan, 2018).

However, Jensen (2020) disagrees with Big Data's support for Six Sigma, the argument is that the DMAIC method on which SS is based is limiting for most complex problems. While Saidi and Soulhi (2018) affirm that the approach mono-process applied by SS has a reductionist view of the interactions between the various industrial equipment of the complex I4.0 and which are connected in real time. Gupta et al. (2020) highlighted several concerns regarding the insertion of Big Data into the LSS environment, due to the technical issues of dealing with large data sets and the needs of LSS, the main ones are related to: i) System design and integration (e.g., integration and cooperation between different resource agents, interactive exploration of process data and data filtration); ii) System performance, since there is no regulation to the input sources and rate of data flow, data grows exponentially beyond the predicted volume (e.g., process-oriented framework, prescriptive framework); iii) Security and reliability of data (e.g., monitoring and distributed infrastructure); iv) Sustaining the control and conducting the experiments (e.g., data management, optimal process setting); v) Distributed material and information flow (e.g., workflow management, decentralization and co-ordination).

Table 2.5 shows the main relationships between Big Data and SS/LSS and Table 2.6 shows the main benefits from relationships.

Table 2.5 – Relationships between Big Data and SS/LSS

Relationship	Description	Authors
Big Data/BDA supporting SS/LSS analyzes	Allows expansion of traditional SS and LSS analysis to include new and advanced analytical techniques and approaches	Stojanovic et al. (2015); Fogarty (2015); Laux et al. (2017); Arcidiacono and Pieroni (2018); Dogan and Gurcan (2018); Stojanovic and Milenovic (2018); Vinodh et al. (2020) and Yadav et al. (2021)
	Big Data enables the expansion of SS analyzes, including anomalies detection, risk, trend, descriptive or predictive analyzes	Dogan and Gurcan (2018); Arcidiacono and Pieroni (2018); Yadav et al. (2021) and Tay and Loh (2021)
	Big Data is more than just solving problems, it is characterized by continuous learning in a dynamic way	Laux et al. (2017)
	Big Data makes the analysis power increases and allow to identify the root causes that generate variations, enhancing the performance of LSS	Arcidiacono and Pieroni (2018); Koppel and Chang (2021); Kregel et al. (2021) and Yadav et al. (2021)
	BDA accelerates the resolution of complex problems and the use of visual analysis (e.g., graphics, charts)	Fahey et al. (2020)
Big Data/BDA supporting SS/LSS information	BDA allows to extract important insights about the processes to achieve the SS objectives and improvements goals	Belhadi et al. (2020); Dogan and Gurcan (2018); Antony and Sony (2019); Koppel and Chang (2021); Yadav et al. (2021) and Kregel et al. (2021)
	BDA can increase and improve process statistical control	Stojanovic et al. (2015); Giannetti and Ransing (2016); Chen et al. (2017) and Koppel and Chang (2021)
	Big Data enhances projects with broader and more comprehensive scope and observations	Fogarty (2015); Arcidiacono and Pieroni (2018); Park et al. (2020); and Kregel et al. (2021)
	Volume, speed (data generation and transmission) and variety (diversity) of Big Data generate faster LSS projects, with precision and information quality	Gupta et al. (2020) and Park et al. (2020)
DMAIC supporting better performance of BDA	DMAIC method can guide the analysis of problems using Big Data, since it enables the broad vision and structuring of complex problems, optimization of data extraction, categorization and classification, and consolidation of solutions in terms of data analysis, quality and relevance	Arcidiacono et al. (2016); Chen et al. (2017); Laux et al. (2017); Chiarini and Kumar (2020) and Clancy et al. (2021)
SS supporting Big Data	SS analytical tools allow to accelerate the process of extracting important Big Data insights so that they are introduced to the production process	Fogarty (2015); Arcidiacono et al. (2016); Arcidiacono and Pieroni (2018); Faheya et al. (2020); Sony (2020) and Chiarini and Kumar (2020)
SS incompatible with Big Data	SS fails to predict the evolution of data in large data sets	Saidi and Soulhi (2018) and Jesen (2020)
	SS is limiting for the most complex problems involving Big Data	Jesen (2020)

Table 2.6 – Benefits of the relationships between Big Data/BDA and SS/LSS

Relationship	Description	Authors
Big Data or BDA supporting SS	The volume of data coming from Big Data and its resources (BDA) can benefit SS/LSS for better decision making	Giannetti and Ransing (2016); Dogan and Gurcan (2018); Laux et al. (2017); Antony et al. (2018); Antony and Sony (2019); Gupta et al. (2020); Rejikumar et al. (2020); Belhadi et al. (2020); Tay and Loh (2021) and Bhat et al. (2021)
	Process improvement and better supply chain management performance	Chen et al. (2017) and Clancy et al. (2021)
	Positive impacts on quality and business performance, such as, reduction of defective products, greater productivity in processes, greater customer satisfaction and cost reduction	Chen et al. (2017); Dogan and Gurcan (2018); Antosz and Stadnicka (2018); Arcidiacono and Pieroni (2018); Mishra and Rane (2019); Karnjanasomwong and Thawesaengskulthai (2019); Viljoen et al. (2019); Yadav et al. (2020); Sony (2020); Clancy et al. (2021); Bhat et al. (2021); Gijo et al. (2021); Yadav et al. (2021) and Tay and Loh (2021)
BD in conjunction with other technologies (CPS, IoT or Simulation) supporting SS	Waste and variation reduction	Sony (2020) And Arcidiacono and Pieroni (2018)
	Process optimization	Arcidiacono and Pieroni (2018); Sony (2020) and Bhat et al. (2021)
	Production cost savings and improved efficiency	Antosz and Stadnick (2018); Mishra and Rane (2019) and Bhat et al. (2021)
	Process delivery time and reliability	Antosz and Stadnick (2018) and Mishra and Rane (2019)
	Product and process quality, quality performance and customer satisfaction	Arcidiacono and Pieroni (2018) and Mishra and Rane (2019); Bhat et al. (2021)

2.4.2.2.3 *Internet of Things e Six Sigma*

Integration with IoT with LSS can be considered one of the main positive potentials in relation to I4.0, due to the intelligence of the data network capable of monitoring processes in real time (Chen et al., 2016; Arcidiacono & Pieroni, 2018; Eleftheriadis & Myklebust, 2016b; Mishra & Rane, 2019; Jayaram, 2016). Park et al. (2020) consider IoT an intensive practice for quality management in the future, and emphasize the idea of an integrated, fast and agile information flow, in all stages of the production system. IoT allows greater data predictability to monitor deviations and identify defects (Eleftheriadis & Myklebust, 2016b). Khan et al. (2017) covered the DMAIC phases for IoT projects. According to Khan et al. (2017), the approach brings insights and identification of activities and skills needed to increase success in IoT projects. According to Arcidiacono and Pieroni (2018), LSS provides quantitative and qualitative process management tools, while IoT leverages process management and improvement through data collection based on predictive analytics and early identification of cause-effect relationships. The IoT allows different processes to feed in real time a cognitive algorithm to monitor deviations in products and processes (Arcidiacono & Pieroni, 2018), improving operational results.

The integration may bring benefits to the management of the supply chain in terms of efficiency, motivated by the LSS approach, provided by the identification of defects and elimination of non-added value activities, and provided by the exchange of data and automation between the manufacturing and logistics systems supported by IIoT (Jayaram, 2016). Fernandez et al. (2021) presented the effectiveness of predictive maintenance automation with the aid of IoT applied in DMAIC project, finding benefits such as improved quality and performance of business processes and return on investment. Tables 2.7 shows the main relationships and benefits, respectively, between IoT and SS/LSS.

Table 2.7 – Relationship between IoT and SS/LSS

Relationship	Description	Authors
IoT supporting SS	Fast and agile integrated information flow at all stages of the production system, by automated data collection, supporting better LSS projects/activities and decisions	Chen et al. (2016) and Park et al. (2020); Puram and Gurumurthy (2021)
	Improves monitoring and control of the system, enable greater data predictability, to monitor deviations and identify defects	Eleftheriadis and Myklebust (2016b); Arcidiacono and Pieroni (2018); Vinodh et al. (2020); Chiarini and Kumar (2020) and Fernandez et al. (2021)
	Monitors process parameters, and deviations in products and process, making measurement systems more accurate	Arcidiacono and Pieroni (2018) and Yadav et al. (2021)
	Better efficiency, and elimination of non-added value activities	Jayaram (2016)
	Improved quality and business process performance such as return on investment, elimination of breakdowns, machine downtime and maintenance costs and increased production	Fernandez et al. (2021) and Yadav et al. (2021)

2.4.2.2.4 *Other technologies*

The study of Giannetti (2017) in behaviors of complex manufacturing processes, identified that the use of technologies like CPS with SS, enabled the acquisition of new insights on the causes of variability, learning about the process and solving problems about tolerance under uncertainty. The literature even shows that SS and Lean can help in the implementation of CPS systems, as in the case of a maintenance service process in which the improvement project allowed the identification of factors that influence decision making (Antosz & Stadnicka, 2018).

For Nicoletti (2013), Nicoletti (2014), Nicoletti (2015), the LSS used in conjunction with digitization will be able to take advantage of the automation possibilities. The use can streamline and reduce waste in purchasing processes (Nicoletti, 2013), add value to customers, improve efficiency, eliminate waste and reduce operational and time-to-market costs (Nicoletti, 2014; Nicoletti, 2015). AI enables real-time control of systems (Gijo et al., 2021). CC can reduce data management costs, improve data sharing and increase visibility and Robotics can ensure orderliness in the plant, make processes predictable, repeatable and reliable (Yadav et al., 2021).

Table 2.8 shows the benefits and main relationships with I4.0 technologies found in SLR, such as CPS, AI, Digitization and CC.

Table 2.8 – Relationship and benefits between I4.0 and SS/LSS

Relationship	**Description**	**Authors**
CPS supporting SS	The use of technologies like CPS with SS, enabled the acquisition of new insights on the causes of variability and tolerance under uncertainty	Giannetti (2017)
	Provides real-time data visibility to SS	Tay and Loh (2021)
SS supporting CPS	SS helps extract useful information from data, minimizing wasted resources, and costs for data collection	Sony (2020)
Artificial Intelligence supporting SS	Enables robust real-time control of systems, to predict CTQ, visualize product performance and process variability, to reduce process interventions and machine downtime and structured analysis for better decision making	Zgodavova et al. (2020); Gijo et al. (2021); Yadav et al. (2021);
	Improve measurement systems, and reduce process interventions	Yadav et al. (2021)
Digitization supporting SS	Digitization used with SS allows to take advantage of the automation possibilities Streamlines and reduces waste in processes Adding value to customers, improves efficiency, eliminates waste and reduces operational and time-to-market costs	Nicoletti (2013, 2014, 2015)
Cloud computing supporting SS	It can reduce data management costs, improve data sharing, increase visibility into process performance, eliminate human and other errors	Yadav et al. (2021)
Robotics supporting SS	Ensure orderliness in the plant, clear pathways and specific items at specific places and make processes predictable, repeatable, reliable, safe, accurate, etc	Yadav et al. (2021)

2.4.2.2.5 *Integration between I4.0 technologies and DMAIC*

Considering that DMAIC is the structure of the SS and its operationalization via projects, the third research question aimed to identify which and how I4.0 technologies are associated with each stage of DMAIC. Regarding Define phase, Big Data allows for expansion of the data structure and mining capacity in Problem Definition (Laux et al., 2017). While the IoT allows real-time data transmission for initial monitoring of processes and products (Arcidiacono & Pieroni, 2018).

In the Measure phase, Big Data helps to accelerate data collection and IoT helps predictive analytics driven by LSS tools (Arcidiacono & Pieroni, 2018). In this step, SS teams can create analytics datasets from Big Data, and combine transactional and interactive data (Laux et al., 2017). The integration of Big Data in the Measure phase provides a better view of the process, accelerating the resolution of complex problems, and reducing the need for lengthy charting and visual comparison by process scientists (Fahey et al. 2020). In this phase, BDA allows the increase in the number of variables and equipment data (Kregel et al., 2021).

In the Analysis phase, Big Data enrich traditional data analytics tools and expand data sources for the decision-making process (Laux et al., 2017). BDA helps to identify potential bottlenecks, to validate hypotheses, and have information of process indicators, such as variability and performance results (Kregel et al., 2021). IoT accelerates the root cause verification process (Arcidiacono & Pieroni, 2018). Big Data, ML and AI can analyze processes without any human learning effort (Dogan & Gurcan, 2018).

In Improve phase, Big Data and analytical techniques make it possible to identify innovations outside the SS team's domain, with better problem solving, and in a more efficient way (Laux et al., 2017). Big Data and CPS help to improve online monitoring of equipment parameters (Antosz & Stadnicka, 2018). In addition, IoT IoT enables devices to be networked, with real-time activity data logging in the information system (Arcidiacono & Pieroni, 2018).

Regarding Control phase, the BDA toolset enables automated monitoring of several target variables simultaneously, with a significant positive impact on the robustness and efficiency of the process (Fahey et al., 2020). Big Data enable more efficient team support and project sustainability (Laux et al., 2017). However, the large volume of data can make monitoring the data flow more cumbersome, making it difficult to practice statistical process control (Laux et al., 2017). CPS in conjunction with Big Data and supported by algorithms, are able to offer necessary data for decision making (Antosz & Stadnicka, 2018). Big Data and IoT promote a network of sensors and devices interconnected efficiently to the information system and able to monitor critical parameters for quality (Arcidiacono & Pieroni, 2018). Data analyzed by Business Intelligence technologies, provides automated measures and immediate reaction of alarms

(Arcidiacono & Pieroni, 2018). The benefits include more effective performance measurement to assist the process of continuous improvement (Arcidiacono & Pieroni, 2018). The control phase of DMAIC is considered a key point, as the control charts prevent abnormalities that impact product quality, and help in solving problems in the initial state of the process (Chen et al., 2017).

However, several authors do not specify the DMAIC phase, pointing out only that the insertion of technologies can be associated with the method. Big Data assist SS methods and tools in decision making in all phases of DMAIC (Antony et al., 2018; Dogan & Gurcan, 2018; Belhadi et al., 2020; Gupta et al., 2020; Tay & Loh, 2021). In this sense, Big Data can support DMAIC reinforcing advanced statistical analysis, better measurement of the process by the storage of huge amounts of information, and creating insights for process improvements and innovations (Fogarty, 2015). Other technologies like ML, AI assist in process control and errors verification (Dogan & Gurcan, 2018). Data, Simulation, IoT applied within DMAIC phases provide rapid analysis of the root cause, reduced production waste, greater savings, increased reliability of the production line and quality and parameters prediction (Mishra & Rane, 2019). The results about DMAIC method integrated with I4.0 technologies found in the literature are presented in Table 2.9.

Table 2.9 - DMAIC and I4.0 Technologies

DMAIC	Technology	Integration / Benefits	Authors
Define	Big Data	It allows the expansion of the existing data and the capacity in data mining for SS projects	Laux et al. (2017) and Clancy et al. (2021)
	IoT	Data transmitted in real time enables to monitor deviations and problems in processes or products	Arcidiacono and Pieroni (2018)
	CPS	Provides better compression of the company's internal and external requirements	Tay and Loh (2021)
Measure	IoT	Helps to quantify the performance, such as, quality of processes, percentage of related assets and work orders	Fernandez et al. (2021)
	IoT	Intelligent data collection on process and product, autonomous feedback to the machine and process control	Chiarini and Kumar (2020)
	IoT and Big Data	Acceleration and exclusion of human error during data collection	Arcidiacono and Pieroni (2018) and Vinodh et al. (2020)
	Artificial intelligence	Helps you to collect real-time data with high speed and availability of new measurement data	Zgodavova et al. (2020)

Table 2.9 - DMAIC and I4.0 Technologies (continues)

	Big Data	Big data can help to identify the main variables and deviations, analyze inefficiencies and/or efficiencies across existing processes	Koppel and Chang (2020); Kregel et al. (2021) and Tay and Loh (2021)
	Big Data	Big Data assists to expand statistical tools, enabling descriptive and prescriptive statistics, and measuring the current status of the process	Faheya et al. (2020) and Chiarini and Kumar (2020)
	Big Data	SS teams can create sets of analytical data (analytic datasets combining, for example, structured, unstructured, transactional and interactive data)	Laux et al. (2017) and Chiarini and Kumar (2020)
Analyze	Big Data	Big Data enables data mining for SS team members to identify potential bottlenecks root causes and cause and effect relationships for problem solving and validates existing hypotheses	Laux *et al.* (2017); Tay and Loh (2021) and Kregel et al. (2021)
	Big Data	Big Data analyzes enrich traditional analytical tools and expand data sources for the decision-making process	Laux *et al.* (2017); Chiarini and Kumar (2020) and Clancy et al. (2021)
	IoT	Speeds up the root cause verification and elimination	Arcidiacono and Pieroni (2018); Vinodh et al. (2020) and Fernandez et al. (2021)
	Artificial Intelligence	Assists in determining causes of non-compliance, process variations such and deviations	Zgodavova et al. (2020)
Improve	Big Data	Big Data enables to identify innovations outside the domain of the SS team, generating better solutions, and more efficiently	Laux *et al.* (2017)
	IoT	Real-time data from an interconnected network allows faster data collection, registration, data visualization and analysis	Arcidiacono and Pieroni (2018) and Fernandez et al. (2021)
	Big Data and CPS	Improvements in online monitoring of parameters	Antosz and Stadnicka (2018)
	Artificial Intelligence	Helps to control and reduce the variability of process outputs	Zgodavova et al. (2020)
	Robots	Improved standardization, error reduction and automation	Chiarini and Kumar (2020)
Control	IoT	Intelligent data collection on process and product, autonomous feedback to the machine, process control	Chiarini and Kumar (2020)
	Big Data	Automated monitoring of several variables simultaneously	Faheya et al. (2020)
	Big Data and IoT	Big Data allow more efficient Statistical Process Control	Laux et al. (2017)
		Promote better monitoring of critical to quality parameters, performance measurement and immediate reaction	Arcidiacono and Pieroni (2018)
	Big Data and CPS	Better decision making supported by algorithms	Antosz and Stadnicka (2018)
	CPS	Provide real-time data for analysis and decision making	Tay and Loh (2021)
All phases	Big Data	Greater speed in creating data, better data variety, veracity, quality, and precision among others, increases the intrinsic value of the data and improving analysis of SS tools and techniques	Arcidiacono et al. (2016); Chen et al. (2017) and Gupta et al. (2020)

Table 2.9 - DMAIC and I4.0 Technologies (conclusion)

Big Data	Solution method enhancement and acceptability and better efficiency and effectiveness	Karnjanasomwong and Thawesaengskulthai (2019)
Big Data	Expand the SS toolkit	Chiarini and Kumar (2020)
Data and IoT	Advanced statistical analysis, enabling better measurement of the processes and insights for improvements and innovations	Forgaty (2015)
Big Data Data and IoT	Big Data can assist in decision making in all phases of DMAIC in a quick and appropriate way	Dogan and Gurcan (2018); Antony et al. (2018); Belhadi et al. (2020) and Gupta et al. (2020)
Digitization	Better use of statistical techniques for solving waste and rework problems	Shivajee et al. (2019)
Big Data, ML e AI	The integration of technologies with methods and tools, assist in decision making.	Dogan and Gurcan (2018)
IoT	Quick analysis of the root cause	Mishra and Rane (2019)

2.5 Gaps and future research

The last research question aimed to identify the main gaps and trends for future research. Answer this question is intended to help future researchers on the subject. The results show that the trend indicated in the literature is that there should be more studies, mainly empirical, on the relationship of SS with I4.0 technologies, emphasizing, mainly, the relationship of SS with Big Data and BDA. This result is in line with the results that this is the technology with the greatest interface with SS and that its introduction generates a high impact on the improvement program, however, this impact needs to be better understood and observed in practice. Another point highlighted is that the authors emphasize the study of technologies and, mainly, Big Data, with the DMAIC method, given that this is the structure of SS/LSS projects and the basis for conducting the program. Other studies highlight the importance of analyzing the strategic impact of the relationship between DMAIC and Big Data and even the relationship with other variables, such as the impact on sustainability and the environment. The literature states that these investigations should be analyzed considering several comparative variables such as size of companies, industry and level of development of the country in which the company is located. The main gaps and trends for future research are presented in Table 2.10.

Table 2.10 - Main Gaps SS and I4.0 Technologies.

Theme	Main Gaps	Authors
I4.0 technologies and implementation	Explore the integration of SS with I4.0 technologies and/or its limitations considering a set of variables (service industries, manufacturing sectors, sizes)	Nicoletti (2014, 2015); Giannetti and Ransing (2016); Eleftheriadis and Myklebust (2016); Saidi and Soulhi (2018); Antony et al. (2019); Antony and Sony (2019); Chiarini and Kumar (2020); Santos and Martins (2020); Sony (2020); Vinodh et al. (2020) and Gijo et al. (2021)
	Test whether LSS increases the impact of Industry 4.0 technologies and performance measurement of company or entire supply chain	Vinodh et al. (2020); Chiarini and Kumar (2020); Tay and Loh (2021) and Yadav et al. (2021)
	Test whether horizontal integration, vertical integration, and end-to-end can increase when applying Industry 4.0 and LSS	Vinodh et al. (2020)
	Examine how the use of Six Sigma supports the readiness of manufacturing organizations to implement Industry 4.0, considering applying the study in different countries	Cresnar et al. (2020)
	Explore how SS statistical tools extended by smart technologies can help to improve and control variation in large data sets	Laux et al. (2017) and Zgodavova et al (2020)
	Explore barriers and critical success factors for LSS in Quality 4.0	Yadav et al. (2021)
	Explore empirical studies about DMAIC's assistance to implement and improve the use of I4.0 technologies	Mishra and Rane (2019) and Basios and Loucopoulos (2017)
Big Data and BDA	Empirical studies on the relationship and integration of Big Data or BDA on SS/LSS and the impact on, for example, data analytics capabilities, decision making, efficiency, operational performance, considering a set of variables (industry, service sector)	Laux et al. (2017); Antony et al. (2019); Karnjanasomwong and Thawesaengskulthai (2019); Antony and Sony (2019); Rejikumar et al. (2020); Faheya et al. (2020) and Kregel et al. (2021)
	Empirical studies on how to implement BDA in LSS projects in several context (for example, manufacturing)	Dogan and Gurcan (2018); Gupta, et al. (2020) and Puram and Gurumurthy (2021)
	Empirical studies on how LSS and BDA can be linked to the business strategy to achieve key performance, observing variables such as, external environment	Gupta et al. (2020)
	Explore the combination of Big Data in DMAIC method to improve and innovate processes including different sectors, such as healthcare	Fogarty (2015) and Koppel and Chang (2020)
	Explore SS and Lean tools for suitability to Big Data coming from Industry 4.0.	Sony (2020)
	Studies about Green Belts and Black Belts training to use BDA and other technologies for effective integration of Industry 4.0 and LSS tools and techniques	Chiarini and Kumar (2020)

Table 2.10 - Main Gaps SS and I4.0 Technologies (Continue)

Environment	Conducting empirical and longitudinal studies on the relationship between LSS and environmental performance considering the impact of the capabilities of the BDA, and considering a broader set of variables (industry, size, level of development of the country, service x manufacturing sectors)	Shivajee et al. (2019) and Belhadi et al. (2020)
	Explore the application of Green lean six sigma in industry 4.0 technologies for environmental performance.	Farrukh et al. (2020)
ICTs	Empirical studies on the impact of the implementation of information and communication technologies (ICTs) or digitalization on LSS and on manufacturing process	Nicoletti (2013); Yadav et al. (2020) and Clancy et al. (2021)
Simulation	Explore the applicability of LSS in Industry 4.0 directed to the application domain, observing tools and types of simulation and automation and the impact on decision making in different contexts (e.g., government and construction)	Uriarte et al. (2020); Bhat et al. (2021) and Puram and Gurumurthy (2021)
IoT	Examine the relevance of data coming from IoT in SS and LSS	Puram and Gurumurthy (2021)
AI	Examine the integration of LSS with Industry 4.0 (artificial intelligence, machine learning and additive manufacturing) adapted to changing economic, social, environmental and technological forces	Puram and Gurumurthy (2021)

2.6 Conclusions

SS is considered one of the most popular CI approaches and has contributed to the advancement of the implementation of I4.0 technologies and is being supported by them. The general objective of this study is to contribute to the advancement of knowledge about the relationship between I4.0 and SS/LSS technologies and to direct future studies on the field, for that, it aimed to answer four research questions through an SLR and generate academic implications. The SLR analyzed 59 articles from 2013 to 2021 extracted from the Web of Science and Scopus databases. It is evident that there is a trend of growth of publications on the subject, with interest from several journals and conferences in publishing on the subject, as well as several authors in studying about it.

SLR identified that there is relationship between SS and several I4.0 technologies, such as, Cloud Compting, Artificial Intelligence and Cyber Physical Systems. Studies on these technologies show a trend of SS in helping to implement these technologies or in supporting the improvement of their use (e.g., Sony, 2020; Tay & Loh, 2021; Yadav et al., 2021).

The main findings show that the relationship between SS and I4.0 technologies is based on obtaining a larger volume of data. The technologies with main evidence in literature of relationships with SS/LSS are Big Data/BDA and IoT. These relationships are mostly positive and show that IoT and Big Data/BDA support SS and projects through availability of large data sets, enabling more advanced statistical analyses, including predictive ones (Laux et al., 2017; Arcidiacono & Pieroni, 2018). The IoT generates data in real-time, from interconnected processes, which allows faster interventions on anomalies, defects and variations, in addition to a more complex view of the production system (Chen et al., 2016; Eleftheriadis & Myklebust, 2016b; Park et al., 2020).

SLR has identified two main Big Data support relationships for SS, centered on obtaining data to analysis and the possibility of SS and DMAIC transforming this set into information, both supporting better project decisions (Laux et al., 2017; Arcidiacono et al., 2016). In addition, there are relationships that indicates that SS and DMAIC structure can also help Big Data/BDA, in the process of extracting insights, structuring complex problems, optimizing data collection, categorization and classification, and consolidating solutions in terms of data analysis, quality and relevance (Arcidiacono & Pieroni, 2018; Arcidiacono et al., 2016; Faheya et al., 2020). However, in an opposite view, some authors indicate that SS is incompatible with Big Data, since SS is limiting for the most complex problems involving Big Data (Jesen, 2020; Saidi & Soulhi, 2018). One of the main points highlighted by the literature is that Big Data can assist in decision making in all phases of DMAIC in a quick and appropriate way.

Important issues in relation to Big Data supporting SS projects is that they must have volume, speed (data generation and transmission) and variety (diversity), enabling faster LSS projects, with precision and information quality (Gupta et al., 2020). For this reason, studies indicate the combination of technologies such as AI, Big Data and IoT, which promotes automatic and real-time data capture, automated reactions on processes and reliable data, which will be crucial for efficient quality management (Park et al., 2020).

DMAIC also benefits from the introduction of technologies, in the Definition phase, technologies such as Big Data and IoT increase data mining capacity of structured or unstructured data and better problem definition (Laux et al., 2017; Dogan & Gurcan 2018; Gupta et al., 2020). In the Measure phase, Big Data provides more data, accelerated data collection without human error (Laux et al., 2017; Arcidiacono & Pieroni, 2018; Fahey et al., 2020). In the Analysis phase, Big Data enriches analytical tools (Laux et al., 2017; Dogan & Gurcan, 2018; Gupta et al., 2020) and IoT accelerates the root cause verification process in conjunction with the LSS tools, which describe the process in depth (Arcidiacono & Pieroni, 2018). In the Improve phase, Big Data makes it possible to identify ideas and suggestions for innovation beyond the domain of the SS team, generating better solutions, and more efficiently (Laux et al., 2017). In the Control phase, Big Data allows automated monitoring of several variables simultaneously (Fahey et al., 2020). Big Data and IoT enables real-time monitoring or statistical monitoring of the process deviations, performance measurements and faster reactions (Laux et al., 2017; Arcidiacono & Pieroni, 2018).

SLR looked at gaps and future studies identified in the literature. The results show that there is a need for studies on the relationships and usability between I4.0 technologies, with an emphasis on Big Data and BDA, integrated with SS and DMAIC, mainly empirical research and comparative in relation to different contexts (size of companies, level of development of the country, different sectors, mainly manufacturing and services). Future research could observe larger set of organizations for an analysis of the effects of I4.0 technologies integrated with SS and on the organization's performance (Yadav et al., 2020; Antony et al., 2019; Chiarini & Kumar, 2020; Farrukh et al., 2020; Tay & Loh 2021; Yadav et al., 2021; Vinodh et al. 2020).

The managerial implications are related to: i) managers can use SS/LSS and DMAIC to deploy and increase the performance of I4.0 technologies; ii) Big Data/BDA can be integrated with SS/LSS allowing better data analysis and use of advanced statistical techniques; iii) the IoT allows real-time data, strengthening monitoring and interventions in the process, in line with the SS principles; iv) managers can reflect and structure organizations so that 4.0 technologies strengthen the DMAIC method. In addition, managers should observe that not only the volume, variety and speed of data are necessary for companies that are inserted in the context of I4.0, but also, a structure for analyzing these data so that they are transformed into insights, anomaly detection, problem solving, management information, new improvement projects and better decision making.

Some limitations of the research should be highlighted, such as, for example, the limitation of the selection of articles from journals and conference proceedings. The books were not covered, it could probably have intrinsic information for this study. Second, documents from Scopus and Web of Science were collected for their international coverage, other databases were not explored. In summary, despite the limitations, as discussed in this section, the study reported the current status, and by itself, can be a broad and interesting path for future research.

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Appendix A

Selected works at RBS

Objective	Method	Technologies	Authors
Examine digital transformations (DT) of supply chains from a process improvement angle using the LSS DMAIC approach	Case study	Cyber-Physical Systems, Big Data, Cloud Infrastructure, Autonomous Robots, Internet of Things, Self-driving vehicles, 3D Printing, Artificial intelligence, Augmented Reality, Drone and Blockchain	Tay and Loh (2021)
Provide Design for Six Sigma (DFSS) professionals, researchers and academics with the ten commandments for project implementation	Delphi Study	Artificial intelligence, Big Data, Internet of Things, Simulation, Rapid Prototypes, Automation and Deep Learning	Gijo et al. (2021)
Determine a methodology (Six Sigma and CRISP-DM) to support the implementation of digital technologies and supply chain digitization for data-based quality management and reduction of manufacturing process waste	Case study	Big Data	Clancy et al. (2021)
Propose the implementation of predictive maintenance through IoT technology in project in operation and maintenance and the Six Sigma DMAIC methodology to improve the Key Performance Indicator	Case study	Internet of Things	Fernandez et al. (2021)
Design a CPS using 8C architecture through LSS principles for a business system	Literature Review	Cyber-Physical Systems and Big Data	Sony (2020)
Propose the Six Sigma approach using massive data generated to identify opportunities for continuous improvement projects in a manufacturing environment, in addition to human input in a measure, define, analyze, improve and control (MDAIC) format	Case study	Big Data	Koppel and Chang (2020)
To introduce the innovative Small Mixed Batches, the standard set of LSS tools extended by intelligent technologies such as artificial neural networks and data-driven machine learning for the turning process in the bakery machine manufacturer	Case study	Artificial Neural Networks, Artificial, Data-driven and Machine Learning	Zgodavova et al. (2020)

Investigate the relationships between improvement programs and Industry 4.0 digital technologies	Bibliometric Analysis	Deep Learnig, 3D Printing, Rapid Prototyping, Artificial intelligence, Cyber-Physical Systems, Augmented Reality, Artificial neural Networks, Internet of Things, Big Data, Cloud Computing, Radio-frequency identification and Trusted Computing	Santos and Martins (2020)
Present a multivariate Six Sigma process improvement case study for Industry 4.0 based on batch production of one of the products in a chemical plant	Case study	Industry 4.0	Palací-López et al (2020)
Ascertain the modalities of leveraging LSS for Industry 4.0 in process industries, and determine applicability of LSS based on industry automation design simulation with emphasis on robust control system for improve productivity and performance	Action research methodology	Simulation and Big Data	Bhat et al. (2021)
Investigate the integration between LSS tools and principles and Industry 4.0 technologies for a new standard of operational excellence through grounded theory methodology	Semi-structured interviews and Case study	Big Data collection and analytics, Artificial intelligence, Machine Learning, Cloud computing, 3D Printing, RFID, Smart sensors, Collaborative and Autonomous Mobile Robots, and Augmented Reality	Chiarini and Kumar (2020)
Explore how the use of management tools supports the readiness of manufacturing organizations to implement Industry 4.0	Survey	Internet of Things, Cloud Computing, Cyber-Physical Systems, Big data and Digitalized	Cresnar et al. (2020)
Investigate Green-LSS constructs to achieve environmental sustainability	Literature Review	Cloud manufacturing, Cyber-Physical Systems, Artificial intelligence, Big Data, Augmented Reality, 3D Printing and Vehicles Electric Vehicles - EV	Farrukh et al. (2020)
Introduce an approach to integrating Process Mining (PM) technologies into the Six Sigma toolset	Multimethod (Design science - Expert evaluation, technical experiment and a multi case study)	Big Data	Kregel et al. (2021)
Review articles published in the International Journal of Lean Six Sigma IJLSS until the year 2020, trends, professional impact and possible future directions	Bibliometric analysis	Big Data, Internet of Things, Simulation, Artificial intelligence, Machine Learning and Additive Manufacturing	Puram and Gurumurthy (2021)
Present a methodology that identifies opportunities for automation and elimination of manual processes through digitized data analysis using a hybrid combination of LSS, CRISP-DM structure and pre-automation.	Case study	CRISP-DM	Adrita et al. (2021)

Explore Critical Success Factors for LSS using Quality 4.0.	Survey	Robotics, Internet of Things, Cyber-Physical Systems, Augmented Reality, Artificial intelligence, Big Predictive Analytics, Machine Learning, 3D Printing, Radio Frequency Identification RFID, Wireless Sensor Network, Bar Coding, Cloud Computing and Communication Networks M2M	Yadav et al. (2021)
Empirically test a model that explores whether LSS and Green Manufacturing whether LSS and GM mediate the relationship between BDA capabilities and Environmental Performance	Survey	Big Data	Belhadi et al. (2020)
Investigate in the literature the application of BDA in each phase of LSS to make reliable and predictable decisions	Literature review	Big Data	Gupta et al. (2020)
Address the connection between analysis and statistics, to other terms such as big data, data science and Six Sigma and present implications, opportunities and challenges for the statistics profession	Case Study	Big Data	Jesen (2020)
Compare the impact of I4.0 and the emerging information and communication technologies (ICTs), IoT, machine learning, AI, robotics and CC, in 22 organizational performance indicators in combinations of LSS and quality management systems (QMS)	Survey	Internet of Things, Machine to Machine Communication, Wireless Sensor Network, Bar Coding, Cloud Computing, Big Data, Cyber-Physical Systems, Augmented Reality, Machine Learning, Artificial Intelligence, Robotics and Additive Manufacturing	Yadav et al. (2020)
Research the characteristics of the fourth Industrial Revolution and present the new paradigm expected from the LSS	Case study	Internet of Things, Artificial intelligence and Big Data	Park et al. (2020)
Research the perceptions of managers working in India on various aspects related to the efficient use of data-based decision making and to understand the relationships between the critical factors that can be integrated in decision making by data between managers working in an LSS organization.	Survey	Data-Driven	Rejikumar et al. (2020)
Present a novel framework which combines SS and Business Analytics aiming better insights to improve the performance of a biopharmaceutical manufacturing process	Case study	Big Data	Fahey et al. (2020)

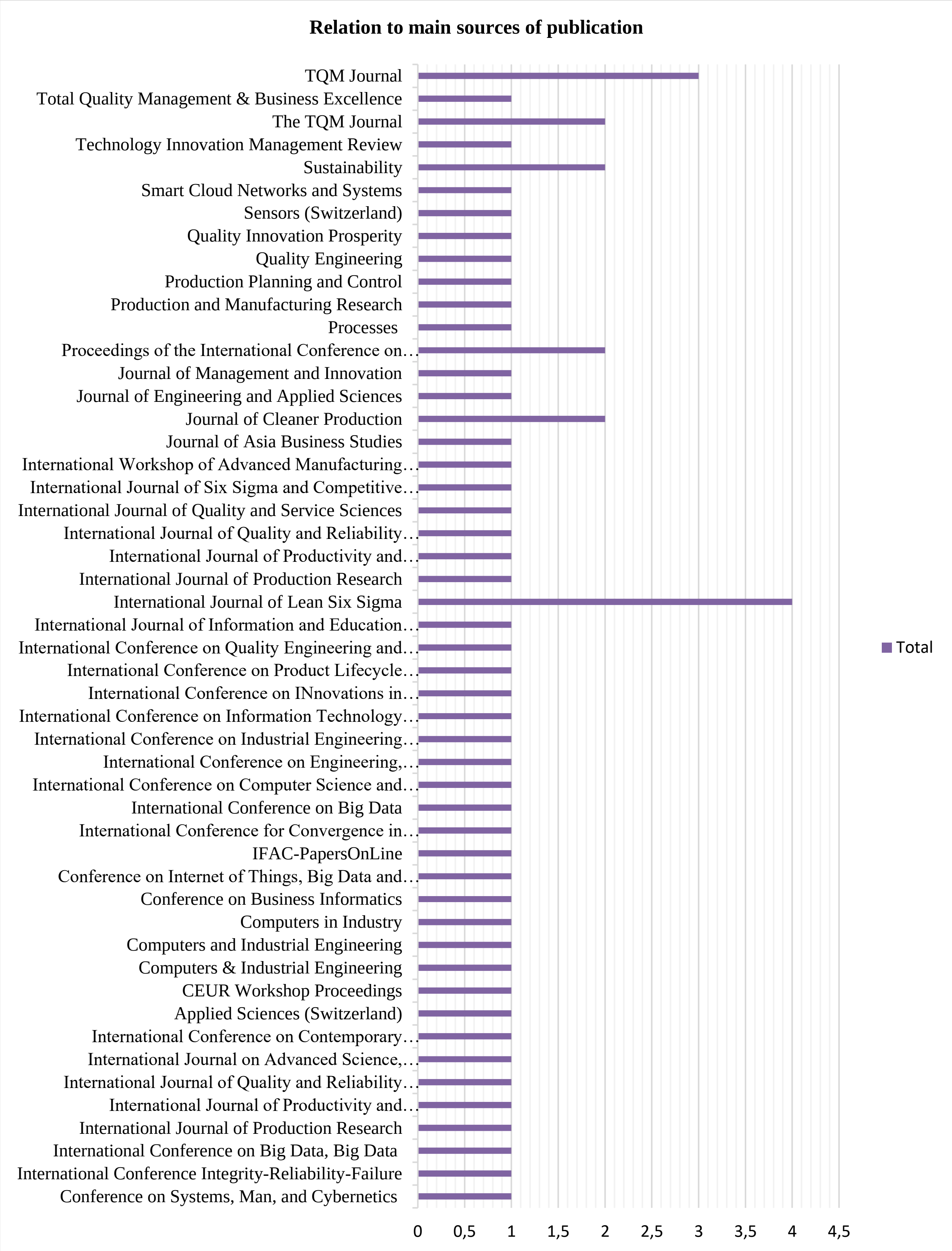
Identify the state of the art, the existing methods and structures to combine Lean and simulation in the Industry 4.0 context, and identify the main research trends and challenges. The main trends identified included SS, as well as sustainability	Literature review	Simulation	Uriarte et al. (2020)
Provides trends and needs for continuous improvement (CI) and sector 4.0.	Literature review	IOT and IOS**,** Big Data, additive Manufacturing, Mobile Computing**,** Augmented Reality, Simulation, Cyber security**,** Autonomous Robots**,** Intelligent Sensors**,** Cyber-Physical Systems and Machine to machine	Vinodh et al. (2020)
Try to develop a structure to identify and analyze elements of the manufacturing conversion cost through the DMAIC approach and quality control (QC) tools, such as Pareto chart, cause and effect diagram and digitization of real data.	Case study	Digitization	Shivajee et al. (2019)
To critically analyze the current developments of the nine pillars Industry 4.0; identify the dynamics of CPSs in the short term and how a multitude of exponential improvements can be realized for the early adopters of a digital strategy	Literature review and Survey	Big Data, Cloud Computing, Additive Manufacturing, Internet of Things, Augmented Reality, Autonomous Robotic**,** Cybersecurity and Design Simulation	Viljoen et al. (2019)
Assess the limitations and emerging trends of SS through an empirical study.	Survey	Big Data	Antony et al. (2019)
Conduct an empirical study of the limitations and emerging trends of SS in manufacturing and service companies.	Survey	Big Data	Antony and Sony (2019)
Explore how the improvement (SS DMAIC) and innovation (TRIZ) methodology can be practically implemented in the manufacturing area in Thailand encompassing big data and analytics.	Case study	Big Data	Karnjanasomwong and Thawesaengskulthai (2019)
Explore the application of analytics and Six Sigma in the manufacturing processes for iron foundries. To establish a causal relationship between the chemical composition and the quality of the iron foundry to reach the level of global reference quality.	Case study	Data**,** Simulation and Internet of Things	Mishra and Rane (2019)
Propose a new method for process control that uses BDA approaches to check the variations from that model in the real-time (as Six Sigma requires) to deal with the multidimensionality and the large size.	Case study	Big Data	Stojanovic and Milenovic (2018)

Propose a methodology, EMBED-X based on the Internet of Things (IoT), for the design of robotic human systems using the concepts of systems engineering, using Lean Six Sigma and analysis in the system development phases.	Case study	Data**,** Drone, Robots and Internet of Things	Sreeram and Shanmugam (2018)
Highlight the limits of the Six Sigma approach by report to I4.0.	Modeling	Machine Learning and Data	Saidi and Soulhi (2018)
Provide professionals and researchers with ten commandments of LSS to achieve and sustain competitive advantages.	Literature review	Big Data	Antony et al. (2018)
Propose a model that allows the application of LSS to make faster, more reliable and adequate decisions based on data.	Literature review	Big Data, Machine Learning and Artificial intelligence	Dogan and Gurcan (2018)
Prove the efficiency of the so-called "Lean Six Sigma 4.0".	Case study	Big Data and Internet of Things	Arcidiacono and Pieroni (2018)
Propose the implementation of the SS methodology integrated with the Lean philosophy and the I4.0 concept.	Case study	Cyber-Physical Systems and Big Data	Antosz and Stadnicka (2018)
Present and apply an InfoQ framework, to evaluate, analyze and improve the quality of the information generated in the variety of data-oriented activities in a Chemical Processing Industry (CPI). The author recommends the framework adoption, as part of the Definition stage in LSS.	Case study	Big Data	Reis (2018)
Discuss Big Data such as features and different considerations (ie hardware, software, platform, NoSql Data Base, languages). It has summarized the Techniques of Big Data and light up on scope with other technologies (i.e. IoT, Agile, LSS).	Literature review	Big Data	Harsh et al. (2018)
Data from multiple sensors within the production process are being analyzed to produce an assessment of product quality using DMAIC for automated identification of causes and deviations.	Case study	Machine Learning and Sensors	Drange et al. (2018)
Propose the Six Sigma DMAIC enhanced with Capability Modeling approach, through which requirements can be considered from an operational and strategic perspective.	Literature review ou case	Cyber-Physical Systems	Basios and Loucopoulos (2017)
Propose a methodology to improve the robustness of manufacturing processes, using data-oriented approaches.	Case study	Industry 4.0	Giannetti (2017)
Provide a comprehensive view of the different phases of the IoT, from collecting sensor data to generating business	Case study	Internet of Things	Khan et al. (2017)

value. The authors propose to use the proven SS methodology for IoT projects.			
Understand how the SS methodology can be combined in another higher education initiative, such as Big Data, in an interest to develop a structure that can be tested, following conceptual research	Case study	Big Data	Laux et al. (2017)
Present the concept of supply chain quality management based on data quality and applying the SS tool to the system	Literature review	Big Data	Chen et al. (2017)
Present a real-time factory control system (RFCS), including power line communication, LonWorks technology and the SS methodology.	Literature review	Internet of Things and Cloud Computing	Chen et al. (2016)
Propose a new algorithm to predict the robustness of a process and quantify the uncertainty in manufacturing operations.	Case study	Data	Giannetti and Ransing (2016)
Use the data from the project "Intelligent correction systems and self-optimization manufacturing failure" to present a process map connecting the philosophy of manufacturing in zero defects with SS and TQM.	Literature review	Artificial Neural Networks, Artificial intelligence, Sensors and Cyber-Physical Systems	Eleftheriadis and Myklebust (2016b)
To present a methodology for the Digital Curation life cycle, determining that all actions pertaining to Data Curation can be executed and optimized using the LSS DMAIC phases.	Case study	Big Data	Arcidiacono et al. (2016)
Propose models using the LSS approach in the global supply chain using I4.0 and IIoT.	Literature review	Internet of Things	Jayaram (2016)
Propose some guidelines on the important constructive elements of quality in digitization, from the point of view of quality management and more steps to start the new digital era of I4.0.	Literature review	Cyber-Physical Systems, Internet of Things, Artificial intelligence and Big Data	Eleftheriadis and Myklebust (2016a)
Develop an approach to a new generation of quality management tools based on analysis of the traditional statistical control of LSS and Big Data.	Case study	Big Data	Stojanovic et al. (2015)
Discuss how to improve innovation processes using the Lean and Digitize Innovation process, integrating digitization with the LSS method.	Literature review	Digitization	Nicoletti (2015)
Understand how LSS can be applied to accelerate the process of exporting important information from Big Data,	Case study	Big Data	Fogarty (2015)

and how Big Data can bring new light and innovation to projects that require the use of Lean Six Sigma.			
Propose a model to define the SLA Service Process in academic services based on the cloud and applied to Six Sigma.	Literature review	Cloud Computing	Oktadini and Surendro (2014)
To present a method that integrates digitization with the traditional LSS model for innovation processes.	Literature review	Digitization	Nicoletti (2014)
Demonstrate how the LSS method can be applied to purchases, to processes that widely use information and communication technology (ICT) systems.	Case study	Digitization	Nicoletti (2013)

Appendix B



Relation to main sources of publication

3 SIX SIGMA, BIG DATA ANALYTICS AND PERFORMANCE: AN EMPIRICAL STUDY OF BRAZILIAN MANUFACTURING COMPANIES

The introduction of several digital technologies in manufacturing organizations has been generated Big Data sets that can be explored using Big Data Analytics (BDA) to bring competitive advantages to organizations. Data exploration can be strengthened when analyzed within Six Sigma business improvement methodology (SS) domains, which may impact organizational performance. Using data from 171 SS experts from Brazilian manufacturing companies, this study aims to test the relationships among BDA, SS practices, and Quality Performance (QP) and Business Performance (BP). Thus, this study empirically investigates these relationships in a developing country, since big data sets and the capability to use them can be highlighted by structured SS analysis structure and procedures, leading to better decision making. Findings show that BDA is beneficial to SS practices, and both BDA and SS practices positively impact QP and BP at Brazilian manufacturing companies. Additionally, this study shows that not only BDA and SS reinforce each other, but when used together, they increase the positive impact on performance. These results can drive BDA investments by managers, and integrate efforts between SS and BDA.

Keywords: Continuous Improvements; DMAIC; Big Data; Industry 4.0; PLS-SEM.

3.1 Introduction

Six Sigma (SS) is one of the most popular and widely used business improvement methodologies, adopted by several manufacturing and service organizations worldwide to increase operational performance (Gijo et al., 2014; Antony et al., 2019; Sony, 2020). SS is a data oriented problem-solving methodology based on a highly structured and disciplined method - DMAIC (Define, Measure, Analyze, Improve and Control) (Antony et al., 2018; Clancy et al., 2021). SS plays an important role in reducing variations, and achieving process performance and product quality improvements (Antony et *al.*, 2018; Sony, 2020). A popular and related topic in both practice and literature is Lean Six Sigma (LSS) (Kregel et al., 2021). LSS is a business strategy that combines Lean management and SS (Snee, 2010). This study indirectly encompasses LSS, similar to other studies (e.g., Kregel et al., 2021).

To remain competitive, many organizations have resorted to emerging Industry 4.0 technologies (I4.0), including Cyber–Physical Systems (CPS), the Internet of Things (IoT), sensors, Artificial Intelligence, Cloud Computing, Augmented Reality, and Robotics (Koppel & Chang, 2020; Yadav et al., 2021). These technologies allow access to large data sets, called Big Data, that can contain different data types for several processes or consumer variables (Koppel & Chang, 2020; Tay & Loh, 2021). Big Data Analytics (BDA) helps deal with Bid Data. BDA manages, processes and analyzes Big Data (Harsh et al., 2018; Rialti et al., 2019; Koppel & Chang, 2020).

Several studies e.g., Gupta et al. (2020), Rejikumar et al. (2020) and Antony and Sony (2019) have shown potential benefits from integrating SS techniques and methods with Big Data. Large amounts of data, autonomous data collection, and data outside the SS team domain can revolutionize knowledge creation and decision making within the SS domain (Laux et al., 2017; Gupta et al., 2020; Belhadi et al., 2020), providing competitive advantages (Koppel & Chang, 2020). Some authors e.g. Fogarty (2015), Arcidiacono and Pieroni (2018) and Stojanovic & Milenovic (2018) argue that Big Data extends traditional SS tools and techniques for more advanced analytic approaches. This enhances classical measurements (Kregel et al., 2021), applying multivariate statistical techniques (Bhat et al., 2021), and embedding descriptive and prescriptive new statistical analytic tools within DMAIC (Chiarini & Kumar, 2020).

Although several authors agree that BDA can benefit SS for better decision making, positively impacting operational performance (Chen et al., 2017; Yadav et al., 2020b), this view is not unanimous. Jensen (2020), argues that DMAIC methods limit complex problems within this context. Saidi and Soulhi (2018), state that mono-process approaches applied by SS have reductionist data views coming from interactions between industrial equipment which are connected in real time. Bhat et al. (2021), affirm that traditional SS statistical toolkits, mainly focused on classical statistical techniques, are seriously handicapped when problem solving using processed data from I4.0.

Although several authors point out potential benefits of SS and BDA, there are still several gaps, like: i) lack of research on the relationship between BDA and SS, which means that more integration and impact studies using empirical evidence are needed (Antony et al., 2019; Belhadi et al., 2020; Gupta et al., 2020;); ii) doubts on SS performance in the I4.0 context, due to the nature of data, where SS tools and techniques may not be able to cope (Palací-López et al., 2020; Bhat et al., 2021; Koppel & Chang, 2020); iii) opposing views about whether BDA in SS used for decision making can improve process efficiency and reduce defective product levels (Sony, 2020; Clancy et al., 2021).

The main objective of this study is to empirically test relationships between BDA, SS practices and Quality Performance (QP) and Business Performance (BP) by surveying manufacturing companies in Brazil. Additionally, two moderating variables were used in the analysis, the use level of I4.0 technologies, and DMAIC and Big Data integration. We chose to study a developing country because there are specific socio-economic factors, which may pose additional barriers to implementing I4.0, like poor technological infrastructure, lack of financial resources (Erro-Garces & Aranaz Nunes, 2020), and employees with low education and development levels (Tortorella et al., 2018). These factors can limit SS implementation in organizations in developing countries (Mustapha et al., 2019). It is important to study SS due to the lack of studies on this topic in this context (Scheller et al., 2021).

This Chapter is structured as follows: Section 3.2 presents the literature review and hypotheses development, Section 3.3 and 3.4 presents the method used and Research instrumen, Section 3.5 shows the empirical results, Section 3.6 followed by Discussion, Theoretical contributions and Managerial implications, and the Conclusions in Section 3.6.

3.2 Theoretical background and hypotheses development

3.2.1 *Six Sigma Practices*

Several critical factors are need for implementing SS, and multiple practices are needed to create a comprehensive organization system for deploying SS (He et al., 2017). Schroeder et al. (2009), identified four practices or elements. A parallel-meso structure (including strategic project selection and leadership engagement), improvement specialists, structured methods, and performance metrics (customer and/or financial oriented). Zu et al. (2008) and Zu et al. (2010), describe SS as an extension of TQM, but with three distinct practices: SS role structure, SS structured improvement procedures; and SS focus on metrics. These SS practices are also supported by several empirical studies (e.g., Lamine & Lakhal, 2018; Costa et al., 2020).

SS role structure is an infrastructure practice, represented by a group of experts in recruiting, selecting, training, and developing individuals in Belt hierarchies (Champions, Master Black Belt, Black Belt, Green Belt, Yellow Belt), who take on different leadership levels in continuous improvement efforts (Zu et al., 2008; Lamine & Lakhal, 2018; Arumugam et al., 2014). Structured improvement procedures are presented via DMAIC, where project teams plan, systematize, and share experience and technical knowledge to improve process/product efficiency (Zu et al., 2008; Lamine & Lakhal, 2018; Costa et al., 2020). Selecting and prioritizing projects are linked to organizational strategies through quantitative metrics represented by a set of statistical tools for tracking, improving, and controlling process variability (Arumugam et al., 2014; Lamine & Lakhal, 2018). Based on similar studies e.g., Patyal and Koilakuntla (2017), Lamine and Lakhal (2018) and Muraliraj et al. (2020) we assumed that these three specific practices were linked to SS implementation.

3.2.2 *Big Data Analytics*

Big Data is a termed used to describe large data sets (Lavalle et al., 2011; Taleb et al., 2021). Although there is no specific consensus as to its definition, it is characterized by seven dimensions, like: volume, velocity, variety, veracity, value, variability; and visualization (Rialti et al., 2019; Faroukhi et al., 2020).

BDA is an integrated approach for collecting and processing Big Data to provide actionable insights for managerial decision-makers (Atker et al., 2016). BDA is defined as a firm’s ability to assemble, integrate, and deploy big data-specific resources (Gupta & George, 2016). Literature states that BDA is created by combining three groups of strategic resources: i) physical resources – in the form of infrastructure, software systems, IT, and technologies; ii) organizational resources – in the form of operational management practices and skills; and iii) human resources – in the form of technical skills, or analytical knowledge (Wamba et al., 2017; Rialti et al., 2019; Belhadi et al., 2020).

BDA infrastructure is related to technical BDA characteristics involving physical or software systems and connectivity for collecting, processing and analyzing data (Akter et al., 2016; Wamba et al., 2017; Rialti et al., 2019; Dubey et al., 2019). BDA can be divided into management skills, responsible for managing industrial operations for better decision making (Belhadi et al., 2020), and data-based decision-making, which is related to a company's ability to make decisions based on Big Data (Dubey et al., 2019; Shamim et al., 2019; Belhadi et al., 2020). Human skills are related to technical knowledge and employee involvement, and require that personnel be highly-skilled with BDA (Rialti et al., 2019; Belhadi et al., 2020). Organizational learning deals with issues related to social and environmental sustainability (Dubey et al., 2019). Managerial or technical skills and organizational learning are fundamental and complementary resources for building BDA (Dubey et al., 2019).

3.2.3 *Hypotheses development*

3.2.3.1 *BDA and Six Sigma Practices*

Since SS is based on descriptive or exploratory data analysis (Gupta et al., 2020), incorporating BDA encourages using advanced tools like multivariate and latent variable analysis (Laux et al., 2017; Palací-López et al., 2020). This increases analytical power, expands descriptive and predictive analyses, and results in more efficient statistical process controls and better understandings for process variations and root causes (Laux et al., 2017; Arcidiacono & Pieroni, 2018; Dogan & Gurcan, 2018). BDA can expand available data sources, and is very helpful in accurate decision-making processes throughout project efforts (Laux et al., 2017; Belhadi et al., 2019; Park et al., 2020).

BDA can automatically identify areas and processes that need improvement, speeding up project-identification and metric focus (Koppel & Chang, 2020). Furthermore, it gives insights on processes (Dogan & Gurcan, 2018), helping achieve improvement goals. BDA can be integrated with DMAIC for a fruitful digital transformation (Tay & Loh, 2021), enabling several variables to be monitored simultaneously and autonomously controlling Statistical Processes (Chiarini & Kumar, 2020). Nonetheless, human-data intelligence, experience, and knowledge from manufacturing process experts must be combined with BDA (Clancy et al., 2021). SS Belt structures will be exposed and have to adapt to Big Data, which can be reinforced via trainings in data science and BDA concepts to extract process insights (Chiarini & Kumar, 2020; Tay & Loh, 2021).

Existing SS tools may not be suitable for Big Data in I4.0 (Sony, 2020), because real systems have many differently formatted variables (continuous, categorical, binomial and profile variables) (Koppel & Chang, 2020), making it difficult to apply traditional SS tools. This environment embeds new statistical analytics within DMAIC (Chiarini & Kumar, 2020). There are concerns regarding system design and integration, system performance, data security and reliability, sustaining controls, conducting experiments, distributing materials, and information flows (Gupta et al., 2020). This leads us to our first hypothesis:

H1: BDA positively effects Six Sigma Practices.

3.2.3.2 *Effects of BDA on quality performance (QP) and business performance (BP)*

According to Akter et al. (2016) and Belhadi et al. (2020), BDA positively affects company performance in many ways. BDA is related to business efficiency and effectiveness, given its high operational and strategic potential (Wamba et al., 2017). BDA can support excellence since it can identify and analyze quality problems, improve firm decision-making processes, and detect profitable and loyal customers (Wamba et al., 2017; 2019). BDA impacts QP, helping reduce defects and resulting in reliable product deliveries, generating cost savings (Arcidiacono & Pieroni, 2018; Mishra & Rane, 2019). However, several gaps exist with respect to using data science to improve process efficiency and reduce defective product levels (Clancy et al., 2021).

Akter et al. (2016), argue that BDA plays a central role in increasing BP, which comes from organizational, physical, and human resource combinations that are valuable and difficult to imitate. Findings from Corte-Real et al. (2017), suggest that BDA can provide business value and competitive advantages by facilitating supply chain and marketing knowledge acquisitions, creating organizational agility. Insights generated from Big Data on manufacturers, customers and rivals can impact firm performance by making it easier to make right decisions at the right time, better managing supply chains and creating new products, or retaining relationships with customers (Chen et al., 2017;

Rialti et al., 2019; Wamba et al., 2019). Nevertheless, BDA impacts on firm performance are still not fully understood (Rialti et al., 2019). Although the idea of analytics has gained momentum in recent years, it requires large-scale implementation to enhance firm performance (Wamba et al., 2019). This leads us to our second hypothesis:

H2a: BDA positively effects Quality Performance (QP)
H2b: BDA positively effects Business Performance (BP)

3.2.3.3 *Effect of Six Sigma on quality performance (QP) and business performance (BP)*

According to Cobbert (2011) and Chaurasia et al. (2016), SS can positively contribute to process management, offering managers and employees direction for achieving effective QP improvements and business excellence performance. SS enhances employee involvement in quality management practices and in decision-making, enabling learning and creating a cooperative organizational environment, which in turn contributes to BP (Patyal & Koilakuntla, 2017). Systematized DMAIC procedures help systematically solve problems, thereby impacting results (Patyal & Koilakuntla, 2017; García-Alcaraz et al., 2020). Antony et al. (2016), also show how SS positively impacts rework and rejection levels, improving on-time deliveries, productivity and product quality, customer satisfaction, and returns-on-investments, which contribute to QP and BP. Additionally, Maheshwar (2012), and Marques and Matthé (2017), identified focused improvement outcomes like decreased product defect rates and increased process performance.

In conjunction to evidence from literature, this study focused on manufacturing companies in a developing country. These companies face specific issues, like low educational and support infrastructures, and lower adoption rates for improvement methodologies (Yadav et al., 2020a). Studying the relationships between SS, QP and BP is relevant in this context. The following hypotheses were proposed.

H3a: Six Sigma Practices positively effect Quality Performance (QP)
H3b: Six Sigma Practices positively effect Business Performance (BP)

3.2.3.4 *Moderating effects*

Several variables can impact the proposed relationships. Three moderating variables were investigated. The first was company size, since larger organizations are correlated with better analytical performance (Wamba et al., 2019), and this can also affect applying continuous improvement methodologies (Lizarelli et al., 2019). Company size can have a moderating effect on all proposed relationships.

One point highlighted in literature was Big Data and DMAIC cycle integrations (e.g., Laux et al., 2017; Mishra & Rane, 2019; Tay & Loh, 2021). Using large datasets can assist in decision making in all DMAIC phases, thereby improving insights. Using advanced statistical analysis results in better measurements, faster analyses, and projects results, for the entire business (Antony et al., 2018; Dogan & Gurcan, 2018; Gupta et al., 2020). Therefore, integration can have a moderating effect on BDA, QP and BP relationships.

SS is related to several I4.0 technologies, like large datasets generated using the IoT, sensors, or technologies, and stored using Cloud Computing (Arcidiacono & Pieroni, 2018; Chiarini & Kumar, 2020; Vinodh et al., 2020). The benefits of these technologies on SS include insignificant error margins, transmitting, processing, and analyzing large amounts of data in real time, reducing dependence on human interventions, etc (Chiarini & Kumar, 2020; Yadav et al., 2021). For this reason, I4.0 technologies can have a moderating effect on SS practices and QP and BP relationships.

3.3 Research design

3.3.1 *Sampling and Data Collection*

We conducted a web-based survey with SS experts working in Brazilian manufacturing companies. The target sample was identified using searches in SS expert groups (e.g., conferences, social media, forums). Professionals were invited to participate in the survey via email and social media, e.g., LinkedIn. When invitations were accepted, an online and self-applied questionnaire developed using Google Forms (Appendix B), was sent to 540 target, and respondents 228 responses were obtained. As established by Hair et al. (2017), missing value handling procedures can be used for reasonable levels of missing data, which must be at most 5% per indicator. In this way, questionnaires with more than 3% missing values were removed (55 respondents). The mean replacement method was used to deal with data and suspicious response patterns like straight lining or inconsistent answers, which were also removed (2 questionnaires) (Hair et al., 2017). The final sample consisted of 171 responses from SS professionals working in manufacturing companies in different sectors (see Table 3.1). To test the non-response bias we split respondents into first (early respondents) and last (laterespondents) quartiles, each one with 43 respondents, according to when the responses were received, to examine differences in responses pattern. These quartiles were considered to be different waves and a Mann-Whitney test was applied to all model items of the questionnaire. The non-parametric test was chosen as the data do not follow a normal distribution. The null hypothesis was that the difference in median is zero between groups. Test p-values were greater than 0.05 for all variables, showing that there are no differences between medians. Thus, it is inferred that responses from first quartile (early respondents) and last quartile (late respondents) were the same, and nonresponse bias was therefore non-existent. The sample consisted of companies mainly from the automotive, food, metallurgy, and chemical sectors. Companies were also mostly large (64%), according to Brazilian (2016) classifications.

Table 3.1 – Sample description.

Description of sampled companies			**Description of respondents**		
Sector	Number	%	**Respondent Training**	Number	%
Automotive vehicles	20	12%	Green Belt	76	44%
Food	17	10%	Black Belt	40	23%
Metallurgy	17	10%	Master Black Belt	22	13%
Chemical	15	9%	Lean/LSS training	25	15%
Machinery and equipment	13	8%	No answer	8	5%
Rubber and plastic products	12	7%			
Celulose and paper	8	5%	**Time of experience (years) with Lean/SS**		
Pharmaceuticals	8	5%	Less than 1	10	6%
Electronics and optical products	7	4%	Between 1 and 2	9	5%
Metal products	5	3%	Between 3 and 5	32	19%
Electrical products	5	3%	Between 6 and 10	57	33%
Maintenance of machinery	5	3%	More than 10	63	37%
Beverage manufacturing	4	2%			
Other transport equipment	3	2%	**Position**		
Textile products	2	1%	Analyst	59	35%
Non-metallic mineral products	1	1%	Manager	36	21%
Other	29	17%	Supervisor	29	17%
			Director	8	5%
Company size			President/CEO	6	4%
Micro (1-19 employees)	9	5%	Engineer	6	4%
Small (20-99 employees)	15	9%	Other	27	16%
Medium (100 – 499 employees)	33	19%			
Large (more than 500)	110	64%	**Department/area**		
No answer	4	2%	Continuous improvement	40	23%
			Projects	33	19%
			Quality	30	18%
			Production	26	15%
			Innovation	4	2%
			Other	38	22%

Table 3.1 shows that 70% of respondents had SS or LSS training and more than five-years' experience in improvement projects. Respondents held different positions, like analysts, supervisors and managers, and worked mainly with continuous improvements (23%). This shows that respondents were qualified to respond to questions on SS structure and data analysis within the company.

3.4 Research instrument and variables

3.4.1 *Variable and research instrument operationalization*

The research instrument was based on multi-item measures, which are more reliable and can better specify the construct domain, making finer distinctions between respondents (Malhotra & Grover, 1998). The construct domain and multi-item measures were defined based on literature on SS and BDA, and measurements were based on existing and validated scales (Malhotra & Grover, 1998). The research instrument was pre-tested with three academics, two industry experts, and three target respondents to receive feedback on questions and scale clarity, as recommended by (Forza, 2002).

The questionnaire was structured into three sections. The first section characterized the companies and respondents. The second section encompassed questions related to BDA and SS constructs, and moderating variables. The third section included statements related to performance. All statements were assessed using a five-point Likert scale, varying from 1 ("strongly disagree") to 5 ("strongly agree"). Respondents were instructed to complete the questionnaire based on current BDA implementation and SS practices, and performance. Appendix A presents these items, constructs, and a brief description on the domain, and references.

3.4.2 *Response bias and common method variance*

Common response sources for dependent and independent variables may cause common method bias (CMB) (Podsakoff et al., 2003). Following recommendations from Podsakoff et al. (2003) for reducing CMB: i) respondents were anonymous; ii) target respondents were knowledgeable on the research topic (SS experts); iii) constructs were based on multi-items and developed based on literature; iv) pre-tests were carried out to improve the questionnaire; an dv) we included an option in the scale measurement for when respondents did not know how to answer a question.

Additionally, to identify whether the final sample suffered from CMB, we conducted Harman's Single Factor Test (Podsakoff et al., 2003), and the test showed that less than 50% of all variance was explained by this single factor, thus ensuring that there was no CMB. The research model is depicted in Figure 3.1.

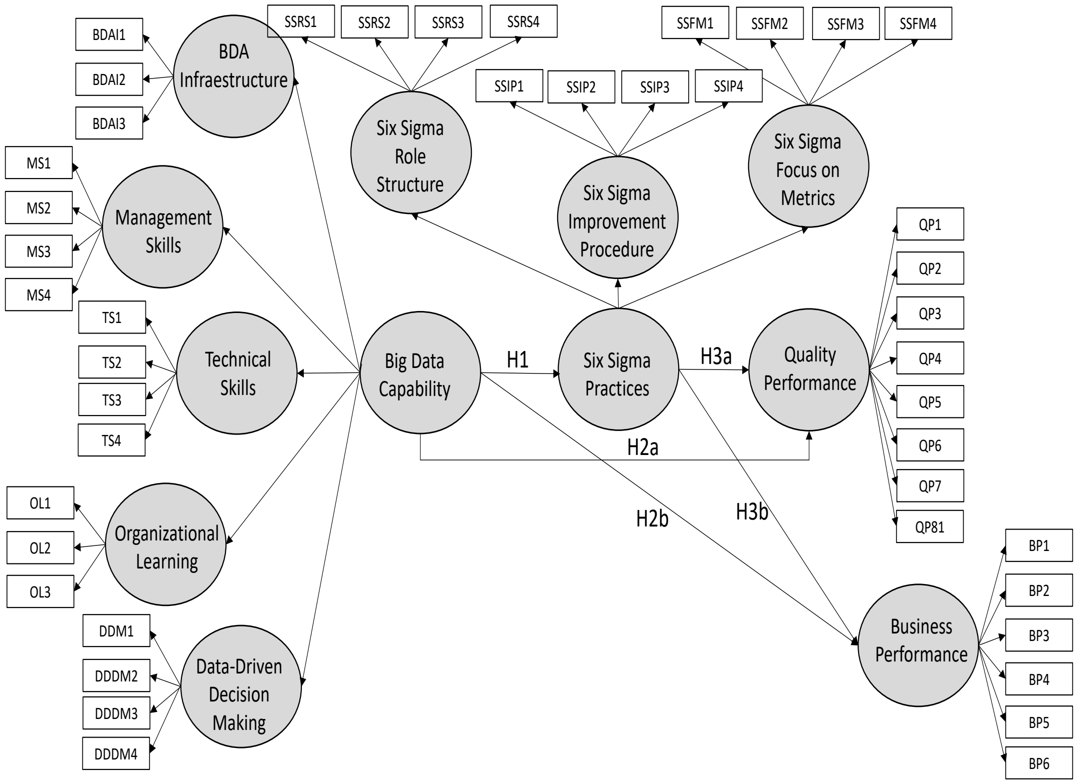


Figure 3.1- The research model.

3.4.3 *Data analysis*

The Partial Least Squares - Structural Equation Modeling (PLS-SEM) method was used to test the research model and hypotheses. Data analysis was supported using the SmartPLS 3.3 software program. PLS-SEM was chosen to deal with the following issues: i) multi-item latent variables; ii) non-parametric measure scales, like ordinal or nominal measurements; iii) complex hierarchical model components; iv) abnormally distributed data (Hair et al., 2014; Hair et al., 2017; Manley et al., 2020).

Although PLS-SEM works with small samples, we verified the adequacy of the sample size using the rule of ten times (minimum sample of 20), using the minimum R-squared method (minimum sample of 88), and the inverse square root method (minimum sample of 60). The final 171 sample was suitable according to all these criteria. The research model is a reflective-reflective hierarchical components model comprising two second-order constructs, BDA and SS practices. Hierarchical model evaluations must consider specific approaches. One adopted in this study was the disjoint two-stage approach (Sarstedt et al., 2019). The same procedures and criteria recommended for measuring models and structuring models in PLS-SEM were applied to assess the results of the disjoint two-stage approach (Sarstedt et al., 2019).

3.5 Results

3.5.1 Measurement model

PLS-SEM method follows a two-step process, assessing the measurement model, and validating the structural model (Hair et al., 2017). As a reflective-reflective model, measurement model analysis followed internal consistency assessments, convergent validity, and discriminant validity (Hair et al., 2020). Reliability and internal consistency are assessed using Cronbach's Alpha (CA) and Composite Reliability (CR) (Hair et al., 2017). CA values varied from 0.881 to 0.966, and CR values ranged from 0.919 to 0.979 (Table 3.2). All CA and CR values were above the 0.70 minimum value (Hair et al., 2017).

Table 3.2 – Convergent validity and reliability results.

Construct	Items	Loadings	CA	CR	AVE	R2
BDA infrastructure (BDAI)	BDAI1	0.924	0.887	0.929	0.815	
	BDAI2	0.870				
	BDAI3	0.913				
Management skills (MS)	MS1	0.890	0.948	0.963	0.866	
	MS2	0.935				
	MS3	0.960				
	MS4	0.937				
Technical skills (TS)	TS1	0.897	0.881	0.919	0.742	
	TS2	0.906				
	TS3	0.905				
	TS4	0.725				
Organizational learning (OL)	OL1	0.970	0.968	0.979	0.940	
	OL2	0.974				
	OL3	0.965				
Data-Driven decision making (DDDM)	DDDM1	0.825	0.882	0.919	0.739	
	DDDM2	0.865				
	DDDM3	0.896				
	DDDM4	0.850				
Six Sigma Role Structure (SSRS)	SSRS1	0.907	0.929	0.950	0.825	
	SSRS2	0.878				
	SSRS3	0.936				
	SSRS4	0.911				
Six Sigma Improvement Procedure (SSIP)	SSIP1	0.869	0.928	0.949	0.823	
	SSIP2	0.934				
	SSIP3	0.941				
	SSIP4	0.882				

Table 3.2 – Convergent validity and reliability results (Continue).

Six Sigma Focus on Mestrics (SSFM)	SSFM1	0.935	0.926	0.948	0.819	
	SSFM2	0.941				
	SSFM3	0.925				
	SSFM4	0.814				
Quality Performance (QP)	QP1	0.900	0.966	0.971	0.810	0.405
	QP2	0.818				
	QP3	0.930				
	QP4	0.904				
	QP5	0.869				
	QP6	0.927				
	QP7	0.913				
	QP8	0.932				
Business Performance (BP)	BF1	0.836	0.934	0.947	0.750	0.233
	BF2	0.811				
	BF3	0.854				
	BF4	0.891				
	BF5	0.936				
	BF6	0.861				
BDA Capability*	BDAI	0.809	0.935	0.951	0.795	
	MS	0.923				
	TS	0.912				
	OL	0.922				
	DDDM	0.888				
Six Sigma Practices*	SSRS	0.920	0.909	0.943	0.847	0.269
	SSIP	0.940				
	SSFM	0.920				

*Construct calculated in the second stage.

Reflective construct convergent validity evaluation encompasses indicator outer loadings (higher than 0.708), statistical significance, and average variance extracted (AVE) (higher than 0.5) (Hair et al., 2017; Hair et al., 2020). Outer loadings for all indicators were statistically significant and higher than 0.708, and all AVE values were above the threshold (Table 3.2). Discriminant validity between constructs was evaluated using the Fornell-Larcker and heterotrait-monotrait ratio (HTMT) for correlation criteria (Hair et al., 2020). The Fornell Larcker and HTMT results are presented in Tables 3.3 and 3.4, respectively. Not all relations are present because the disjoint two-approach does not evaluate higher order and lower order constructs in the same nomological network (Sarstedt et al., 2019). Convergent validity was guaranteed in the measurement model.

Table 3.3 – Fornell-Larcker results.

	BDAI	BP	DDDM	MS	OL	QP	SSIP	SSRS	SSFM	TS	BDAC	SSP
BDA Infrastructure	**0.90**											
Business Peformance	0.31	**0.87**										
Data-Driven Decision Making	0.60	0.36	**0.86**									
Management Skills	0.73	0.38	0.77	**0.93**								
Organizational Learning	0.66	0.35	0.78	0.83	**0.97**							
Quality Peformance	0.35	0.65	0.53	0.45	0.43	**0.90**						
Six Sigma Imp. Procedure	0.39	0.39	0.51	0.43	0.45	0.54	**0.91**					
Six Sigma Role Structure	0.34	0.38	0.41	0.35	0.39	0.51	0.78	**0.91**				
Six Sigma Focus on Metrics	0.37	0.44	0.53	0.43	0.40	0.57	0.81	0.72	**0.90**			
Technical Skills	0.68	0.34	0.76	0.79	0.83	0.48	0.46	0.45	0.42	**0.86**		
BDA Capability*	-	0.39	-	-	-	0.51	-	-	-	-	**0.89**	
Six Sigma Practices*	-	0.44	-	-	-	0.59	-	-	-	-	0.52	**0.92**

In bold AVE
* Construct calculated in the second stage.

Table 3.4 – HTMT results.

	BDAI	BP	DDDM	MS	OL	QP	SSIP	SSRS	SSFM	TS	BDAC	SSP
BDA Infrastructure												
Business Peformance	0.33											
Data-Driven Decision Making	0.68	0.38										
Management Skills	0.79	0.39	0.85									
Organizational Learning	0.70	0.36	0.85	0.86								
Quality Peformance	0.37	0.66	0.57	0.47	0.44							
Six Sigma Imp. Procedure	0.43	0.39	0.56	0.46	0.47	0.57						
Six Sigma Role Structure	0.36	0.39	0.44	0.38	0.41	0.54	0.84					
Six Sigma Focus on Metrics	0.40	0.44	0.57	0.46	0.42	0.59	0.87	0.77				
Technical Skills	0.75	0.36	0.86	0.86	0.89	0.52	0.50	0.49	0.47			
BDA Capability*	-	0.40	-	-	-	0.53	-	-	-	-		
Six Sigma Practices*	-	0.45	-	-	-	0.63	-	-	-	-	0.56	

* Construct calculated in the second stage.

3.5.2 *Structural Model*

The second step in evaluating the model is measuring the model structure. Inner VIF values were used to check the collinearity of the model (Hair et al., 2017). This was satisfied for all endogenous constructs, since values were less than 5.0 (Table 3.4). Other structural model evaluation results are related to significance and relevance for path coefficients, obtained using the bootstrapping method (5000 sub-samples), and the model's predictive capacity, observing the coefficient of determination (R^2), the effect size, and the predictive relevance (Hair et al., 2017; Hair et al., 2020). Table 3.5 shows the results for the hypothesis testing.

Table 3.5 – Hypothesis testing (bootstrapping procedure - 5000 sub-samples).

Hypotheses	VIF	f2	Path (β)	Standard Deviation	p-value	Result
H1: BDA Capability ->Six Sigma Practices	1.00	0.37	0.52	0.07	0.000	Supported
H2a: BDA Capability -> Quality Performance	1.37	0.09	0.28	0.08	0.001	Supported
H3b: BDA Capability -> Business Performance	1.37	0.05	0.22	0.09	0.016	Supported
H3a: Six Sigma Practices-> Quality Performance	1.37	0.25	0.45	0.08	0.000	Supported
H3b: Six Sigma Practices -> Business Performance	1.37	0.10	0.33	0.10	0.001	Supported
BDA Capability -> Quality Performance*	-	-	0.23	0.06	0.000	Supported
BDA Capability -> Business Performance*	-	-	0.17	0.06	0.005	Supported

*Indirect effect.

The results show that there are positive and statistically significant impacts for BDA and SS practices (β = 0.52; p-value = <0.001). This shows that investments in data analysis brings positive results for SS practices, especially improving procedures and focusing on metrics. BDA directly and positively affects QP (β = 0.28; p-value = 0.001), and BP (β = 0.22; p-value = 0.016). SS practices also directly and positively affect QP (β = 0.45; p-value = <0.001), and BP (β = 0.33; p-value = 0.001). In this sense, the intensity with which SS affects QP and BP is higher than for BDA. In the proposed model, SS practices mediate analysis between BDA and performance. Thus, indirect effects show that there is complementary mediation, and indirect and direct effects are significant and have the same direction.

R^2 values measure in-sample predictive power, and R^2 values above 0.26 are high for social sciences (Cohen, 1988; Hair et al., 2017). Table 2 shows that QP variance was highly explained by exogenous constructs (R^2 =0.405) in this study, and slightly smaller predictive effects were observed for BP (R^2 =0.233), and SS practices (R^2 =0.269). Table 6 shows that BDA has a large effect ($f2$=0.37) on SS practices, and SS has a substantial impact on QP ($f2$=0.25), while BDA has a small effect on QP and BP. To assess the statistical model's predictive power, we followed steps proposed by (Shmueli et al., 2019). $Q^2_{predict}$ values were larger than 0, and values generated by the PLS-SEM analysis were less than the values generated by the linear regression model using mean absolute error (MAE), for most indicators. This suggests that the model has medium predictive power (Shmueli et al., 2019).

3.5.3 *Moderating Effects*

The moderating variables were company size, DMAIC and BDA integration, and I4.0 technologies (Figure 3.2). The first variable is binary (large-, small-, or medium-sized companies). The moderating effect results were obtained using multigroup analysis, as indicated by Sarstedt et al. (2011), and Hair et al. (2017). For the multigroup analysis, we assessed configural invariance and compositional invariance using the MICOM procedure (Henseler et al., 2016; Hair et al., 2018). No group showed a difference in path coefficients (all p-values>0.05) (Table 3.6), i.e., size did not impact the relationships.

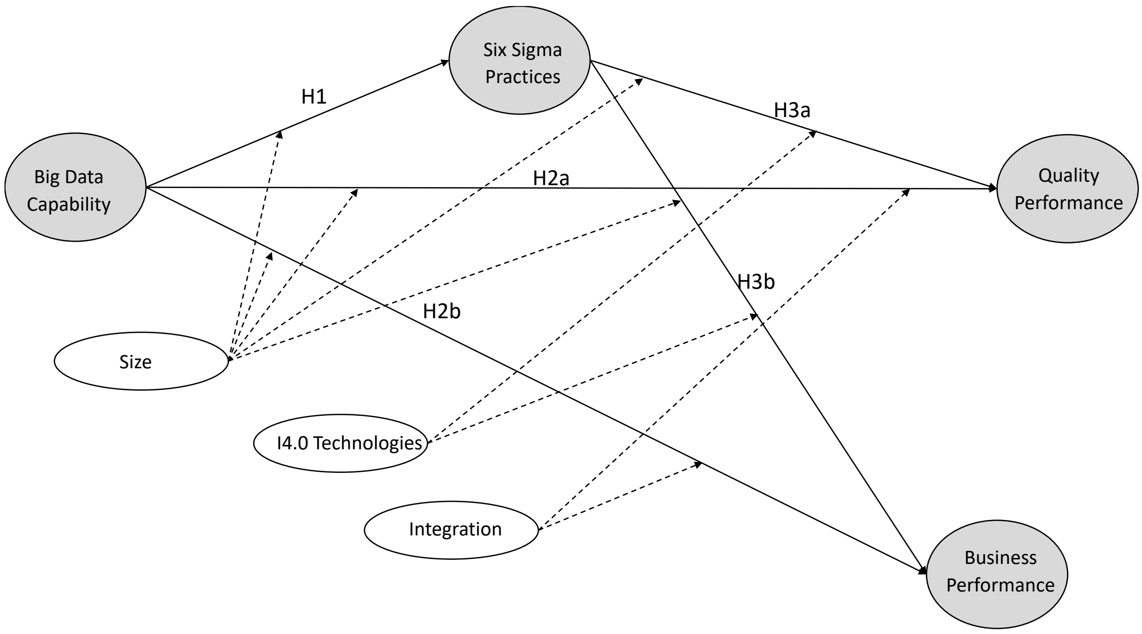


Figure 3.2 - Research model with moderating variables.

Table 3.6 – Difference of the path coefficients between size (permutation test - 2000 permutations).

Hypotheses	Path Coefficients (β) Group 1	Group2	p-value	Difference
H1: BDA Capability -> Six Sigma Practices	0.472	0.485	0.937	Not Supported
H2a: BDA Capability -> Quality Performance	0.315	0.254	0.773	Not Supported
H2b: BDA Capability -> Business Performance	0.307	0.223	0.723	Not Supported
H3a: Six Sigma Practices-> Quality Performance	0.470	0.412	0.781	Not Supported
H3b: Six Sigma Practices -> Business Performance	0.335	0.286	0.832	Not Supported

*Group 1= Micro, small and medium companies (n=57); Group 2 = Large companies (n=110)

The second and third moderating variables were multiple-item categorical constructs presented in Appendix A. These moderating variables meet all relevant criteria in terms of internal consistency reliability, convergent validity, and discriminant validity, as recommended by (Hair et al., 2017). The moderating variable effect results for integration and I4.0 technologies are presented in Table 3.7.

Table 3.7 – Moderating variables Integration and Technologies of I4.0

Hypothesis	*Path coefficients*	*p-value*	Result
Moderator - Integration between BDA and DMAIC			
Integration*BDA Capability à Business Performance	0.072	0.381	Not Supported
Integration*BDA Capability àQuality Performance	0.135	0.049	Supported
Moderator - I4.0 Technologies			
I4.0 Technologies*Six Sigma -> Business Performance	-0.079	0.302	Not Supported
I4.0 Technologies*Six Sigma -> Quality Performance	0.096	0.202	Not Supported

The results show that DMAIC and BDA integration positively influences BDA and QP, and integration can help reduce product and process problems (Figure 3). I4.0 technology effects were not statistically significant. In other Words, using more sensors, IoT, and/or other technologies did not influence SS, QP or BP relationships.

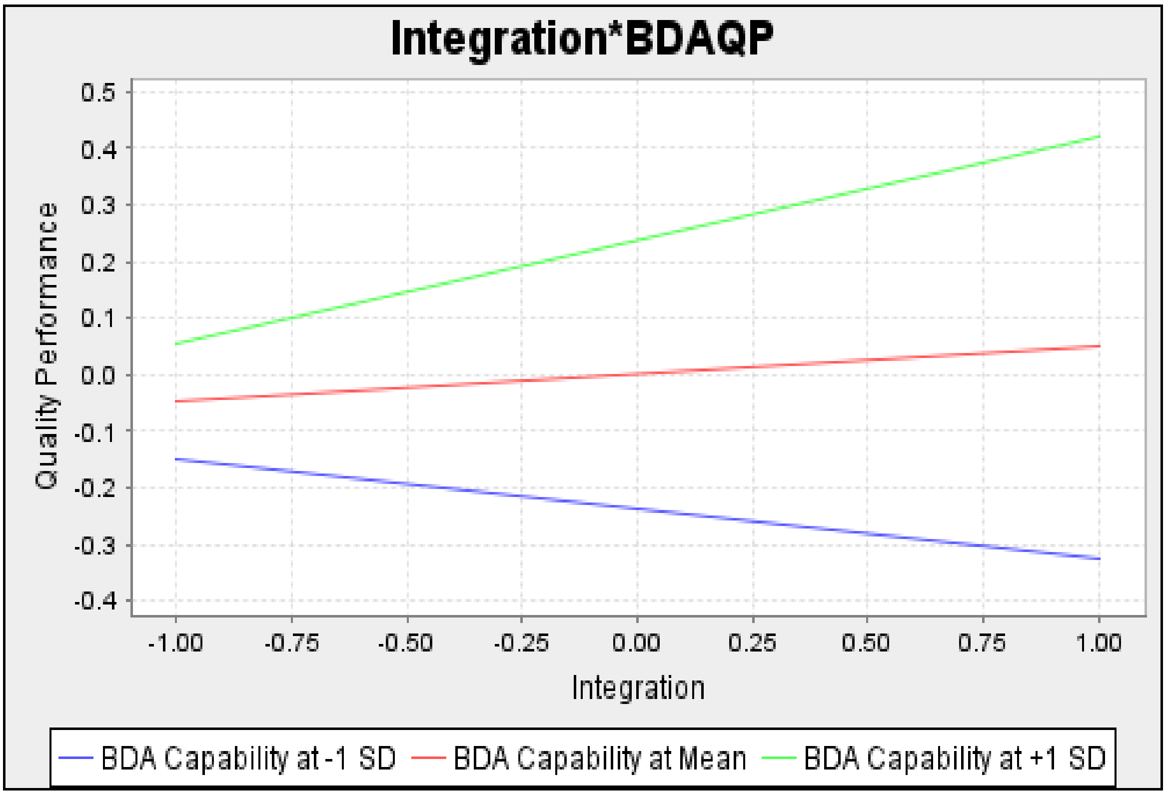


Figure 3.3 - Integration moderator effect.

3.6 Discussion

3.6.1 *Summary of the findings*

This study investigated the effects of BDA and SS practices on QP and BP, and the effects of moderating variables like company size, DMAIC and Big Data integration, and I4.0 technologies. The findings show that all hypothesized relationships in the proposed model are supported. The results also show that neither company size nor I4.0 technologies affected the conceptual model relationships. We identified a positive moderating effect for SS and Big Data integration in improving BDA and QP relationships.

3.6.2 *Theoretical contributions*

This study offers key theoretical contributions. First, our study advances empirical understandings on BDA and relationships between BDA, QP and BP, since these relationships are still not fully understood (Rialti et al., 2019). This study empirically confirms that BDA positively impacts QP, showing that physical, organizational, and human structures improve quality problem analysis, and decision-making processes, improving performance quality for products and processes, in addition to improving customer satisfaction. These results reinforce insights from previous studies (e.g., Wamba et al., 2017; 2019; Mishra & Rane, 2019), and fill several gaps on using data science to improve process efficiency and reduce defective products (Clancy et al., 2019). This study also confirms that increased Big Data use generates outcomes related to company performance and improvements (Rialti et al., 2019; Akter et al., 2016), in the form of cost reductions, increased revenue, profits, and returns on investments.

Second, this study confirms empirical evidence from literature (e.g., Antony et al. 2017; Antony et al., 2019), that SS practices positively affect QP and BP. This was confirmed for a developing country, where challenges related to employee education (Tortorella et al., 2018), lack of financial resources (Erro-Garces & Aranaz Nunes, 2020), and lower adoption rates for improvement methodologies (Yadav et al., 2020a), may exist.

Third, the main findings show that there is a positive and statistically significant impact from using BDA in SS practices, corroborating other studies (e.g., Belhadi et al., 2020). BDA helps identify problems, processes, and areas that need improvement, using infrastructure that supports data analysis (Dogan & Gurcan, 2018; Koppel & Chang, 2020), supporting SS metric focused practices. BDA helps in DMAIC phases and tools, and in structurally planning and executing projects, in line with assumptions presented by other authors (Chiarini & Kumar, 2020; Tay & Loh, 2021). BDA also reinforces the SS hierarchical structure, by promoting better decision making, and using large datasets in trainings (Chiarini & Kumar, 2020; Tay & Loh, 2021), thereby increasing competencies. Additionally, this study confirms that impacts on QP and BP are reinforced by SS practices. Therefore, SS approaches and BDA integration confirms benefits highlighted by several authors (e.g., Antony & Sony, 2019; Gupta et al., 2020; Rejikumar et al. 2020), like fewer human errors during data collection, better identifying opportunities outside the SS team domain, better decision making, simultaneously monitoring several variables, and including advanced analytical approaches (Laux et al., 2017; Arcidiacono & Pieroni, 2018; Belhadi et al., 2019).

Fourth, moderating variables showed that firm size does not affect these relationships, despite being associated with better BDA development (Wamba et al., 2019). Although literature presents evidence for this relationship between SS and several I4.0 technologies (Arcidiacono & Pieroni, 2018; Chiarini & Kumar, 2020; Vinodh et al., 2020), these did not affect relationships between BDA, QP and BP within Brazilian organizations. This may be due to not very widespread or integrated I4.0 technology use in the companies studied. This study more concretely confirmed that BDA tool and DMAIC phase integration allows for better structured DMAIC, and better project results (Antony et al., 2018; Dogan & Gurcan, 2018; Gupta et al., 2020), confirmed given the positive moderating effect of BDA and QP relationships.

3.6.3 *Managerial implications*

Our findings can guide managers and experts involved in implementing BDA and SS in manufacturing companies. First, this research model shows that BDA can be reinforced to achieve better performance results. Understanding these factors gives a broader and deeper vision of BDA. Second, these findings also show that BDA and SS are complementary, reinforced by SS practices by strengthening BDA, and in turn SS reinforces BDA impacts on QP and BP, generating competitive advantages. Third, the results do not depend on company size, indicating that SS managers should encourage SS and BDA integration in different contexts. Fourth, reinforced DMAIC and BDA integration can enrich traditional data analytics tools, and extend data sources, resulting in more assertive decision-making. In other words, this shows practitioners that they should incorporate Big Data and analytics in DMAIC phases, and direct SS tools to adapt to this new context.

3.7 Conclusions

Although SS is a data driven methodology and Big Data, and BDA have gained strength recently, doubts exist about whether there is a positive relationship between them. This study shows that BDA relationships are beneficial to SS practices, and that there are many opportunities for exploring both research and practitioners. Additionally, this study shows that not only BDA and SS reinforce each other, but that when used together they positively impact QP and BP.

This study was limited with respect to the adopted research approach. Data were obtained via an email survey questionnaire, and this may have resulted in a lack of control over the respondents. Data were collected only for Brazilian companies, where it may be difficult to implement BDA approaches. It is important to explore whether the findings reported in this study are the same for companies in other countries, with different degrees of development. Future research could include different methodologies, like longitudinal cases, to develop a deeper understanding of causalities behind the findings reported in this paper. Lastly, studies focusing on specific industry relationships would be interesting to determine if results vary according to industrial sector.

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Appendix A

Constructs, variables, and references

Construct	Description	Item	Code	Authors
BDA infrastructure (BDAI)	BDA infrastructure involves tools, physical and software systems to collect, process and analyze data	Our company is in the process of implementing or implemented BDA enabler architecture	BDAI1	Akter et al. (2016); Shamim et al. (2019); Singh and Singh (2019); Rialti et al. (2019) and Belhadi et al. (2020)
		Our company is in the process of implementing or implemented data driven sensors	BDAI2	
		Our big data management infrastructure is flexible	BDAI3	
Management skills (MS)	MS are responsible of the management of operations for better decision making; ensure coordination between all components of BDA structure	Managers of our company can interpret the outputs of BDA which are useful for swift decision making	MS1	Akter, et al. (2016); Gupta and George (2016); Shamim et al. (2019); Rialti et al. (2019) and Belhadi et al. (2020)
		Our managers have a good sense of where to adopt BDA	MS2	
		Managers in our company understand the implications of BDA outcomes	MS3	
		Our managers encourage BDA decision making	MS4	
Technical skills (TS)	TS facilitate the implementation of BDA and improve its processes. TS development requires hiring skilled people on BDA and employee involvement.	We possess skilled people in the latest technologies of BDA	TS1	Kim et al. (2012); Gupta and George (2016); Akter, et al. (2016); Wamba et a. (2017); Singh and Singh (2019); Dubey et al. (2019); Rialti et al (2019) and Belhadi et al. (2020)
		Our company hires high-skilled people on BDA	TS2	
		Our company have a plan to improve the technical skills of employees	TS3	
		The technical skills make it easy for us to analyze data	TS4	
Organizational learning (OL)	OL allows sharing BDA knowledge and feedbacks within the company	BDA Knowledge is shared within the company	OL1	Akter et al. (2016); Gupta and George (2016); Dubey et al. (2019) and Belhadi et al. (2020)
		Our employees transfer their knowledge about BDA	OL2	
		Feedback of employees about BDA is systematically considered	OL3	
Data-Driven decision making (DDDM)	Data-driven processes involve collecting data based on measurable insights and datasets for making better development strategies and	Our company consider data as an asset	DDDM1	Gupta and George (2016); Laux et al. (2017); Shamim et al. (2019);
		Our employees base most decisions on data rather than instinct	DDDM2	
		Our management assess strategies and take corrective action based on the insights obtained from data	DDDM3	

	enhance data analysis accuracy	Decision-making based on BDA is part of our organizational culture	DDDM4	Belhadi et al. (2019); Dubey et al. (2019); Rialti et al. (2019); Gupta et al. (2020); Bhat et al. (2021) and Tay and Loh (2021)
Six Sigma Role Structure (SSRS)	The organization uses improvement specialists who are developed through Six Sigma training and who have specific leadership roles and responsibilities in improvement teams	We use a black/green belt role structure (or equivalent structure) to prepare and deploy individual workers for continuous improvement programs	SSRS1	Zu et al. (2008); Zu et al. (2010); Sin et al. (2015); Lamine and Lakhal (2018); and Costa et al. (2020)
		In our plant, members of improvement teams have their roles and responsibilities specifically identified	SSRS2	
		The black/green belt role structure (or equivalent structure) helps our plant to recognize the depth of workers' training and experience	SSRS3	
		Our plant uses differentiated training so that workers who have different roles in the black/green belt role structure (or equivalent structure) can obtain the necessary knowledge and skills to fulfill their job responsibilities	SSRS4	
Six Sigma Improvement Procedure (SSIP)	The organization follows a standardized procedure in planning and conducting improvement projects and uses appropriate Quality Management tools in each step	In our plant, continuous improvement projects are conducted by following a formalized procedure (such as DMAIC-Define, Measure, Analyze, Improve and Control).	SSIP1	Zu et al. (2008); Zu et al. (2010); Sin et al. (2015); Lamine and Lakhal (2018); and Costa et al. (2020)
		We use a structured approach to manage quality improvement activities	SSIP2	
		We have a formal planning process to decide the major quality improvement projects	SSIP3	
		All improvement projects are reviewed regularly during the process	SSIP4	
Six Sigma Focus on Mestrics (SSFM)	The organization uses metrics to measure performance, and to set improvement goals	Our plant uses metrics to set strategic goals for quality improvement in order to improve plant financial performance	SSFM1	Zu et al. (2008); Zu et al. (2010); Lamine and Lakhal (2018); and Costa et al. (2020)
		Merics are used to link quality performance to strategic goals	SSFM2	
		Financial performance (e.g., cost savings, sales) is part of the criteria for evaluating the outcomes of quality improvements in our plant	SSFM3	
		Our plant systematically uses a set of measures (such as defects per million opportunities, sigma level, process capability indices, defects per unit, and yield) to evaluate performance	SSFM4	
		The quality of the organization's services and products has increased	QP1	

Quality Performance (QP)	Impact on the organization's performance measured through the quality of products and processes	The variability of the organization's process has decreased	QP2	Zu et al. (2008); Sreedharan et al. (2016); Tlapa et al. (2016); Patyal et al. (2017); Costa et al. (2020); García-Alcaraz et al. (2020) and Ben Ruben et al. (2020)
		The delivery of the company's products and services has become more reliable	QP3	
		The cost of losses and rework (as a percentage (%) of sales) in the organization has decreased	QP4	
		Production lead time decreased in the organization	QP5	
		Customer satisfaction with the quality of products and services increased	QP6	
		Machine uptime has increased in the organization	QP7	
		The rate of product and process defects has decreased in the organization	QP8	
Business Performance (BP)	Impact on the organization's performance measured through financial and business profitability indicators	The organization's sales (and its revenue) increased	BF1	Zu et al. (2008); Habidin e Yusof (2012); Shereederan et al (2016); Tlapa et al. (2016); Patyal et al. (2017); Costa et al. (2020) and García-Alcaraz et al. (2020)
		The organization's market share (Market share) grew	BF2	
		The unit cost of manufacturing decreased by the organization	BF3	
		The organization's profits increased	BF4	
		The return on investments increased in the organization	BF5	
		Process efficiency increased in the organization	BF6	
Integration between DMAIC and BDA (INT)	The integration of Big Data Analytics with Six Sigma methods and tools helps decision making in all phases of DMAIC	In our company, Big Data allows the expansion of existing data for use in the Definition phase	INT1	Forgaty (2015); Laux et al. (2017); Arcidiacono e Pieroni (2018); Antony et al. (2018); Dogan e Gurcan (2018); Belhadi et al. (2020); Gupta et al. (2020); Fahey et al. (2020); Tay and Loh (2021); Chiarini and Kumar (2020) and Clancy et al. (2021)
		In our company, the integration of Big Data with Six Sigma methods and tools helps decision making in the Definition phase	INT2	
		In our company, Big Data provides more data for the Measure phase	INT3	
		In our company, the integration of Big Data with Six Sigma methods and tools helps decision making in the Measurement phase	INT4	
		In our company, the use of Big Data enriches the analytical tools for decisions in the Analysis phase	INT5	
		In our company, the use of Big Data extends data sources for decisions in the Analysis phase	INT6	

		In our company, the use of Big Data makes it possible to identify ideas and suggestions for innovation beyond the domain of the Six Sigma team, generating better and more efficient solutions	INT7	
		In our company, the integration of Big Data with Six Sigma methods and tools helps decision making in the Improvement phase	INT8	
		The integration of Big Data with Six Sigma methods and tools helps decision making in the Control phase	INT9	
		In our company, the use of Big Data and Analytics tools enable the automated monitoring of several variables simultaneously in the Control phase	INT10	
I4.0 Technologies (TEC)	Adoption and use by the company of tools that cover the scope of I4.0	The organization is implementing / using Internet of Things	TEC1	Tortorella et al. (2018, 2019a, 2019b)
		The organization is implementing / using sensors for identifying conditions for production	TEC2	
		The organization is implementing/using production equipment with digital interface or sensors	TEC3	
		The organization is implementing/using additive Manufacturing, rapid prototyping or 3D	TEC4	
		The organization is implementing/using Augmented Reality	TEC5	
		The organization is implementing/using Artificial Intelligence	TEC6	
		The organization is implementing/using Cloud Computing System (Cloud Computing)	TEC7	

Appendix B

Online Google Forms.

Apresentação

Eu, Daniele Maia, mestranda vinculada ao Programa de Pós Graduação de Engenharia de Produção (PPGEP) da Universidade Federal de São Carlos (UFSCar), convido você para participar da pesquisa intitulada “Uso do Big Data no contexto Six Sigma: impactos nas organizações de manufatura”, desenvolvida sob a orientação da Profa. Dra. Fabiane Letícia Lizarelli (fabiane@dep.ufscar.br).

O objetivo da pesquisa é identificar se as organizações estão utilizando grandes conjuntos de dados para apoiar as decisões de projetos Seis Sigma e quais impactos essa utilização gera. Para isso, será avaliado o grau de adoção das capacidades de análise de Big Data, o uso desses dados para a tomada de decisão no DMAIC e o impacto da adoção nas empresas de manufatura.

Os dados serão utilizados de forma agregada, não sendo possível a identificação de nenhum respondente. O respondente não precisa se identificar e não há resposta correta ou errada. Se houver interesse, um relatório executivo será enviado para o respondente no final da pesquisa, caso deixe seu contato no final do questionário (opcional).

O tempo médio para a resposta é de 15 minutos.

Sua resposta fortalece a pesquisa no Brasil e pretende apoiar a tomada de decisões de gestores Green e Black Belts no país.

No caso de dúvidas ou sugestões, por favor, contate danieledrpmaia@gmail.com

Seção A - Caracterização da Organização e do Respondente

2.1 Por favor, classifique o setor que a empresa atua (utilizamos o CNAE para a classificação).
É possível selecionar mais de uma opção

- ☐ Fabricação de produtos alimentícios Fabricação de bebidas
- ☐ Fabricação de produtos do fumo
- ☐ Fabricação de produtos têxteis (fiação, tecidos, artefatos têxteis, entre outros)
- ☐ Confecção de artigos do vestuário e acessórios
- ☐ Preparação de couros e fabricação de artefatos de couro, artigos para viagem e calçados
- ☐ Fabricação de produtos de madeira Fabricação de celulose, papel e produtos de papel
- ☐ Fabricação de coque, de produtos derivados do petróleo e de biocombustíveis
- ☐ Fabricação de produtos químicos
- ☐ Fabricação de produtos farmoquímicos e farmacêuticos
- ☐ Fabricação de produtos de borracha e de material plástico
- ☐ Fabricação de produtos de minerais não-metálicos (vidro, cimento, concreto, gesso, cerâmicos)
- ☐ Metalurgia
- ☐ Fabricação de produtos de metal, exceto máquinas e equipamentos (caldeiras, material metálico, equipamento bélico, entre outros)
- ☐ Fabricação de equipamentos de informática, produtos eletrônicos e ópticos
- ☐ Fabricação de máquinas, aparelhos e materiais elétricos
- ☐ Fabricação de máquinas e equipamentos
- ☐ Fabricação de veículos automotores, reboques e carrocerias
- ☐ Fabricação de outros equipamentos de transporte, exceto veículos automotores (aeronaves, embarcações, veículos ferroviários, entre outros)
- ☐ Fabricação de móveis
- ☐ Manutenção, reparação e instalação de máquinas e equipamentos
- ☐ Outro:

2.2 Por favor, indique se a empresa é Nacional ou Multinacional

- ☐ Nacional
- ☐ Multinacional
- ☐ Não sei avaliar
- ☐ Outro:

2.3 Por favor, indique o número de empregados que a empresa possui atualmente

- ☐ 1 - 19
- ☐ 20 - 99
- ☐ 100 - 499
- ☐ > 500

☐ Não sei avaliar

2.4 Qual é seu cargo atual na empresa?

☐ Presidente/CEO
☐ Diretor
☐ Gerente
☐ Supervisor
☐ Analista
☐ Não quero responder
☐ Outro:

2.5 Qual o departamento que você trabalha?

☐ Qualidade
☐ Produção
☐ Trabalho com melhoria de processos em outras áreas
☐ Não quero responder
☐ Outro:

2.6 Sobre sua experiência

A quanto tempo você trabalha para esta empresa

☐ Menos de um ano
☐ Entre 1 e 2 anos
☐ Entre 3 e 5 anos
☐ Entre 6 e 10 anos
☐ Não quero responder

Quantos anos de experiência você tem em projetos de melhoria de processos de negócios (nesta ou outras empresas)?

☐ Menos de um ano
☐ Entre 1 e 2 anos
☐ Entre 3 e 5 anos
☐ Entre 6 e 10 anos
☐ Não quero responder

Programas de Melhoria

2.7 Sobre sua experiência com Programas de Melhoria

☐ Possui Treinamento em Lean/Lean Six Sigma
☐ Sou White Belt- GB
☐ Sou Green Belt - GB
☐ Sou Black Belt - BB

□ Sou Master Black Belt - MBB
□ Não quero responder
□ Outro:

2.8 Por favor, indique em qual nível a empresa implanta os seguintes programas para aumentar o desempenho operacional	Nenhuma Implantação	Pouca Implantação	Alguma implantação	Implantação extensiva	Implantação completa
Gestão da Qualidade Total (TQM)	□	□	□	□	□
Programas de Excelência (por exemplo, PNQ)	□	□	□	□	□
Melhoria Contínua/Kaizen	□	□	□	□	□
Six Sigma	□	□	□	□	□
Lean Management	□	□	□	□	□
Lean Seis Sigma	□	□	□	□	□

2.9 Por favor, indique se a empresa possui alguma das seguintes certificações

□ ISO 9001
□ ISO 14001
□ OHSAS 18001
□ Nenhuma certificação
□ Não sei responder
□ Outro:

Seção B: Capacidade de Análise de Big Data

3.1 Por favor, indique em que grau concorda com as afirmações abaixo em relação à implantação do Big Data em sua empresa.	Discordo fortemente	Discordo	Não concordo nem discordo	Concordo	Concordo fortemente
Nossa empresa está em processo ou implementou uma arquitetura de dados para Big Data Analytics (p.ex., Hadoop, NoSQL)	□	□	□	□	□
Nossa empresa está em processo ou implementou sensores para captação de dados	□	□	□	□	□
Nossa infraestrutura de gerenciamento de big data é flexível para aceitar diversos tipos de dados e de diferentes fontes (p.ex., sensores, sistemas inteligentes)	□	□	□	□	□
Nossa empresa atualmente utiliza novas formas de sistemas de banco de dados distribuídos (p.ex., NoSQL ou Cassandra	□	□	□	□	□
Nossa empresa investe em software de análise de Big Data (p.ex., SAS Enterprise, Miner, Tableau)	□	□	□	□	□
Nossa empresa investe em processos que garantem a disponibilidade de dados de alta qualidade e adequados para os colaboradores	□	□	□	□	□

Os gestores de nossa empresa podem interpretar os resultados da análise de Big Data, que são úteis para uma tomada de decisão rápida	□	□	□	□	□
Nossos Gestores tem uma boa noção de onde adotar o Big Data Analiyics	□	□	□	□	□
Os gestores em nossa empresa entendem as implicações dos resultados do Big Data Analytics	□	□	□	□	□
Nossos gestores incentivam a tomada de decisão baseada em Big Data Analytics	□	□	□	□	□
Possuímos pessoal especializado e certificado nas mais recentes tecnologias para análise de Big Data	□	□	□	□	□
Nossa empresa contrata pessoal altamente qualificado em Big Data Analytics	□	□	□	□	□
Nossa empresa possui um plano para aprimorar a qualificação técnica e o número de colaboradores com qualificação em Big Data Analytics	□	□	□	□	□
As habilidades técnicas tornam mais fácil para nós analisarmos os grandes conjuntos de dados	□	□	□	□	□
O conhecimento sobre Big Data Analytics é compartilhado dentro da empresa	□	□	□	□	□
Nossos colaboradores compartilham seus conhecimentos sobre Big Data Analytics	□	□	□	□	□
O feedback dos colaboradores sobre Big Data Analytics é considerado sistematicamente	□	□	□	□	□
Nossa empresa investe na documentação de processos e procedimentos para análise de Big Data	□	□	□	□	□
Nossa empresa considera os dados um ativo	□	□	□	□	□
Nossos funcionários baseiam a maioria das decisões em dados, e não no instinto	□	□	□	□	□
Nossa empresa tem recursos gerenciais para tomar ações sobre insights derivados de análises de Big Data	□	□	□	□	□
Nossa gestão mensura resultados estratégicos e toma medidas corretivas com base nos insights obtidos a partir dos dados	□	□	□	□	□
A tomada de decisões com base no Big Data Analytics faz parte da nossa cultura organizacional	□	□	□	□	□
Nossa empresa incentiva os funcionários a aproveitarem suas habilidades analíticas de big data para resolver problemas	□	□	□	□	□
Seção C: Implantação do Seis Sigma					

4.1 Por favor, indique em que grau concorda com as afirmações abaixo em relação à implantação do Lean Six Sigma/Six Sigma em sua empresa	Discordo fortemente	Discordo	Não concordo nem discordo	Concordo	Concordo fortemente
Usamos uma estrutura de funções de Black/Green Belt (ou equivalente) para preparar e alocar trabalhadores individuais para programas de melhoria contínua.	□	□	□	□	□
Em nossa empresa, os membros das equipes de melhoria têm suas funções e responsabilidades especificamente identificadas	□	□	□	□	□
A estrutura de funções Black/Green Belt (ou equivalente) ajuda nossa empresa a identificar as especificidades de habilidades, treinamento e experiência dos trabalhadores	□	□	□	□	□
Nossa empresa usa treinamento diferenciado para que os trabalhadores com papéis específicos na estrutura Black/Green Belt (ou equivalente) possam obter o conhecimento e as habilidades necessárias para cumprir suas responsabilidades de trabalho	□	□	□	□	□
Em nossa empresa, o papel na estrutura Black/Green Belt (ou equivalente) é considerado ao tomar decisões de remuneração e promoção	□	□	□	□	□
Em nossa empresa, os projetos de melhoria contínua são conduzidos seguindo um procedimento formalizado (como DMAIC - Define, Measure, Analyze, Improve and Control)	□	□	□	□	□
Usamos uma abordagem estruturada para gerenciar as atividades de melhoria da qualidade	□	□	□	□	□
Temos um processo de planejamento formal para decidir os principais projetos de melhoria da qualidade	□	□	□	□	□
Todos os projetos de melhoria são revisados regularmente durante o processo de melhoria	□	□	□	□	□
Nós mantemos registros sobre como cada projeto de melhoria contínua é conduzido	□	□	□	□	□
Nossa empresa usa métricas para definir os objetivos estratégicos para melhoria da qualidade, a fim de melhorar o desempenho financeiro da empresa	□	□	□	□	□
As métricas são usadas para vincular o desempenho da qualidade aos objetivos estratégicos	□	□	□	□	□
O desempenho financeiro (por exemplo, economia de custos, vendas) faz parte dos critérios para avaliar os resultados das melhorias de qualidade em nossa empresa	□	□	□	□	□

Nossa empresa usa sistematicamente um conjunto de medidas (como defeitos por milhão de oportunidades, nível sigma, índices de capacidade do processo, defeitos por unidade e rendimento) para avaliar o desempenho	□	□	□	□	□
Nossa empresa traduz as necessidades e expectativas dos clientes em metas de qualidade	□	□	□	□	□
Seção D: Análise de Big Data em DMAIC					
5.1 Por favor, indique em que grau concorda com as afirmações abaixo em relação a adoção da análise de Big Data em conjunto com o Lean Six Sigma/Six Sigma	Discordo fortemente	Discordo	Não concordo nem discordo	Concordo	Concordo fortemente
Na nossa empresa, o Big Data permite a ampliação dos dados existentes para uso a fase de Definição	□	□	□	□	□
Na nossa empresa, o Big Data permite aumento da capacidade de mineração de dados, impactando a fase de Definição	□	□	□	□	□
Na nossa empresa, o Big Data auxilia na disponibilidade de dados estruturados e não estruturados para análise e definição do problema	□	□	□	□	□
Na nossa empresa, a integração do Big Data com os métodos e ferramentas Seis Sigma auxilia a tomada de decisão na fase de Definição	□	□	□	□	□
Na nossa empresa, o Big Data auxilia na aceleração da coleta de dados para a fase de Medição	□	□	□	□	□
Na nossa empresa, o Big Data auxilia na exclusão de erro humano durante a coleta de dados para a fase de Medição	□	□	□	□	□
Na nossa empresa, o Big Data fornece maior quantidade de dados para a fase de Medição	□	□	□	□	□
Na nossa empresa, a integração do Big Data com os métodos e ferramentas Seis Sigma auxilia a tomada de decisão na fase de Medição	□	□	□	□	□
Na nossa empresa, o Big Data permite a análise de possíveis causas e relações de causa e efeito para solução de problemas na fase de Análise	□	□	□	□	□
Na nossa empresa, o uso de Big Data enriquece as ferramentas analíticas para as decisões na fase de Análise	□	□	□	□	□
Na nossa empresa, o uso de Big Data amplia fontes de dados para as decisões na fase de Análise	□	□	□	□	□
Na nossa empresa, a integração do Big Data com os métodos e ferramentas Seis Sigma auxilia a tomada de decisão na fase de Análise	□	□	□	□	□

Na nossa empresa, o uso de Big Data possibilita identificar ideias e sugestões de inovação além do domínio da equipe de Seis Sigma, gerando melhores soluções e mais eficientes	□	□	□	□	□
Na nossa empresa, a integração do Big Data com os métodos e ferramentas Seis Sigma auxilia a tomada de decisão na fase de Melhoria	□	□	□	□	□
A integração do Big Data com os métodos e as ferramentas Seis Sigma auxiliam a tomada de decisão na fase de Controle	□	□	□	□	□
Na nossa empresa, o uso de Big Data permite um maior número de medições de desempenho, possibilitando reações mais rápidas e focadas para a fase de Controle	□	□	□	□	□
Na nossa empresa, o uso de Big Data facilita o monitoramento Critical to Quality (CTQ) na fase de Controle	□	□	□	□	□
Na nossa empresa, o uso de Big Data e ferramentas de Analytics possibilitam o monitoramento automatizado de diversas variáveis simultaneamente na fase de Controle	□	□	□	□	□
Na nossa empresa, o uso de Big Data pode melhorar o monitoramento do fluxo de dados na fase de Controle	□	□	□	□	□
Na nossa empresa, o uso de Big Data pode auxiliar no monitoramento estatístico do processo na fase de controle	□	□	□	□	□

Seção E - Desempenho da qualidade e desempenho do Negócio

6.1 Por favor, indique em que grau concorda com as afirmações abaixo para a sua empresa em relação ao Desempenho da Qualidade	Discordo fortemente	Discordo	Não concordo nem discordo	Concordo	Concordo fortemente
A qualidade dos serviços e produtos da organização aumentou	□	□	□	□	□
A variabilidade do processo da organização diminuiu	□	□	□	□	□
A entrega de produtos e serviços da empresa se tornou mais confiável	□	□	□	□	□
O custo de perdas e retrabalho (em relação a porcentagem (%) das vendas) na organização diminuiu	□	□	□	□	□
O lead time de produção diminuiu na organização	□	□	□	□	□
A satisfação do cliente com a qualidade dos produtos e serviços aumentou	□	□	□	□	□
O tempo de disponibilidade de máquina aumentou na organização	□	□	□	□	□
A taxa de defeitos de produtos e em processos diminuiu na organização	□	□	□	□	□

6.2 Por favor, indique em que grau concorda com as afirmações abaixo para a sua empresa em relação ao Desempenho do Negócio	Discordo fortemente	Discordo	Não concordo nem discordo	Concordo	Concordo fortemente
As vendas (e sua receita) da sua organização aumentaram	□	□	□	□	□

A participação de mercado (Market Share) da sua organização cresceu	□	□	□	□	□
O custo unitário de fabricação diminuiu em sua organização	□	□	□	□	□
Os lucros da sua organização aumentaram	□	□	□	□	□
O retorno sobre os investimentos aumentou na sua organização	□	□	□	□	□
A eficiência do processo aumentou em sua organização	□	□	□	□	□
Seção F: Outras tecnologias					
7.1 Por favor, indique em qual nível a empresa implanta as seguintes tecnologias	Discordo fortemente	Discordo	Não concordo nem discordo	Concordo	Concordo fortemente
Internet of Things (IoT)	□	□	□	□	□
Sensores para identificação de condições para a produção	□	□	□	□	□
Equipamentos de produção com interface digital ou sensores	□	□	□	□	□
Manufatura Aditiva, prototipagem rápida ou 3D	□	□	□	□	□
Realidade aumentada (Augmented Reality)	□	□	□	□	□
Inteligência Artificial	□	□	□	□	□
Sistema de Computação em Nuvem (Cloud Computing)	□	□	□	□	□

https://docs.google.com/forms/d/1AZR-lRthJ1NZMaArEgcq2gytmYkFiEDTK7yam959FF8/edit

4 CONCLUSION OF THIS RESEARCH

This chapter presents the main contributions of this study, theoretical contributions and managerial implications, limitations and suggestions for new directions for future research on the subject.

4.1 Research contributions

To achieve the study goals, the research was developed in two stages, represented here by two distinct articles. Firstly, a SLR was carried out in order to identify existing research on the relationships of I4.0 technologies and SS methodology, such as the main forms of support in this context. Results show a growing trend of publications on the topic, and researchers' interest. As I4.0 becomes more evident and applied by organizations, research into the relationship with SS increases.

The main findings point to the relationship of I4.0 and SS technologies based on obtaining a greater volume of data, coming from IoT and other technologies and the capability to handle this Big Data, supported by Big Data Analytics. IoT generates real-time and integrated information flow, which allows faster interventions on anomalies, defects and variations, better supporting SS projects. And the volume of data coming from Big Data and its resources (BDA) helps to obtain data for analysis, and the possibility of SS and DMAIC to transform that set into information, both supporting better decision-making. The main benefits of the integration of SS and Big Data/BDA are the positive impacts on the quality and performance of the business, such as reduction of defective products, greater productivity in the processes, greater customer satisfaction and cost reduction.

Considering the evidence of the relationship between SS and Big Data/BDA, hypotheses and a theoretical model was developed to be tested in the second article. The proposed model aimed to investigate through a survey, the relationships between the BDA capability, SS practices and quality and business performances. The survey was conducted with SS specialists from manufacturing companies, with a total of 171 responses. The proposed model and hypotheses were confirmed through the PLS-SEM, the effects of BDA and SS practices has a positive and significant effect on QP and BP. BDA capability and SS practices positively impact QP and BP. The main results point to a positive and statistically significant impact of the use of BDA capability in SS practices. A positive mediated effect of SS was identified, in which the integration between Big Data and SS has a greater effect on improving quality and business performance.

The model also considered the effects of moderating variables such as company size, integration of DMAIC and Big Data and I4 technologies. Company size and I4.0 technologies did not affect the conceptual model relationships. The results show that DMAIC and BDA integration positively influences BDA and QP, and integration can help reduce product and process problems.

Therefore, findings show that BDA capability helps to identify problems, processes and areas that need improvement, supporting SS data analysis metrics, and in the DMAIC phases and tools. This support promotes better decision-making, and competitive advantage. Another point considered important is that BDA and SS reinforce each other and, when integrated, positively impact performance.

The managerial implications are related to: i) managers can use SS / LSS and DMAIC to implement and increase the performance of I4.0 technologies; ii) Big Data / BDA can be integrated with SS / LSS allowing better data analysis and use of advanced statistical techniques; iii) the IoT allows real-time data, strengthening monitoring and interventions in the process, in line with the SS principles; iv) managers can structure organizations so that 4.0 technologies strengthen the DMAIC method; v) it is not enough for companies to have Big Data, a BDA structure is needed, so that information is transformed into valuable insights for better decision-making.

4.2 Limitations and Future Research

Some main research difficulties were highlighted during the development of this study. from the SLR was limited by documents from two databases, the Scopus and Web of Science, other databases were not explored. Furthermore, only journal and conference articles were included, probably the selection of books could have intrinsic information for this study. Chapter 3 was limited to the research approach adopted. Data was obtained through email and social networks such as LinkedIn, which may have resulted in a lack of control over the experts interviewed. Furthermore, the study was conducted in Brazilian manufacturing companies only, where it may be difficult to implement BDA approaches.

Future studies should examine whether the results reported in this study are the same for companies in other countries. Include different methodologies such as longitudinal cases to develop a deeper understanding of the causalities behind the results reported. Finally, surveys evidencing industry-specific relationships would be interesting to determine whether results vary by industry.

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