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

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Relations between Industry 4.0 and Lean Six Sigma: Analysis of Big Data Analytics and Organizational Factors

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Dissertação submetida ao Programa de Pós-Graduação em Engenharia de Produção da Universidade Federal de São Carlos, como parte dos requisitos para obtenção do título de Mestre em Engenharia de Produção

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RESUMO

A Indústria 4.0 tem transformado profundamente o ambiente produtivo, impondo novos desafios às organizações, como a gestão de grandes volumes de dados, a necessidade de customização em massa e a busca por maior eficiência operacional. Nesse cenário, a integração entre Big Data Analytics (BDA) e Lean Six Sigma (LSS) se apresenta como uma via estratégica para potencializar a melhoria contínua, promover decisões baseadas em evidências e sustentar o desempenho organizacional. A presente dissertação tem como objetivo investigar, com base na literatura e empiricamente, as relações entre o BDA e o LSS, buscando compreender se há um impacto das capacidades BDA (gerenciais e tecnológicas) sobre os esforços LSS, fatores organizacionais que influenciam essa integração e seus impactos sobre o desempenho organizacional. A pesquisa foi conduzida em duas frentes. Na primeira, desenvolveu-se uma Revisão Sistemática da Literatura (RSL) sobre tecnologias da Indústria 4.0 e LSS, a qual revelou que a produção científica sobre o tema, embora crescente, permanece recente e predominantemente conceitual. A RSL destacou o BDA como a tecnologia de maior impacto sobre o LSS, ao fornecer dados em tempo real e análises avançadas. Também identificou que fatores organizacionais, como liderança, cultura e treinamento são críticos para o êxito da integração entre LSS e Indústria 4.0. Na segunda frente, foi realizado um survey com 184 profissionais da indústria de manufatura no Brasil, analisado por meio de Partial Least Squares Structural Equation Modeling (PLS-SEM). Os resultados empíricos demonstram que as capacidades gerenciais de BDA exercem efeito positivo e significativo sobre os esforços de LSS, enquanto as capacidades tecnológicas isoladas não produzem impacto relevante. Verificou-se ainda que o LSS atua como mediador indispensável para que o BDA contribua para o desempenho operacional e de qualidade, não havendo impacto direto no desempenho financeiro. Por outro lado, tanto a DDC quanto o TMS não apresentaram moderação significativa. Esses achados ampliam a literatura ao fornecer evidências quantitativas inéditas em país em desenvolvimento, demonstrando que o valor do BDA não reside na infraestrutura tecnológica em si, mas em sua capacidade de ser traduzido em práticas de melhoria contínua mediadas pelo LSS. Do ponto de vista gerencial, os resultados reforçam a importância de investir em capacidades gerenciais de analytics, em alinhamento estratégico com o LSS, para transformar dados em ganhos sustentáveis de desempenho.

Palavras-chave: *Big Data Analytics; Lean Six Sigma; Indústria 4.0; Cultura orientada a dados; Suporte da alta gestão; PLS-SEM; Revisão Sistemática da Literatura.*

ABSTRACT

Industry 4.0 has profoundly transformed the production environment, imposing new challenges on organizations, such as the management of large volumes of data, the need for mass customization, and the pursuit of greater operational efficiency. In this context, the integration between Big Data Analytics (BDA) and Lean Six Sigma (LSS) emerges as a strategic pathway to enhance continuous improvement, promote evidence-based decision-making, and sustain organizational performance. The main objective of this article is to investigate the impact of BDA capabilities, subdivided into technological and managerial, on LSS efforts, while also examining whether LSS acts as a mediator between BDA and organizational outcomes (financial, operational, and quality). The moderating roles of data-driven culture (DDC) and top management support (TMS) in the relationship between BDA and LSS are also analyzed. The research was conducted in two stages. First, a Systematic Literature Review (SLR) was developed, which revealed that although scientific production on the topic is increasing, it remains recent and predominantly conceptual. The SLR highlighted BDA as the technology with the greatest impact on LSS by providing real-time data and advanced analytics for tools such as SPC, VSM, Poka-Yoke, and VoC. It also identified that organizational factors such as leadership, culture, and training are critical to the successful integration of LSS and Industry 4.0. In the second stage, a survey was conducted with 184 professionals from the Brazilian manufacturing industry, analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The empirical results demonstrate that managerial BDA capabilities exert a positive and significant effect on LSS efforts, whereas technological capabilities alone do not produce a relevant impact. It was further found that LSS acts as an indispensable mediator for BDA to contribute to operational and quality performance, with no direct impact on financial performance. Conversely, neither DDC nor TMS showed significant moderation. These findings extend the literature by providing novel quantitative evidence in a developing country, demonstrating that the value of BDA does not lie in technological infrastructure itself, but in its capacity to be translated into continuous improvement practices mediated by LSS. From a managerial perspective, the results reinforce the importance of investing in managerial analytics capabilities, strategically aligned with LSS, in order to transform data into sustainable performance gains.

Keywords: *Big Data Analytics; Lean Six Sigma; Industry 4.0; Data-driven culture; Top management support; PLS-SEM; Systematic Literature Review.*

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AR- Augmented reality

BDAM- BDA management capabilities

BDAT- BDA technology capabilities

BDA- Big Data Analytics

CPS - Cyber-Physical Systems

DDC- Data-driven culture

DOE - Design of Experiments

FMEA- Failure Mode and Effects Analysis

FP- Financial Performance

HOC - Higher-order construct

I4.0-Industry 4.0

IoT - Internet of Things

ISO – International Organization for Standardization

KPI – Key Performance Indicator

LSS – Lean Six Sigma

TT - LSS tools and techniques

MM- Measurement metrics

MFV – Mapeamento do Fluxo de Valor

OEE – Overall Equipment Effectiveness

OP- Operational Performance

PLS-SEM – Partial Least Squares Structural Equation Modeling

QMS – Quality Management System

QP- Quality Performance

RFID - Radio Frequency Identification

SPC Statistical Process Control

SLR - Systematic Literature Review

TMS- Top Management Support

TQM – Total Quality Management

VSM - Value Stream Mapping

VR- Variability reduction

VIF - Variance Inflation Factor

VOC- Voice of the Customer Analysis

WE- Waste elimination

WoS - Web of Science

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1. INTRODUCTION

Industry 4.0 refers to the digital transformation of manufacturing systems through the integration of cyber-physical systems, the Internet of Things (IoT), Big Data Analytics (BDA), machine learning, and industrial information integration, enabling real-time data management and greater production efficiency and flexibility (ZHANG et al., 2021; NOVAK et al., 2021; CHEN, 2016; LI & XU, 2020; GAJDZIK et al., 2020). The Industry 4.0 (I4.0) era has imposed new paradigms of production and management by integrating technologies into highly complex and interconnected processes. This technological advancement has generated unprecedented opportunities, but also significant challenges: in addition to handling large volumes of heterogeneous data, firms face pressures for higher quality, cost reduction, mass customization, and real-time adaptability (CHEN, 2016; LI & XU, 2020; KUMAR et al., 2020; YONG et al., 2020).

In this scenario, Lean Six Sigma (LSS) remains one of the most widely used methodologies for continuous improvement, recognized for its ability to eliminate waste, reduce variation, and promote sustainable results (SNEE, 2010; ANTONY, 2011; SINGH & RATHI, 2019; BELHADI et al., 2020, 2023). By combining Lean efficiency principles with Six Sigma's statistical rigor, LSS has proven to be a robust strategy for enhancing quality, productivity, and customer satisfaction (ARNHEITER & MALEYEFF, 2005; AWASTHI & KAROUT, 2017; MACIAS-AGUAYO et al., 2022). However, traditional statistical tools of LSS show limitations in the face of growing data complexity in digital environments (PONGBOONCHAI-EMPL et al., 2023).

Several authors argue that the integration between LSS and I4.0 technologies can enhance the potential of both approaches (JAYARAM, 2016; ARCIDIACONO & PIERONI, 2018; KAMBLE et al., 2018; TAY & LOH, 2022). The integration of LSS with Industry 4.0 technologies is increasingly recognized as a promising avenue for advancing quality management systems and improving organizational performance (SONY, 2020; ARCADIACONO & PIERONI, 2018; KAMBLE et al., 2018; et al., 2021; YADAV et al., 2020). Recent studies highlight that such convergence enhances evidence-based and agile decision making, increases operational efficiency, and strengthens process innovation (ANTONY et al., 2023; MAGANGA & TAIFA, 2023; SHIVAM & GUPTA, 2023). Understanding this integration is therefore essential for organizations to not only adopt Industry 4.0 technologies but also align these innovations with structured improvement and process-control practices, ensuring sustainable gains in performance and competitiveness.

Among the technologies that compose Industry 4.0, BDA stands out as a key enabler of integration with LSS. BDA has been highlighted as the most promising technology to support LSS projects, enabling predictive analysis, root cause identification, real-time statistical control, and enhanced forecasting (GUPTA et al., 2019; BELHADI et al., 2020; ZULFIQAR et al., 2024; WANKHEDE et al., 2025). BDA provides the ability to collect, process, and analyze massive and complex data sets in real time, which is essential for driving process improvements and evidence-based decision making (GUPTA et al., 2019; PONGBOONCHAI-EMPL et al., 2023). The effectiveness of LSS tools depends heavily on robust datasets and advanced analytical techniques, and BDA fulfills this requirement by supplying accurate and timely information to all DMAIC phases (KUMAR et al., 2021; ANTONY et al., 2018). Through BDA, organizations can detect anomalies, forecast trends, and perform risk analyses, thereby enhancing the precision of continuous improvement initiatives and strengthening the overall impact of LSS on operational and quality performance (YADAV et al., 2021; VINODH et al., 2021). Still, the literature shows that empirical studies on this integration remain scarce, especially in developing countries, with research concentrating mainly on conceptual analyses or reviews (BUER et al., 2018; SORDAN, 2020; SINGH et al., 2023; FAYYAZ et al., 2024).Organizational factors play a decisive role in the successful integration of LSS with Industry 4.0 technologies and with BDA. Recent studies emphasize that leadership commitment, a data-driven culture, adequate training, and cross-functional collaboration are essential to translate digital capabilities into continuous improvement and measurable performance outcomes (ANTONY et al., 2023; VINODH et al., 2021; URIATE et al., 2020). In the context of LSS and Industry 4.0, such factors ensure that technological innovations—such as real-time process monitoring and cyber-physical systems—are effectively aligned with the structured problem-solving and waste-reduction principles of LSS (MAGANGA & TAIFA, 2023; SHIVAM & GUPTA, 2023). Likewise, when LSS is integrated with BDA, organizational readiness and leadership support are critical for converting advanced analytics into actionable insights across DMAIC phases, enabling data-driven decision making and sustained quality improvement (YADAV et al., 2021; ANTONY et al., 2023). Organizational factors such as a data-driven culture and top management support are frequently mentioned as determinants for the success of LSS–I4.0 integration, by fostering the strategic use of information and enabling acceptance of new practices (DUBEY et al., 2019; SONY et al., 2020; MACIAS-AGUAYO et al., 2023; SKALLI et al., 2024; TISSIR et al., 2024). Yet, empirical evidence confirming the moderating role of these factors remains limited. Understanding these organizational enablers is therefore fundamental for both researchers and practitioners seeking to maximize the impact of LSS in digitally transforming environments.

Despite the increasing interest in combining Industry 4.0 and Lean Six Sigma (LSS), important research gaps remain. The current body of literature is still recent and largely conceptual, providing limited empirical evidence on how specific Industry 4.0 technologies—particularly Big Data Analytics (BDA)—interact with LSS to generate measurable organizational outcomes (ANTONY et al., 2023; MAGANGA & TAIFA, 2023; SHIVAM & GUPTA, 2023). Furthermore, only a few studies investigate these relationships in developing-country contexts, where patterns of technological adoption and organizational structures differ from those in advanced economies (ANTONY et al., 2023; YADAV et al., 2021). Another shortcoming concerns the scarce analysis of organizational factors, such as leadership support and data-driven culture, which can enable or hinder the effective integration of digital technologies with LSS (VINODH et al., 2021; URIATE et al., 2020). Addressing these gaps is essential to provide robust guidance for organizations seeking to translate digital capabilities into sustainable quality and performance improvements.

This dissertation aims to investigate, in an integrated manner, the relationships among Industry 4.0, more specifically Big Data Analytics, and Lean Six Sigma, seeking to understand both the conceptual foundations and the organizational factors that influence this integration, as well as its practical impacts on organizational performance. To achieve this objective, the dissertation is organized into two scientific papers that together provide a comprehensive investigation of the topic.

In light of this, the present study seeks to address two research questions:

RQ1: How is the literature on the relationship between Industry 4.0 and Lean Six Sigma characterized, as well as the influence of organizational factors on this relationship?

RQ2: Do Big Data Analytics (BDA) capabilities—both technological and managerial—positively impact organizational performance (financial, operational, and quality) mediate by Lean Six Sigma (LSS) efforts?

RQ3: Do data-driven culture and top management support moderate the relationship between BDA and LSS?

To address these questions, the study adopts two complementary approaches. The first paper conducts a Systematic Literature Review (SLR) in the Scopus and Web of Science databases, characterizing the state of the art, identifying the main technologies associated with LSS (with emphasis on BDA and IoT), and mapping organizational factors influencing integration. The first paper aims to answer the first research question.

The second paper develops an empirical study that evaluates, through a survey applied to 184 professionals from the Brazilian manufacturing sector with experience in BDA and LSS, how Big Data Analytics capabilities relate to Lean Six Sigma efforts and to performance outcomes The data were analyzed through PLS-SEM, considering higher-order constructs and testing mediation and moderation effects. The second paper aims to answer the second and third research questions.

This dissertation is organized into three main sections. Section 1 presents the general introduction, outlining the research background, objectives, and methodological approach, as well as the theoretical and practical relevance of the study. Section 2 contains the first article, which consolidates and analyzes the literature to identify Quality 4.0 competencies and research gaps, providing the conceptual foundation for the empirical investigation. Section 3 comprises the second article, which reports the survey-based empirical study examining how Big Data Analytics capabilities interact with Lean Six Sigma practices and organizational factors to influence performance. Finally, the dissertation closes with the overall conclusions, highlighting theoretical contributions,

2. PAPER 1: THE RELATIONSHIP BETWEEN INDUSTRY 4.0 AND LEAN SIX SIGMA AND THE INTERFERENCE OF ORGANIZATIONAL FACTORS: A SYSTEMATIC REVIEW OF THE LITERATURE

ABSTRACT

Faced with this scenario, in which consumption requirements go beyond the classic variables of volume and variety of products, emerging new demands such as customization and continuous support, the combination of Lean Six Sigma (LSS) and Industry 4.0 (I4.0) tools makes essential for maintaining business competitiveness. Industry 4.0 is a concept that refers to a high level of integrated technology adoption. Lean Six Sigma tools are characterized by a great improvement system, based on waste elimination and continuous improvement. However, there is a scarcity of studies that investigate the relationship between the two themes. That said, the main objective of this article is to explore and understand the link between I4.0 and LSS technologies and how organizational factors can interfere with it. The objective is achieved through a systematic literature review, for which the Scopus and Web of Science databases were consulted. The research identifies the main links and how this occurs, and suggestions for future studies are proposed. SLR allowed viewing Big Data Analytics as the main technology related to LSS practices and as organizational factors that most interfere in this relationship culture and leadership. The results made it possible to advance in the state of the art, promoting the literature on the integration of Industry 4.0 and management approaches such as Lean Six Sigma. Regarding practice, the results acquired will guide the training of professionals who intend to work in I4.0 integration with the LSS.

Keywords: *Lean Six Sigma. Industry 4.0. Lean & Industry 4.0. Systematic Review of Literature.*

2.1 INTRODUCTION

Given the complex and competitive nature of today's business, resulting from technological development and globalization, organizations are required to perform better, focusing on increasing productivity and quality (SCHUMACHER et al., 2016; PAGLIOSA et al., 2019). In this context, the Lean Six Sigma (LSS) methodology gains prominence, being acknowledged for its capacity to attain improved outcomes, such as cost reduction, quality enhancement, and customer satisfaction, in addition to optimization of production time (MACIAS- AGUAYO et al., 2022). For the LSS to be successful, some factors must be managed, including organizational culture, communication, training, and leadership (SONY et al., 2020).

To face today's challenges, companies must make the most of the solutions offered by technologies (PONGBOONCHAI-EMPL et al., 2023). Industry 4.0 (I4.0) has brought numerous changes in the trends of industries, companies, and societies by digitizing traditional processes and uniting the virtual and physical world (ZHANG et al., 2021). I4.0 is related to the interaction of technologies in order to reach large amounts of data, allowing precise management of processes (NOVAK et al., 2021). Some of the main technologies that constitute I4.0 are Cyber-Physical Systems (CPS), the Internet of Things (IoT), Big Data Analytics (BDA), Machine Learning, and industrial information integration (CHEN, 2016; LI and XU, 2020). In the same sense, the focus of I4.0 is on the integration between machines, control systems, and network communication, so that it is possible to increase production efficiency and flexibility (GAJDZIK et al., 2020).

LSS and Industry 4.0 technologies are known for their positive impact on organizational performance and it is believed that these two elements are complementary to each other (JAYARAM, 2016). This integration will help organizations to be able to efficiently meet the needs of their customers (SONY, 2020). I4.0 is beneficial for the LSS in the different phases in carrying out the LSS projects (ARCADIACONO and PIERONI, 2018; KAMBLE et al., 2018; TAY and LOH, 2022). I4.0 can help organizations overcome LSS difficulties (ONUR and OMER 2018). According to Kumar et al. (2021), the effectiveness of LSS tools relies on substantial datasets to drive process enhancements, facilitated by the availability of data and analytical techniques within the realm of I4.0 technologies.

The LSS approach can also positively influence I4.0, allowing organizations to prioritize and structure areas for using technologies (TAY and LOH, 2022). Furthermore, among the main reasons that lead manufacturers to reject the adoption of I4.0 are the fear of the unknown and resistance to change, obstacles that can be mitigated through the LSS approach, due to the manufacturers' familiarity with these strategies over decades of use, even for a different type of implementation (BUTT, J. 2020).

Although studies are known in the literature that integrate technologies with Lean methodology (RANE et al., 2017; SOUTHARD et al., 2012), it is important to note that there is a scarcity of research investigating the relationship between LSS and I4.0 (BUER et al., 2018; SORDAN, 2020; SINGH et al., 2023).

According to Gupta et al. (2022), it is also necessary to understand how organizational factors and needs are present and can influence this interaction. As shown by Yadav et al. (2021), I.40 and its influence on LSS depend on several aspects, such as organizational culture and practices. Due to the converging and diverging characteristics of I4.0 and LSS, it remains unclear whether their simultaneous will lead to better performance. While existing reviews have contributed significantly to the literature, the focus has primarily centered on identifying I4.0 technologies and techniques related to LSS, along with their potential performance effects (MACIAS-AGUAYO et al., 2022). However, these approaches fail to provide a comprehensive insight into how I4.0 technologies effectively support LSS tools (PONGBOONCHAI-EMPL et al., 2023).

Given this gap, the motivation for the present study arises from the necessity to critically review and assess pivotal aspects of the integration process between Industry 4.0 and LSS within organizations. Furthermore, there is a need to comprehend the organizational factors associated such as culture, leadership, and training, which may interfere with these integrations. Within this context, the following questions (QRs) are presented:

RQs 1: How is the literature on the topic of relationships between I4.0 and LSS characterized?

RQs 2: How I4.0 technologies are related to the LSS goals and tools?

RQs 3: How I4.0 technologies support DMAIC?

RQs 4: How do organizational factors influence the relationship between I4.0 and LSS?

This article is structured as follows: Section 2 provides a description of Industry 4.0, Lean Six Sigma concepts and the relationship between I4.0 and LSS. In section 3, the method and steps used to carry out the systematic literature review are presented. In section 4, the results are described and analyzed. Finally, the fifth and last section presents the conclusion, with the main academic and managerial implications and directions for future studies.

2.2 Theoretical Basis

This section seeks to briefly discuss the topics: Lean Six Sigma, Industry 4.0, and the relationship between I4.0 and LSS.

2.2.1 Lean Six Sigma

LSS was considered a new global trend, resulting from the integration of Lean and Six Sigma elements (CHEN and LYU, 2009; SUNDER, 2015). LSS, has become, from the beginning of the 2000s, a continuous improvement methodology with great popularity worldwide and considered one of the most efficient business excellence strategies (BAKAR et al., 2015; DAHLGAARD and DAHLGAARD -PARK, 2006). Lean is associated with the production system that emerged at Toyota and have the concern to identify and eliminate non-adding value activities in the processes (HOLWEG, 2007). Six Sigma was developed at Motorola in the late 1980s to improve the production system, maximize business results and reduce variations (MURALIRAJ et al., 2018; WALSH et al., 2000). After the diffusion of Lean and Six Sigma, organizations from different sectors began to adopt both approaches in order to obtain better continuous improvement results (LEE and WEI, 2009).

Although there are indications of the incorporation of LSS by companies (George Group in the United States) since 1980, in the literature it was introduced only around the 2000s (SALAH et al., 2010; KRISHANK and KUMAR, 2012). LSS capitalizes on strengths of Lean management approach, such as the search for increased added value in all operations and customer satisfaction and of Six Sigma, that is, data-based decision making and variation decrease in characteristics of quality (ARNHEITER and MALEYEFF, 2005). This allows the achievement of highly qualified products, reduced costs and delivery times (MUHAREN and GRAHAM-JONES, 2014; SINGH and RATHI, 2019), increased performance of organizational processes and satisfaction of customer needs (SNEE, 2010; AWASTHI and KAROUT, 2017). For Snee (2010), LSS is positively different from other approaches by focusing on final results and leadership, in addition, it uses a systematic and disciplined approach, DMAIC.

Among the various LSS tools, are those from Lean, such as, Value Stream Mapping (VSM), Kanban, Kaizen, 5S, Total Productive Maintenance (TPM), and Poka-Yoke (KUMAR et al., 2006). Da Silva et al. (2022) highlight the "Single-Minute

Exchange of Die (SMED), which allow production with less setup time, Ishikawa Diagram, Failure Mode and Effects Analysis (FMEA), and Voice of the Customer Analysis (VOC). The methodology achieves positive results through statistical tools from Six Sigma, such as Statistical Process Control (SPC), Design of Experiments (DOE), and analysis of variance (BHUIYAN and BAGHEL, 2005).

However, the implementation of the LSS is associated with several organizational factors, which can be barriers or enablers (SINGH and RATHI, 2019). The effectiveness in implementing new LSS projects is grounded in several facilitators, among them being the commitment of top management, the conduct of comprehensive training, and the fostering of effective communication (SINGH and RATHI, 2020). The main challenges organizations may face in implementing LSS are the lack of support from the top management, resulting in a low level of stakeholders' commitment, resistance to change, lack of awareness and understanding of LSS tools and their benefits, as well as the lack of communication, resulting in a non-alignment of employees' efforts (ALBLOOSHI et al., 2020).

For Lean Six Sigma to achieve its goals and overcome the main challenges, the involvement of top management, assertive leadership and organizational culture must be evaluated (TSIRONIS and PSYCHOGIOS, 2016). Therefore, the implementation of the LSS is not only supported by the technical knowledge of the tools but also by organizational factors, namely: Culture, environment and work procedures (ALBLOOSHI et al., 2020). In the same notion, Hilton and Sohal (2012) argue that the successful implementation of LSS is influenced by both technical and interpersonal skills.

2.2.2 Industry 4.0

I4.0 has achieved significant popularity in academia and the manufacturing practice, being considered a key factor for organizational success (FETTERMANN et al., 2018). The term was introduced in 2011 by the German Federal Government, to encourage industries toward digitization and automation (HENNING et al., 2013). According to Kamble et al. (2018), Industry 4.0 can be defined as a paradigm that connects physical devices to a network. Continuous interactions with information exchange can be performed between machines, humans, and even between humans and machines (WAN et al., 2016).

I4.0 comprises a variety of technologies that connect cyber and physical environments (LU, 2017). The combination of these technologies results in the development of smart factories, that are highly efficient in the use of resources to meet organizational objectives (WITTENBERG, 2016). Among the technologies that are part of I4.0 are: Big Data Analytics (BDA), Internet of Things, (IoT), Cyber-Physical Systems (CPS), Augmented reality (AR), Robotics and Simulation (OESTERREICH and TEUTEBERG , 2016; Da SILVA et al., 2020; DUMAN and AKDEMIR, 2021).

Each technology plays an extremely important role in I4.0, BDA extracts information for data-driven decision making (SONG et al., 2016). The IoT allows the creation of virtual networks that provide information support to production lines (XU et al., 2018). CPS results in agile, dynamic, and flexible processes according to the specific needs of customers (SONY and NAIK, 2020). While IoT and BDA help to obtain information and develop communication protocols in production lines (RAJPUT and SINGH 2019). Therefore, the positive impacts of Industry 4.0 are achieved mainly when the use of technologies is integrated (BUCHI et al., 2020; BETTIOL et al., 2022).

According to Lasi et al. (2014), I4.0 offers customization facilities, flexibility, minimization of the product development period, assertive decision making, and resource efficiency. Data analysis technologies allow for a vast amount of data about customers and the company's production processes, which allows creation of products in less time and the development of customized design and sales processes (FENG and SHANTHIKUMAR, 2018). I4.0 is beneficial for both customers and manufacturers, with the customer's point of view being to offer products customized to their needs, and from the manufacturers' point of view, by achieving greater efficiency and flexibility of production resources, minimizing waste through digitization and control (SONY, 2020).

Despite the many benefits of I4.0 technologies, it is important to highlight some challenges related to organizational factors, especially during the implementation process, such as skilled workforce, data security work standardization, resistance to change and knowledge about the possible benefits of I4.0 (KUMAR et al., 2020; RAMADAN ET., 2022). Despite the high technology involved, aspects related to people, for example, employee involvement, will continue to play an important role in organizational performance in the context of Industry 4.0 (TORTTORELA et al., 2018). Yong et al. (2020) reinforce the challenge in the development of human resources, both due to the need for highly qualified professionals and the resistance of employees.

2.2.3 I4.0 and LSS

Despite having different approaches, I4.0 and LSS share similar goals, such as increasing the flexibility and productivity of production systems (Frank 2014; KAMBLE et al., 2018). According to Sony (2020), LSS, by having an approach aimed at reducing waste, can mitigate some of the difficulties faced by I4.0. For example, LSS can help reduce unnecessary data collection and analysis since some data does not add value to the process and, consequently, LSS can minimize costs (SONY, 2020). According to Arcidiacocon and Pieroni (2018), the combination of I4.0 and LSS allows to increase the processes' capability with the use of simulation and data analysis. The fusion between I4.0 and LSS provides technologies for cutting-edge quality systems, allowing faster process control, since there is real-time product information and identification of improvement opportunities with the help of big data databases (VINODH et al., 2021). in this way, guaranteeing better organizational results (YADAV et al., 2020). This integration is a promising area for academics and practitioners worldwide (URIATE et al., 2020).

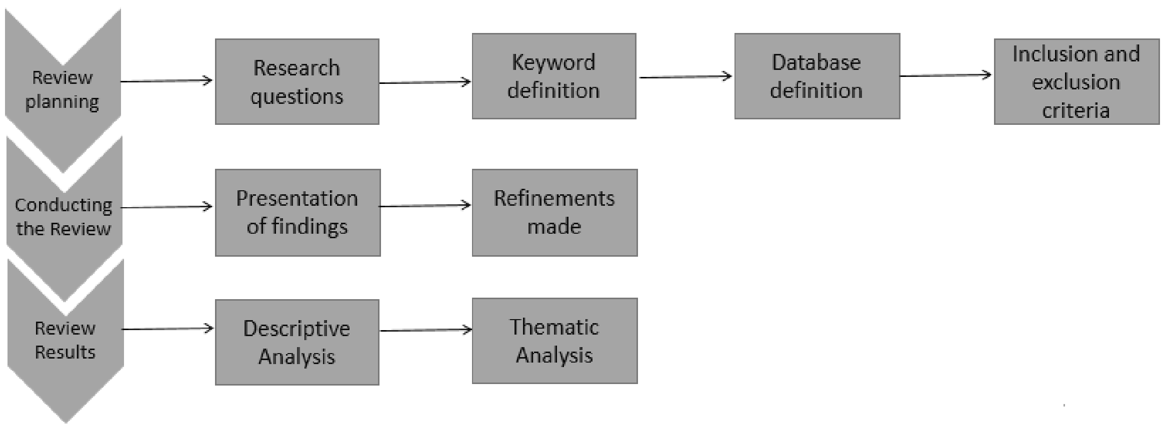
Among the main reasons for rejecting I4.0 adoption, are the fear of the unknown and the resistance to change, LSS can minimize them, since organizations have been used to this methodology for years and can integrate it into the use of I4.0 technologies (Butt, 2020). However, for LSS to support I4.0, in addition to having knowledge on how to structure organizational processes, it is essential that employees are trained and have extensive knowledge to work in synergy with technologies (TAY and LOH, 2022). It is also necessary to establish a defined change management strategy for the digital LSS (FERNÁNDEZ et al., 2019). Tay and Loh (2022) also argue that it is necessary to explore human interactions and technologies to understand the influence of digitization on LSS projects.

2.3 METHOD

This paper performs a Systematic Literature Review (SLR) on research on the integration of I4.0 and LSS. The main objective of the SLR is to create a theoretical-scientific basis, that is, to identify the state of the art on a given subject (LEVY and ELLIS, 2006). According to Walsham (2006), the review should receive due attention and be conducted in a systematic and rigorous manner, allowing greater reliability in the study. For Bezerra et al. (2019), SLR allows identifying gaps, consolidating theory and gaining insight into possible research topics.

For the SLR goal to be achieved, a protocol must be established and followed. The identification and analysis of the related documents was based on the three stages proposed by Tranfield et al. (2003) and Tranfield et al. (2009), as illustrated in Figure 1. In the first stage, planning was carried out (preparation of the conduction protocol, definition of research questions, choice of keywords, database, inclusion and exclusion criteria); in the second stage, conducting the review (presentation of findings, number of documents found and refined at each stage); in the third and last stage, the results of the review are presented.

Figure 1 - Methodological Protocol of the Systematic Literature Review



Source: Adapted from Denyer and Tranfield (2009).

2.4 Planning

The Web of Science (WoS) and Scopus databases were defined as sources for searching the documents to be analyzed in this research. The choice was made because they are important scientific databases (BUER et al., 2018). WoS is a multidisciplinary database, which makes it possible to obtain high-impact research in the social sciences, arts and humanities (DE-LA-TORRE-UGARTE et al., 2011). Furthermore, according to Modak et al. (2020) Scopus has evolved to complement the WoS science base. The research questions that the study aims to address were introduced in the Introduction.

In order to guide the identification of keywords and the string formulation, a preliminary review of the literature on Industry 4.0 (CHEN, 2016; LI and XU, 2020; KUMAR et al., 2006) and Lean Six Sigma was carried out (ANTONY, 2011; SONY et al., 2020). In this way, the established string is broad enough to not restrict the results but is also specific to the point that the searches found are related to the topic (THOMÉ et al., 2016). The final search term in the databases is shown in Table 1. No time cut was performed and searches up to April 2023 were included in the analysis.

TABLE 1 - Search term used in the research.

Search Term
("Industry 4.0" OR "embedded systems" OR "4th industrial revolution" OR "cyber-physical system" OR "cyber-physical*" OR "big data" OR "internet of thing*" OR "IOT" OR "industrial internet of thing*" 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 "digitalization" OR " digitization ") AND ("Lean six sigma" OR "Lean sigma" OR "LSS" OR "Lean 6 sigma")

Source: authors (2022).

As shown in Figure 1, one of the main planning stages is to establish the inclusion and exclusion criteria for the articles to be analyzed. Thus, the established criteria are shown in Table 2.

TABLE 2 - Inclusion and exclusion criteria.

Topic	**Inclusion Criteria**	**Exclusion Criteria**
Duplication	Is not duplicate paper.	Is a duplicate paper.
Language	Be written in English.	Not be written in English.
Source	Journal and conference papers.	Other type of document (e.g., books chapters, editorial).
Theme	The document is related to LSS and I4.0	The document is not related to LSS and I4.0
Focus	The paper deals with the relationships between Industry 4.0 technologies and Lean Six Sigma and	The paper does not address the relationships between Industry 4.0 technologies and Lean Six Sigma

Source: Authors (2023).

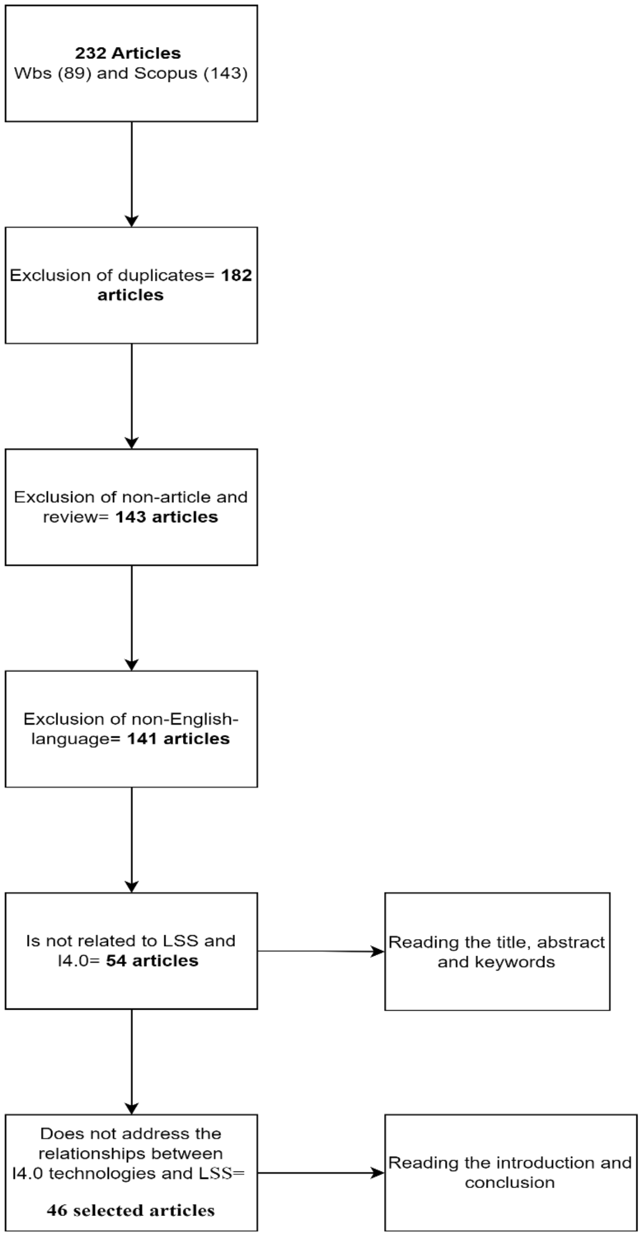
This article conducted a quality assessment through the evaluation of clear, well-structured, and meticulously presented research methods. The papers underwent a rigorous evaluation, ensuring the consistency of the research methods in each article, and verifying the presence of logical sequences and replicability of the steps.

2.5 Conducting

The string was applied to the two pre-defined databases using the specified keywords to search through titles, abstracts, and keywords. As a result, a total of 232 publications were initially retrieved. After removing duplicate articles, the count was reduced to 182 articles (Figure 2). These articles were then subjected to the predetermined selection criteria. In terms of source type, conference papers, books, and documents other than journal articles were excluded. Additionally, articles not published in English were also eliminated. Consequently, articles that do not specifically address the relationships between Industry 4.0 and Lean Six Sigma were excluded.

To ensure the selection of high-quality articles, the title, keywords, and abstract of each article were reviewed. Only those deemed relevant to the topic of Industry 4.0 and Lean Six Sigma were included. Subsequently, a comprehensive examination of the introduction and conclusion sections of these articles was conducted. Only documents that provided insights into the relationships between Industry 4.0 and Lean Six Sigma were retained for the study. This thorough review process resulted in a total of 46 journal articles for analysis. These selected articles were then meticulously analyzed using Excel software to extract critical theoretical frameworks and findings.

Figure 2 - RSL filters



Source: authors (2023).

2.6 Results

The outcomes will be comprehensively presented in Section 4 via a descriptive analysis, addressing the initial inquiry regarding the characterization of the literature on the subject of relationships between I4.0 and LSS. This presentation will encompass factors such as the volume of publications, prominent authors, publishing sources focused on the topic and the array of technologies associated with LSS.

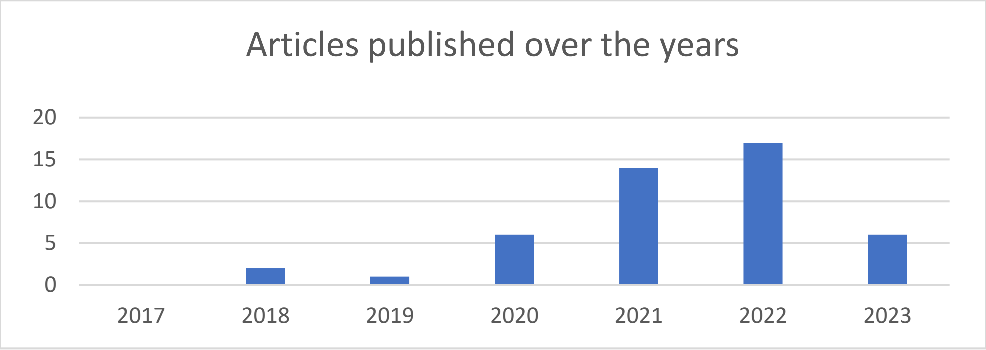
In addition to the descriptive analysis, a thematic study was conducted by examining the selected articles' content in-depth. Thematic analysis allows researchers to identify, analyze, and report patterns in the form of data from a sample (SNYDER, 2019). This process aimed to provide insights into the defined research questions, comprehending the relation between Industry 4.0 technologies and Lean Six Sigma (LSS) objectives and tools and how Industry 4.0 technologies support DMAIC. Furthermore, an exploration was undertaken into how organizational factors influence the relationship between Industry 4.0 and LSS.

The selected articles were thoroughly read multiple times, aiming to extract meanings and patterns from each one. Qualitative data from the sample articles were individually extracted and stored in a separate Excel spreadsheet, with each discovery placed in an individual cell. The Excel spreadsheet included the article's title, year of publication, journal, authors, article type, and other characteristics of these articles encompassing the implications of LSS, I4.0, and organizational factors (TRANFIELD et al., 2003).

2.6.1 Descriptive analysis

Publications over time can be seen in Figure 3. Concerning the years of publications, it was possible to observe a high growth from the year 2020, inferring that it is a current, relevant topic and indicating a favorable scenario for publications within and the increased interest of researchers.

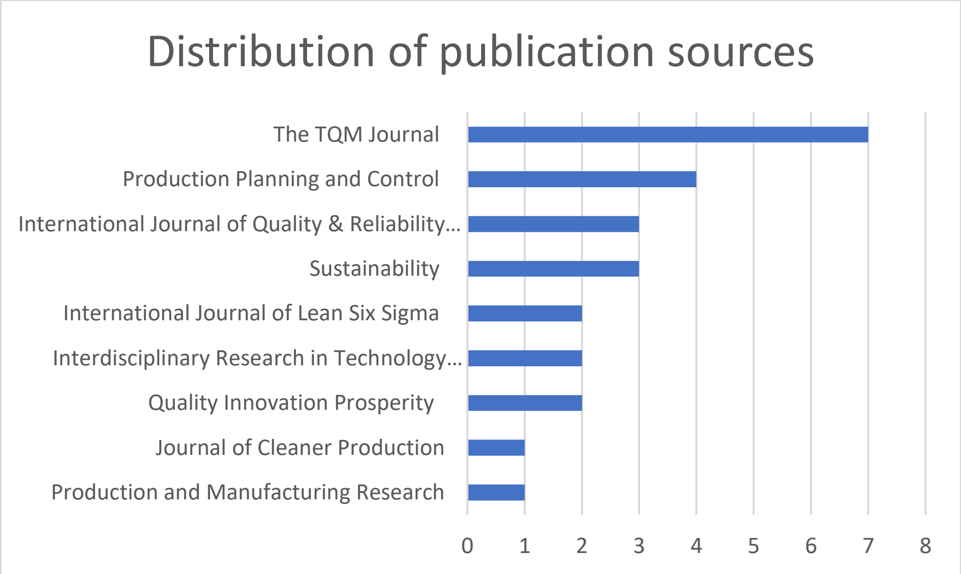
FIGURE 3- Articles published over the years.



Source: authors (2022).

There are different sources of publications, as shown in Figure 4. The TQM Journal was the one that published the most documents on the subject, and besides it, there was more than one publication on the subject in the following journals: Production Planning and Control, International Journal of Lean Six Sigma, Quality Innovation Prosperity, Sustainability and International Journal of Quality & Reliability Management.

FIGURE 4- Distribution of publications sources.



Source: authors (2023).

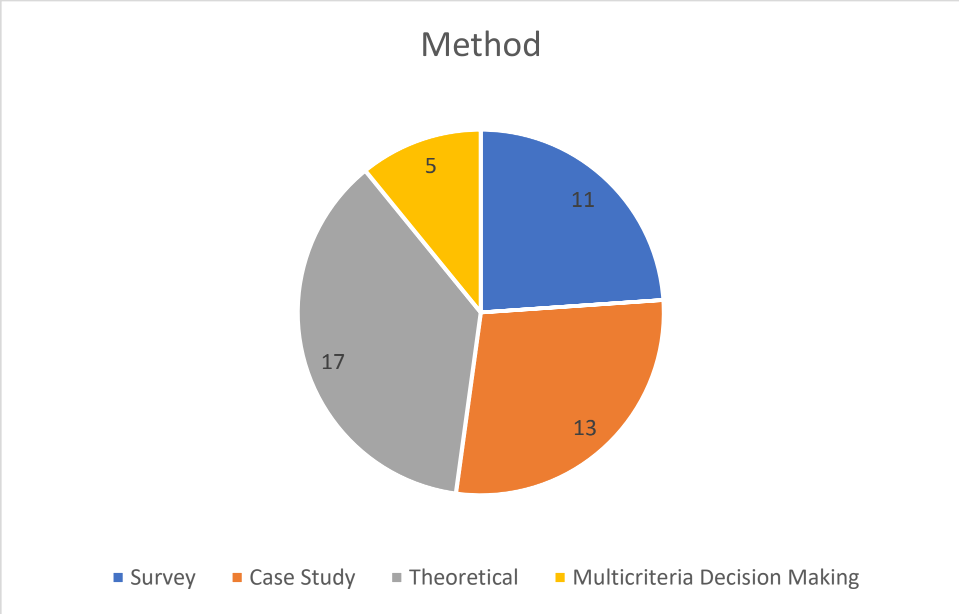
The principal authors who have made significant contributions to the subject have also been identified, as illustrated in Figure 5. At this juncture, it is noteworthy that among these authors, S. Singh has published 6 articles, P. Kumar has authored 4 articles, and J. Antony has contributed 3 articles on the topic.

FIGURE 5-Authors who contributed the most to the theme.

Source: authors (2023).

When analyzing the research methods used, it was observed that conceptual/theoretical studies were the most commonly employed research method, appearing in 17 out of the 46 articles reviewed. This suggests that there is still a predominance of this type of study to the detriment of empirical studies, the field of knowledge is still in formation and, for this reason, a significant number of studies with the exploration of concepts and the development of new theoretical insights. Case studies were employed in 13 studies, demonstrating their usefulness in delving into this complex phenomenon. Case studies provided rich and contextualized insights, contributing to both theoretical and practical understandings of how I4.0 can be integrated with LSS. Surveys were the third most utilized method (11 articles). In this sense, the surveys allow for exploratory and descriptive analyses of how the LSS is being used in conjunction with the I4.0 enabling researchers to identify patterns, trends, and perspectives within a specific population. Additionally, it is noteworthy that five studies also utilized the Multicriteria Decision Making method, further diversifying the array of methods employed in the investigation of the integration of Industry 4.0 (I4.0) with Lean Six Sigma (LSS). These findings highlight the diversity of research methods used and emphasize the strengths and contributions of theoretical analysis, surveys, and case studies in advancing knowledge. The research methods are presented in Figure 6.

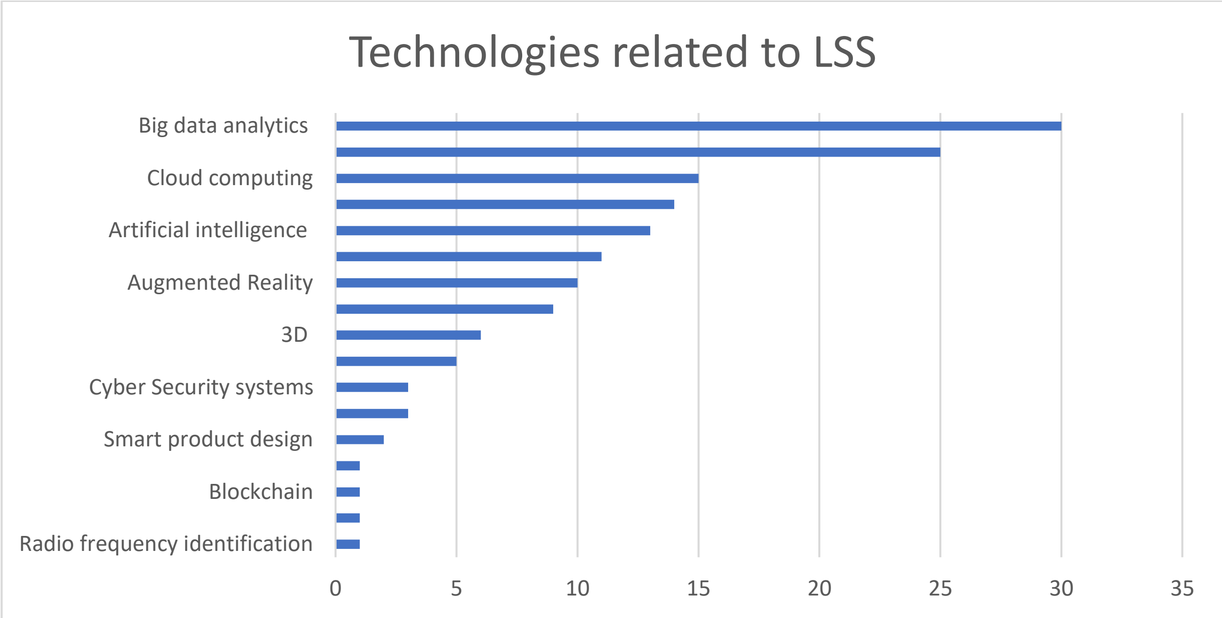
FIGURE 6- Research methods used.



Source: authors (2023).

It is also important to point out which are the main technologies of Industry 4.0 that are related to Lean Six Sigma, as shown in Figure 7. The observation reveals that multiple technologies are referenced in various publications; for instance, BDA is cited in 30 publications, while IoT appears in 25 publications. It can be observed too that Industry 4.0 technologies have proven to be highly beneficial for the LSS methodology, boosting the efficiency and effectiveness of LSS practices. Among the various technologies depicted in the figure, BDA stands out as one of the highlights, capable of handling massive volumes of information.

FIGURE 7 – Technologies related to Lean Six Sigma.



Source: authors (2023).

2.6.2 Thematic analysis

2.6.2.1 Relationship between Industry 4.0 technologies and Lean Six Sigma

Each of the I4.0 technologies can help with different aspects of LSS, as evidenced in Table 3. LSS tools have a high dependence on data to drive process improvements, and this can be solved with the availability of reliable data in real-time, in addition to their analysis (KUMAR et al., 2021). Big Data Analysis (BDA) can effectively address huge amounts of data, assisting in decision-making and avoiding any unnecessary activity or investment in human or physical capital (GUPTA et al., 2019). Although applications of BDA in process improvement are in their infancy, the field can enable more customer-centric production flows, which is one of the LSS principles (ANTONY et al., 2018). According to Gupta et al. (2019), the benefits of uniting BDA in LSS projects are manifold. Through BDA, multiple sources of variability can be analyzed, for example; machines, human labor, and processes, helping to detect anomalies, with process forecasting, trends, and risk analysis (YADAV et al., 2021). For Pongboonchai-Empl et al. (2023) the main advantage of BDA for LSS is the provision of insights into huge amounts of data in real-time, of different types and with non-linear relationships, generating a better understanding of the process, greater hits, and cost reduction.

Highlighting the root causes that influence variation from the established pattern and that must be eliminated to obtain optimized processes is the key concept of LSS (ARCIDIACONO and PIERONI, 2018). According to Vinodh et al. (2021), the IoT assists in analyzing the root cause of the problem, being beneficial to LSS. IoT allows the transmission of important data to a smartphone or tablet to monitor deviations to processes in advance, with another advantage being the increase in customer involvement, due to feedback facilitated by technology (ARCIDIACONO and PIERONI, 2018).

In LSS the forecasting aspect has a positive influence, especially in the improvement phase, as results can be predicted and managers can choose an appropriate strategy, this occurs through the availability of data (EFIMOVA and BRIS, 2021). Radio Frequency Technology Identification (RFID) allows for achieving fast and reliable data collection (Yadav et al., 2021), and in this way, it allows product traceability, increased communication and quality by providing real-time data (RIFQI et al., 2021). Additionally, it allows for establishing an error-proofing system in purchases, given that orders are placed automatically when stock levels are low (RIFQI et al., 2021). In addition, system data obtained by RFID can be analyzed by predictive algorithms considering processing time, machine availability, failure occurrence, and cycle time, aiming to increase the overall equipment effectiveness (OEE) (SORDAN et al., 2021).

In LSS projects, information extraction and flows become key activities, especially since most of the methodology tools are purely statistical (RIFQI et al., 2021). Blockchain through algorithms is capable of optimizing processes and ensuring communication and connectivity (KUMAR et al., 2021). In the same sense, Rifqi et al. (2021) explain that technology contributes to data quality assurance and continuous monitoring.

With Simulation, the potential of LSS capability can be explored, given that the technology provides reliable data through digitization, both at the strategic and operational levels (BHAT et al., 2021). For Butt (2020) processes can be improved through rapid prototyping and virtual analysis of complex scenarios.

According to Sodhi (2020), the LSS methodology is based on data collection and analysis to comprehend the causes of issues and identify appropriate solutions. In this regard, cloud computing technology proves beneficial by enabling the storage and analysis of large amounts of data (PONGBOONCHAI-EMPL et al., 2023).

CPS offers control and monitoring of data from all entities in the value chain, thus offering improvements in LSS performance (KUMAR et al., 2021). According to Tay and Loh (2022), efficient decision-making is enabled through real-time visualization and analysis of critical data on a dashboard. CPS can be used in parallel with simulation to examine the effects of changes before implementation (KUMAR et al., 2021). The use of IoT and CPS technologies can increase responsiveness to changes and manufacturing flexibility (AMJAD et al., 2021).

According to Snee (2010), the LSS aims to obtain improvements in the performance of the processes. Robotics technology can achieve this objective (YADAV et al., 2021). For Da Silva et al. (2022) a robot can be connected to BDA algorithms through digitization, which allows actions with little human interference.

Another technology that can be used for the LSS to reach its goal is AI, through AI-enabled advanced analyses, corporate managers can access real-time information regarding crucial product quality indicators, this dynamic facilitates not only time reduction but also process variability minimization. (KUMAR et al., 2021). According to Samanta et al. (2022), the use of AI improves production planning and control, by providing predictive information about customer demands, which allows managers to plan and make more assertive decisions about the process and inventory.

Technologies such as Machine Learning, AR, and AI allow for reduced variation in the process and downtime by finding, minimizing, or regulating process parameters (YADAV et al., 2021). For Rifqi et al. (2021) Machine Learning creates a culture of safety and quality by performing activities properly and finding levers that ensure alignment throughout the process.

AR technology through tablets and monitors will increase the efficiency of manual activities and learning at work, improving the cycle time (SORDAN et al., 2021). Santos et al. (2022) conducted empirical studies in the chemical sector, demonstrating Lean Six Sigma integration with Industry 4.0 technologies. They employed augmented reality glasses for real-time field interventions, enhancing remote collaboration and engagement. Data sharing improved team involvement in projects, enabling real-time monitoring of production and equipment, leading to standardized processes and reduced variability in chemical composition. Notably, the use of technology streamlined chemical mixing, boosting manufacturing line productivity.

TABLE 3 - I4.0 Technology Contributions to LSS Aspects

Technology	How it relate to the LSS	Authors
BDA	Decision-making based on data Analysis of multiple sources of variability	Kumar et al. (2021); Gupta et al. (2019); Antony et al. (2018);

	Better process understanding (trends and forecasting)	
IoT	Analysis of root causes Monitoring of deviations and variability Customer involvement due to feedback	Vinodh et al. (2021) Arcidiacono and Pieroni (2018)
RFID	Achieving fast and reliable data collection Increased traceability and communication by providing real-time data Helps in error-free (Just in Time) supply system Increase the overall equipment effectiveness	Yadav et al. (2021) Rifqi et al. (2021) Sordan et al. (2021)
Blockchain	Improvement of communication and connectivity Data quality assurance and continuous monitoring	Kumar et al. (2021) Rifqi et al. (2021)
Simulation	Reliable data through digitization Rapid prototyping and virtual analysis	Bhat et al. (2021) Butt (2020)
CPS	Monitoring of data from all value chain and critical points of the processes Decision-making based on real-time data Analyze the effects of changes	Kumar et al. (2021) Tay and Loh (2022)
Robotics	Improvement in processes with little human interference	Da Silva et al. (2022) Yadav et al. (2021)
AI	Identify patterns of waste Predictive information that improves process planning and control Better regulation of process parameters	Kumar et al. (2021) Samanta et al. (2022) Yadav et al. (2021)
Machine Learning	Better communication between machines and materials Establishing a culture of quality and safety	Yadav et al. (2021) Rifqi et al. (2021)
AR	Faster maintenance Easier training	Sordan et al. (2021) Santos et al. (2022)

Source: authors (2023).

LSS aims to reduce costs, enhance quality, increase customer and shareholder satisfaction (ALBLIWI et al., 2014; LAUREANI and ANTONY, 2012), and eliminate non-value-added activities (SINGH and RATHI, 2019). Thus, Table 4 shows the I4.0 technologies that help achieve these goals.

TABLE 4 - Impact of I4.0 technologies on LSS

Technologies	Lean Six Sigma goals				
	Reduce costs	Enhance quality	Eliminate non-value-added activities	Increase customer and shareholder satisfaction	Authors
BDA	X	X	X	X	1, 3, 4, 9, 10, 12, 13, 14, 15, 17
IoT		X	X	X	1, 2, 4, 5, 9, 11, 16

Simulation	X		X		4, 5, 6, 9, 13
Blockchain		X	X		9, 17
CPS	X		X		2, 4, 5, 9, 10, 11, 16
RFID		X	X		8, 10, 13
Bar code			X		13
Robotics			X		4, 11, 13, 14
Machine learning		X	X		9, 13, 14
AI		X	X		4, 9, 13, 16

1- Antony et al. (2018);
2- Arcdiacon and Pieroni (2018);
3- Gupta et al. (2019);
4- Butt (2020);
5- Amjad et al. (2021);
6- Bhat et al. (2021);
7- Chiarini and kumar (2021);
8- Efimova and Bris (2021);
9- Kumar et al. (2021);
10- Sony et al. (2021);
11- Sordan et al. (2021);
12- Vinodh et al. (2021);
13- Yadav et al. (2021);
14- Da Silva et al. (2022);
15- Rifqi et al. (2022);
16- Tay and Loh (2022);
17- Pongboonchai-Empl et al. (2023)

Source: authors (2023).

2.6.2.2 How technologies affect the LSS tools

The various technologies of Industry 4.0 can support or be used in conjunction with tools that constitute LSS. The interaction of Lean Six Sigma tools with BDA, Simulation, and Augmented Reality (AR) has digitized and improved Just in Time practices and principles directing to JIT 4.0. This is also the case for Total Productive Maintenance 4.0 (TPM 4.0), Value Stream Mapping 4.0 (VSM 4.0), Kaizen 4.0, Kanban 4.0, and Poka-Yoke 4.0 (RIFQI et al., 2021).

By using interconnected devices and sensors, the process is continuously tracked and therefore supports tools such as root cause analysis and Statistical Process Control (SPC) (PONGBOONCHAI-EMPL et al., 2023). SPC is one of the main tools of LSS, this tool is based on data analysis to find the causes and variations of the process, in this way, IoT and BDA can support providing accurate data in real-time so that in cases of deviations in the process, the correction should be immediate to avoid failures (BAG et al., 2023).

According to Sordan et al. (2021) process mapping can be facilitated by simulation, CPS, and BDA, that is, traditional mapping techniques such as VSM can be supported in the context of real-time forecasting and monitoring. In addition to helping the process mapping, these technologies make it easier to monitor the condition of machines, in the context of Total Productive Maintenance (TPM).

Radio Frequency Identification (RFID) and Bar Code impact Poka-Yoke and 5S tools, as they help to increase order, and organization and ensure that errors are minimized (YADAV; SHANKAR; SINGH, 2021). For Kumar et al. (2021) RFID, through advanced systems for collecting and handling data in real-time, achieves greater visibility of the process and the decisions to be made, thus making the VSM more reliable to detect waste and track manufacturing flows. The authors also discuss the impact of 3D printing on the SMED tool, by reducing configuration, waiting, processing, lead time, and cost times, and consequently increasing stakeholder satisfaction.

Tools like Poka-yoke and Jidoka experience significant enhancement through integrating advanced sensors and AR, especially when applied in assembly and logistics activities. This advancement is clearly illustrated in the study conducted by Chiarini and Kumar (2021), in which a particular company adopted an innovative approach. In this context, employees responsible for tightening critical safety screws use 3D glasses equipped with AR technology, projecting a green light to identify the correct screws. Furthermore, these 3D glasses only allow the operator to proceed with other tasks when the screw is tightened to the correct torque, ensuring effective quality control and further enhancing operational efficiency.

BDA helps the Kanban tool, as the available data can change the flow of material to direct delivery from the warehouse to the machines, which increases the traceability capacity and reduces stock and necessary space in the warehouse (BAG et al., 2023).

BDA can holistically analyze signals throughout manufacturing, especially possible root causes of problems (Ishikawa diagram) (TAY and LOH 2022). For Arcidiacono and Pieroni (2018), BDA overcomes the limitations of traditional consumer analysis tools, by providing information about the entire experience and needs of customers in VOCs.

IoT can support in Poka-Yoke by automatically detecting errors by sensors and actuators (KUMAR et al., 2021). Tools such as VSM and 5S can benefit from IoT, as this technology enables continuous monitoring of the entire process through the collection and analysis of interconnected data (CHIARINI and KUMAR 2021). As shown in Table 5 below.

TABLE 5 - Impact of I4.0 technologies on LSS tools

TECHNOLOGY	IMPACT ON LSS TOOLS	AUTHORS
Simulation	Kaizen; Kanban; Poka-Yoke; VSM;	Amjad et al. (2021); Rifqi et al. (2021); Sordan et al. (2021);

	JIT; TPM	
RFID	5-S; Poka-Yoke; VSM;	Chiarini and Kumar (2021); Kumar et al. (2021); Yadav et al. (2021);
Bar code	5-S; Poka- Yoke;	Chiarini and Kumar (2021); Yadav et al. (2021);
3D printing	SMED; Poka- Yoke; Jidoka;	Kumar et al. (2021); Yadav et al. (2021);
Robotics	VoC	Tay and Loh (2022);
CPS	TPM; VSM; SPC;	Kumar et al. (2021); Sordan et al. (2021);
BDA	SPC; Kaizen; Kanban; Poka-Yoke; TPM VSM; Ishikawa diagram; VoC	Arcidiacono and Pieroni (2018); Yadav et al. (2020); Kumar et al. (2021); Rifqi et al. (2021); Sordan et al. (2021); Tay and Loh (2022); Bag et al. (2023);
IoT	Poka- Yoke; VoC; VSM; 5S SPC	Chiarini and Kumar (2021); Kumar et al. (2021); Sordan et al. (2021); Tay and Loh (2022); Bag et al. (2023);
AR	Kaizen; Kanban; Poka-Yoke; Jidoka; VSM; TPM;	Chiarini and Kumar (2021); Rifqi et al. (2021); Sordan et al. (2021); Da Silva et al. (2022);

Source: authors (2023).

2.6.2.3 How technologies affect each phase of DMAIC

Knowing that LSS projects use the DMAIC method (SORDAN et al., 2021), it is pertinent to establish how I4.0 technologies help in each step of DMAIC. Initially, several studies pointed out BDA as applicable in all DMAIC phases, due to their inherent characteristics of volume, speed, and variety (SONY et al. 2021; TAY and LOH 2022; GUPTA et al., 2020; BAG et al., 2023). BDA can provide and analyze vast amounts of data, enabling the identification of complex patterns, establishing deep correlations, defining problems more precisely, and consequently, offering valuable insights into processes and their root causes (ARCIDIACONO and PIERONI, 2018; CHIARINI and KUMAR, 2020; YADAV et al., 2021).

Silva et al. (2022) emphasize that in the Definition stage, one of the most used tools is the voice of the customer analysis (VOC), which can be supported by BDA and IoT by providing information about numerous customer requirements (ARCADIANO and PIERONI, 2018).

Once the main points of the project are defined, the second DMAIC phase takes place, which is the practical measurement of the processes and problems faced, and for this, the VSM tool can be used, which can use simulation to validate the VSM information (AMJAD et al., 2021). VSM can also be aided by RFID by being able to track resources needed in real-time for performance improvement (KUMAR et al., 2021; SORDAN et al., 2021). IoT technology plays a key role in the measurement phase since it is capable of automatically recording data through an interconnected network of smart sensors (FERNANDEZ et al. 2021). IoT enables real-time data collection, where information is automatically recorded through an interconnected network of smart devices (ARCIDIACONO and PIERONI, 2018; CHIARINI and KUMAR, 2021). BDA is a data science technique that plays a crucial role in this phase by collecting data and identifying factors with the greatest impact on product or process failures (PONGBOONCHAI-EMPL et al., 2023).

With the data obtained previously, the stage of Analyze, which includes statistical analysis, and for this FMEA and Ishikawa Diagram are used. The FMEA tool can be performed through simulation (YADAV et al., 2021), and the Ishikawa diagram can be better used with BDA (TAY and LOH et al., 2022). According to Bag et al. (2023), the Process Control SPC tool aims to identify process variations through data analysis, and this analysis is facilitated with the support of IoT and BDA technologies. Another technology that plays a crucial role in this phase is the CPS enables real-time data visualization and the analysis of critical information through a control panel (TAY and LOH 2022).

The fourth phase of DMAIC refers to the implementation of process improvements, for example, TPM and 5S are used. According to Yadav et al. (2021), RFID assists in 5S with clutter reduction. In addition, TPM can be supported by augmented reality and CPS, as it provides data that indicate possible failures (KUMAR et al., 2021; RIFGI et al., 2021). BDA plays a pivotal role in this phase, as it identifies impactful factors and failures in the product or process through decision tree algorithms, classification, and regression, this identification is crucial for suggesting improvements (PONGBOONCHAI-EMPL et al., 2023). The Internet of Things (IoT) enables automated data management, eliminating the chances of unnecessary breakdowns and downtime, and leading to significant improvements in process quality and performance (FENÁNDEZ et al., 2021).

Finally, the last phase of DMAIC takes place. According to Yadav et al., (2021), barcodes and RFID can help ensure error-proof (Poka-Yoke) and process control. For Kumar et al. (2021), BDA supports SPC by facilitating data collection and variation control. Through the IoT, data is processed using algorithms, providing insights and guidelines to keep the process under control (FERNÁNDEZ et al., 2021). Table 6 summarizes the list of I4.0 technologies in each DMAIC phase.

TABLE 6 - How I4.0 technologies impact each DMAIC phase

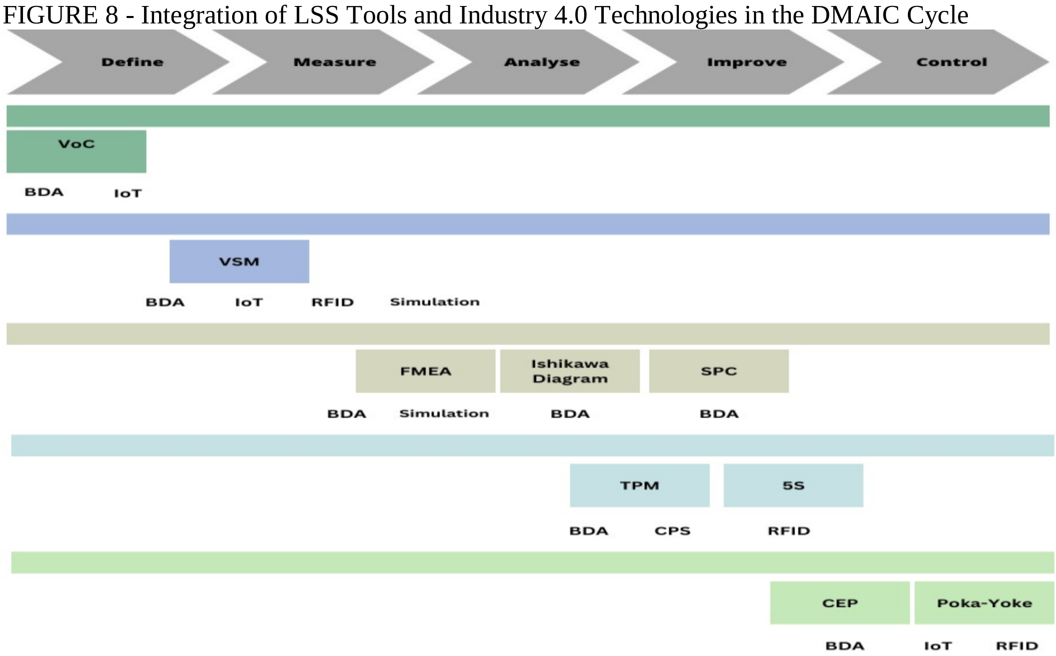
	Technologies I4.0	As	authors
D	BDA; IoT	For a project to be defined or a problem to be identified, there is a need for information about numerous customer requirements, process data, deviations, and variability, which can be provided by BDA and IoT.	1 and 9
M	BDA; Simulation; IoT; RFID	To map, measure, and understand the process, it is essential to collect a variety of data. IoT and BDA should help in this process. To Measure phase, simulation can validate VSM and RFID can track resources needed in real time.	1, 2, 3, 5 and 10
A	BDA; Simulation	BDA and simulation support quality tools to analyze processes statistically.	6, 8, 9 and 10
I	BDA; AI; RFID; CPS	For the implementation of process improvements, it is crucial to maintain organization, in this context, the 5S tool plays a significant role and is enhanced through the support of technologies such as RFID and BDA. Furthermore, rapid detection of potential failures is essential, and this is enabled by the data provided by technologies like BDA, IoT, CPS, and AR	6, 7, 8 and 9
C	BDA; RFID; IoT; bar code	Barcode and RFID help ensure error-proofing. BDA supports statistical process control by facilitating data collection, moreover, Through IoT data is processed to provide insights aimed at keeping the process under control.	3, 4 and 5

1- Arcdiacon and Pieroni (2018);
2- Amjad et al. (2021);
3- Kumar et al. (2021);
4- Fernández et al. (2021);
5- Sordan et al. (2021);
6- Yadav et al. (2021);
7- Rifqi et al. (2022);
8- Tay and Loh (2022);
9- Bag et al. (2023);
10- Pongboonchai-Empl et al. (2023);

Source: authors (2023).

In Figure 8, each phase of the DMAIC cycle, applied in the LSS methodology, is presented. In each stage of this cycle, the key tools of LSS that play a fundamental role in its development have been highlighted. Furthermore, the influence of I4.0 technologies on each of these tools is observed, emphasizing that advanced technologies such as IoT, BDA, RFID, simulation, and CPS are integrated to optimize the effectiveness of each phase of the DMAIC cycle.

FIGURE 8 - Integration of LSS Tools and Industry 4.0 Technologies in the DMAIC Cycle



Source: authors (2023).

2.6.3 Impact of organizational factors on the relationships between I4.0 and LSS

The literature review did not find any articles focusing exclusively on how organizational factors impact the relationships between LSS and I4.0, however information on the topic was obtained from several selected papers. According to Bhat et al. (2021), the involvement of management in decision-making, the availability of employees and social interaction are the factors that enable an effective implementation of technologies in the LSS environment.

Top management support positively impacts the implementation of change management in an organization, such as those that occur through the insertion of industry 4.0 technologies (SONY et al., 2021). For the relationship between LSS and industry 4.0 to be fruitful, in addition to addressing process changes, the organization needs to ensure that employees are trained in order to be efficient in their roles using advanced technologies and quality tools (KHANZODEet al., 2021; TAY and LOH et al., 2022). The training and development of human capacity leads to a decrease in resistance to the acceptance of technologies, increasing the ability to provide and analyze information correctly (RIALTI et al., 2019).

LSS practices and I4.0 technologies promote the capture of large amounts of data, quality management, connectivity and new insights. With that said, it is important that there is a data-oriented organizational culture that embraces change in a strategy (SONY et al., 2021). Leadership is one of the critical success factors in the relationship between I4.0 and LSS, and this relationship requires a leadership style that considers innovation, learning and positive relationships between companies as well as experience in Lean improvement techniques. In addition, leaders need to be capable of developing a highly motivated workforce capable of dealing with change (ANTONY et al., 2020; SONY et al., 2021; WHITMORE et al., 2020). For Sordan et al. (2021) there are two central pillars for the relationship between I4.0 and LSS: the technical infrastructure, such as effective data delivery and the management approach, which includes communication, motivation, employee participation and management change.

For Samanta et al. (2022) for the integration between LSS and I4.0 to be successful, some points must be worked on, such as an organizational culture that adopts change management, as this helps people to better accept and adapt to new technologies and work methods. Another fundamental factor is efficient communication at all levels of the company so that there is a better understanding and acceptance of the concepts and rules in the implementation of LSS and I4.0 (SAMANTA et al., 2022). In summary, Table 7 provides a comprehensive synthesis of the discussions on how organizational factors impact the relationship between LSS and I4.0.

TABLE 7 - Impact of organizational factors on the relationships between I4.0 and LSS

Factors	How to support LSS and I4.0 integration	Authors
Top management	Involvement of management in decision-making	Bhat et al. (2021)
	Support to management change in the insertion of industry 4.0 technologies	Sony et al. (2021) Sordan et al. (2021)

Communication	Communication at all levels of the company so that there is a better understanding and acceptance of the concepts and rules in the implementation of LSS and I4.0	Sordan et al. (2021) Samanta et al. (2022); Gupta et al. (2020)
Employees	Availability to learn and implement technologies	Bhat et al. (2021)
	Social interaction and employee participation to effective implement I4.0 technologies	Bhat et al. (2021) Sordan et al. (2021)
	Training to decrease in resistance and be efficient in their roles using advanced technologies and quality tools and analyze information correctly	Khanzode et al. (2021) Tay and Loh et al. (2022); Rialti et al. (2019)
	Motivation to use the technologies together with LSS	Sordan et al. (2021)
Culture	Data-oriented organizational culture that embraces change in a strategy	Sony et al. (2021)
	Change management to better accept and adapt to new technologies and work methods	Samanta et al. (2022) Gupta et al. (2020)
Leadership	Leadership that considers innovation, learning, positive relationships between companies and knowledge in LSS methods and tools	Antony et al. (2020) Sony et al. (2021) Whitmore et al. (2020)
	Leadership capable of develop highly motivated workforce capable of dealing with change	Antony et al. (2020) Sony et al. (2021) Whitmore et al. (2020)
Technical infrastructure	Support for data collection, data delivery and others	Sordan et al. (2021)

Source: authors (2023).

2.6.4 Possibilities for future studies

To gain greater knowledge of the influence of digitization and LSS, future studies can explore possible human and technological interactions, collecting data relevant to the topic (TAY and LOH 2022). Future studies should include samples from developing countries so that motivations, barriers, and impact on the performance of the relationship between I4.0 and LSS can be captured (SONY et al., 2021). It is also crucial to thoroughly investigate when I4.0 technologies should be deployed in LSS projects (CHIARINI and KUMAR 2020).

Research on the integration between Industry 4.0 and Lean Six Sigma technologies focuses on specific technologies, with a framework in order to understand which are the points of contact between the technologies and the LSS (SORDAN et al., 2021). In addition, little has been studied about the best way to manage changes and implement new technologies at an operational level (TAY and LOH, 2022).

Future research can focus on identifying the levels of big data training required for professionals involved in LSS projects and optimizing the implementation of big data in LSS projects, addressing varying degrees of specificity. Additionally, it is crucial to investigate the strategic integration of LSS and BDA to maximize organizational performance (GUPTA et al., 2019).

Bhat et al. (2021) verified in their study the modalities of leveraging the LSS for I4.0, and further research will help to understand the framework and appropriate strategies for issues involving sustainability, such as the circular economy. In the same sense, it is necessary to investigate the human aspect in projects and the relationships between human behavior and processes, also how I4.0 can influence both (WHITMORE et al., 2020). Future studies should look at what levels of staff need training in I4.0 technologies, for example from BDA to LSS projects and how communication and cultural change can impact (GUPTA et al., 2020; SAMANTA et al., 2022). Some limitations of the present study should be highlighted, such as the use of two databases and the focus only on peer-reviewed articles, that is, journal articles.

2.7 CONCLUSION

Despite the growing interest in the relationship between I4.0 and the LSS methodology, no article has comprehensively reviewed the relationship between I4.0 and LSS and its interaction with organizational factors. Thus, this article aimed, through an SLR, to verify the behavior of publications and analyze them in the domain of the theme of the relationship between I4.0 and LSS, and how organizational factors interfere with it. The study aimed to answer four research questions.

The study aimed to answer four research questions. The first aimed to characterize the literature that addresses the relationship between I4.0 technologies and LSS. The findings show that interest has grown in the last three years, due to the increase in papers published in the area, but that the topic is recent. However, studies on the subject are still predominantly theoretical and conceptual due to its recent nature and innovative character, showing that the subject still needs empirical studies and further advances. It was also possible to identify that the main technologies that relate to the LSS are BDA and IoT, due to their nature of analysis and data collection, respectively. This is because LSS is a data-driven methodology (ANTONY et al., 2018).

The second research question addressed how I4.0 technologies influence LSS practices and tools. After conducting a comprehensive descriptive and thematic analysis of relevant articles, a deeper understanding of this phenomenon was achieved. LSS tools that apparently benefit most from I4.0 technologies are Poka-Yoke, VSM, SPC, and VoC. Among the technologies that most relate to LSS tools are: Big Data, IoT, Simulation and RFID. Contact with these technologies transforms LSS tools into 4.0 tools (RIFQI et al., 2021). Regarding LSS practices, it can be observed that CPS has a role similar to that of IoT for LSS, increasing data availability, enabling decision-making based on real-time data and analysis of the effects of changes (KUMAR et al., 2021; TAY and LOH, 2022). Blockchain allows for increased communication and connectivity (KUMAR et al., 2021; RIFQI et al., 2021), enabling faster and anywhere access to collected data. Technologies such as AI and Machine Learning make it possible to identify patterns of waste, carry out prediction models and better regulate process parameters (KUMAR et al., 2021; YADAV et al., 2021; SAMANTA et al., 2022).

The research also aimed to understand how the DMAIC phases are influenced by I4.0 technologies. The findings related to how I4.0 technologies relate to LSS and DMAIC, show that BDA helps in data analysis, for identifying variations, root cause identification, process control and predictive analysis (KUMAR et al., 2021; GUPTA et al., 2019; ANTONY et al., 2018), thus helping in all phases of DMAIC (Sony et al. 2021; BAG et al., 2023). While sensor technologies such as IoT and RFID allow for real-time data collection, monitoring of deviations and variability, greater communication between stakeholders, process steps and supply chain and greater inventory control (YADAV et al., 2021; RIFQI et al., 2021; VINODH et al., 2021; SORDAN et al., 2021). This technology also assists in the various phases of DMAIC as it allows data collection for project definition, measurement, analysis and control (ARCADIANO and PIERONI, 2018).

This study contributes to the literature on the topic, since several authors have pointed out that I4.0 is beneficial for the LSS in the different phases of LSS projects (ARCADIANO and PIERONI, 2018; KAMBLE et al., 2018; TAY and LOH, 2022). However, these studies do not advance how these technologies can help. The findings indicate that technologies such as BDA help in all phases of DMAIC (SONY et al. 2021; TAY and LOH 2022; GUPTA et al., 2020; BAG et al., 2023) because they allow data analysis for the definition of a problem, measuring its impact, analyzing its causes and even proposing improvements and control. These findings corroborate the statements of authors such as Pongboonchai-Empl et al. (2023). IoT also helps in several phases, since it allows the capture of data in real time (YADAV et al., 2021), which can facilitate the definition of problems to be eliminated, analysis of the causes of variations and process control.

Answering the fourth research question, it was possible to identify the main organizational factors that affect the relationships between the I4.0 technologies and the LSS. Among the factors, the involvement of Top Management in decision-making and change management stands out (BHAT et al., 2021; SONY et al., 2021; SORDAN et al., 2021), the importance of Employees for the social interaction, participation, training, motivation and availability to learn, implement and use the technologies integrated into the LSS (RIALTI et al., 2019; BHAT et al., 2021; SORDAN et al., 2021), the Ledearship capable of developing and motivating employees for this integration and the Data-oriented culture focused on change management (ANTONY et al., 2020; SONY et al., 2021; WHITMORE et al., 2020). Therefore, it is possible to highlight the importance of change management for this integration and the support both from Top Management, Leadership and the creation of a culture of support for this change.

The study holds significant academic implications by filling a gap in the literature, as it focuses on the relationship between LSS and I4.0, as noted by Buer et al. (2018) and Singh et al. (2023). Furthermore, the research explores how I4.0 technologies can support various LSS tools, as Pongboonchai-Empl et al. (2023) mentioned. The present study also addresses the influence of organizational factors on the LSS and I4.0 relationship, addressing a literature gap identified by Yadav et al. (2021).

From a managerial perspective, this study offers several relevant contributions. Firstly, it provides an in-depth understanding of the relationship between LSS and I4.0, highlighting how technologies can influence LSS projects. This is particularly important for professionals seeking to comprehend this relationship to achieve enhanced organizational outcomes. The research addresses the impacts of technologies on LSS, such as the focus on using data collected by the IoT to enable real-time problem identification and subsequent process control and variability management. When these technologies are used in conjunction with BDA, it allows for more precise measurements with advanced statistical techniques and analyses to identify root causes and exercise subsequent control. Additionally, tools like Blockchain offer professionals greater agility and enhance data communication in LSS projects. The study underscores the importance of an environment conducive to change management, with the support of the entire organizational structure, including senior management, leaders, and employees.

The findings also showed that additional research should be carried out in order to provide the steps for effective implementation of I4.0 technologies and LSS, observing empirical studies (SONY et al., 2021; TAY and LOH 2022) focusing on which and how technologies should be integrated, barriers and impact on performance. Another point to be highlighted for future studies is the importance of organizational factors such as employee involvement (WHITMORE et al., 2020), communication and change management (GUPTA et al., 2020).

3. PAPER 2: THE ROLE OF BIG DATA ANALYTICS CAPABILITIES IN ENHANCING LEAN SIX SIGMA EFFORTS AND THE IMPACT ON ORGANIZATIONAL PERFORMANCE: AN EMPIRICAL STUDY IN BRAZILIAN MANUFACTURING

This study aims to investigate the impact of Big Data Analytics (BDA) capabilities (technological and managerial) on Lean Six Sigma (LSS) efforts, and the mediating role of LSS on the relationship between BDA and organizational (financial, operational and quality) performance. It also examines whether data-driven culture (DDC) and top management support (TMS) moderate the relatioship between BDA and LSS.

A survey was conducted with 184 professionals from Brazilian manufacturing companies experienced in both LSS and BDA. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM), including higher-order constructs and moderation/mediation analysis.

The results show that BDA management capability has a positive and significant effect on LSS efforts, while BDA technological capability does not. Furthermore, LSS fully mediates the effect of BDA management on operational and quality performance. However, DDC and TMS did not moderate the relationship between BDA and LSS.

The findings highlight the importance of focusing on the managerial aspects of BDA to enhance LSS initiatives. They also demonstrate that LSS is a necessary factor for BDA to achieve impact on the organization's performance. Managers should prioritize strategic and well-structured data analysis aligned with continuous improvement practices to improve performance outcomes.

This study contributes to the scarce empirical literature that integrates BDA and LSS, particularly in the context of developing economies. It provides novel insights into the mediating role of LSS in the impact of BDA on operational and quality performance.

Keywords: *Big Data Analytics, Lean Six Sigma, Data-driven culture, Top management support, Organizational performance, PLS-SEM, Manufacturing*

3.1 Introduction

Lean Six Sigma (LSS) is a well-established business process improvement methodology that combines Lean management principles for efficiency, reduction of waste and non-value-added activities with Six Sigma analytical and statistical methodologies for defect elimination and systematic problem solving (SNEE 2010; BELHADI et al. 2020, 2023; CHERRAFI et al. 2017; SKALLI et al., 2024). However, new challenges arise in the era of Industry 4.0, more complex processes, greater quality constraints, customization, vast amounts of heterogeneous data recorded by machines and interconnected systems, which require a paradigm shift in the LSS methodology (PONGBOONCHAI-EMPL et al., 2023).

There are several studies that indicate the relevance of the integration between LSS and Industry 4.0 (I4.0) technologies (CHIARINI and KUMAR, 2021), since I4.0 technologies can make LSS reach new heights and overcome limitations (GUPTA et al., 2019; PONGBOONCHAI -EMPL et al., 2023; MAIA et al., 2023). Big Data and Big Data Analytics (BDA) have been addressed by several authors in literature as being the main potential technology for integration with LSS (E.G. GUPTA et al., 2019; BELHADI et al., 2020; TAY and LOH, 2021, ZULFIQAR et al., 2024; WANKHEDE et al., 2025).

BDA can help LSS overcome the limitations of traditional LSS statistical methods and tools. It enables the expansion of LSS through the incorporation of advanced analytical techniques, including anomaly detection, risk assessment, trend analysis, as well as descriptive and predictive analytics based on large-scale data analysis (GUPTA et al., 2019; PONGBOONCHAI -EMPL et al., 2023; MAIA et al., 2023).

BDA has a great potential to bring positive impacts to LSS approach by providing information about process capability and analysis tools to understand and solve complex problems (BELHADI et al., 2020; 2023; GUPTA et al., 2019). Additionally, can control their operations in real time, perform event-based inspection, predictive maintenance and make data-driven decisions (BELHADI et al., 2020; 2023; FAYYAZ et al., 2024; TISSIR et al., 2024). The combination enables organizations to identify patterns, trends, and opportunities for improvement in their processes (RAUT et al., 2019). However, there are limited empirical examples of the use and impact of BDAs in LSS projects, mainly in developing countries (BELHADI et al., 2020; FAYYAZ et al., 2024) and more studies on the topic are needed.Studies are needed because LSS presents challenges in a large data volume scenario (PONGBOONCHAI-EMPL et al., 2023). For effective integration it is necessary adequate infrastructure and development of new knowledge and skills (GUPTA et al., 2019; CHIARINI and KUMAR, 2021).

Studies have become more relevant, due to the impact between LSS and BDA on the organization's performance. The integration of BDA with LSS can enhance operational efficiency, reduce costs, and foster sustainability, making its application a relevant contribution to both theory and practice (BELHADI et al., 2020; 2023; CITYBABU and YAMINI, 2024). The literature emphasizes the need to investigate BDA capabilities to understand their role in driving economic performance through LSS continuous improvement (FAYYAZ et al., 2024). The integration also helps reduce costs, defects, and non-value-added activities, while enhancing product/service quality, cycle time, and customer satisfaction (ABLIWI et al., 2015; PONGBOONCHAI-EMPL et al., 2023). Consequently, LSS–BDA integration can positively influence operational (Chiarini and Kumar, 2021), financial (FAYYAZ et al., 2024), and quality performance (PONGBOONCHAI-EMPL et al., 2023; ZULFIQAR et al., 2024).

Studies addressing the integrated relationship between LSS, BDA, and performance remain scarce, as most research focuses on pairwise analyses (BELHADI et al., 2020). Given the topic’s novelty, organizational relevance, and limited empirical evidence, further studies are needed to establish a conceptual framework supported by data (BELHADI et al., 2020, 2023; FAYYAZ et al., 2024).

Belhadi et al. (2020) emphasize the need for quantitative research and relational models involving BDA, LSS, and performance, including broader sets of mediators, moderators, or contextual variables. Several factors can influence how BDA is integrated with LSS (ZULFIQAR et al., 2023; MACIAS-AGUAYO et al., 2024). This study focuses on two moderators: top management support and data-driven culture.

Top management support is a key enabler of integration, as it provides strategic guidance, resources, and fosters a shared vision and employee commitment (MACIAS-AGUAYO et al., 2023; SKALLI et al., 2024; TISSIR et al., 2024). Recent studies identify it as the most significant enabler across industries, firm sizes, and national contexts (ZULFIQAR et al., 2023). Likewise, a data-driven culture supports the integration of LSS and Industry 4.0 technologies by maximizing the strategic use of data (DUBEY et al., 2019). Since LSS is inherently data-driven (Gupta et al., 2019), its integration with BDA relies on analytics to support effective, evidence-based decisions (BELHADI et al., 2020; SKALLI et al., 2024).

Therefore, the main gaps that this research aims to address are related to the lack of empirical studies exploring the impact of BDA on LSS (BELHADI et al., 2020; PONGBOONCHAI-EMPL et al., 2023; FAYYAZ et al., 2024), and whether the combination of BDA and LSS can yield better performance for companies (BELHADI et al., 2020, 2023; FAYYAZ et al., 2024). Further research is especially necessary when considering the impact on different types of performance, such as economic (FAYYAZ et al., 2024), operational (Chiarini and Kumar, 2021; Skalli et al., 2024), and quality (ZULFIQAR et al., 2024). The literature and experts in operations management reinforce the need for further investigations to establish a conceptual relationship between LSS and BDA, supported by empirical evidence (Chiarini and Kumar, 2021; Belhadi et al., 2020). Additionally, although BDA is widely recognized for its importance, few empirical studies have been conducted, especially in developing countries (BELHADI et al., 2020). Therefore, this study aims to answer the following research questions:

RQ1: Does BDA positively impact LSS?
RQ2: Does BDA mediate by LSS impact financial/operational/quality performance?
RQ3: Do data-driven culture and top management support act as moderators in the relationship between BDA and LSS?

In this study, the research questions are answered through a survey with professionals from manufacturing companies located in Brazil, which is a developing country. Manufacturing companies were chosen because they have faced the challenge of incorporating new technologies with process improvement methodologies, such as LSS (SKALLI et al., 2023; KUMAR et al., 2024). The structure of the article is organized as follows: Section 2 explores the theoretical constructs underpinning the study and presents the development of the hypotheses. Section 3 details the research methodology adopted, while Section 4 focuses on the data analysis and the results obtained. In Section 5, the managerial implications of the findings are discussed. Finally, Section 6 concludes the article by highlighting the study's limitations and suggesting an agenda for future research.

3.2 Theoretical Background and Hypothesis

3.2.1 Lean Six Sigma

LSS is recognized as a holistic methodology that combines two complementary approaches to continuous improvement: Lean and Six Sigma (CHERRAFI et al., 2017; SORDAN et al., 2020; BELHADI et al., 2023). Lean principles focus on waste elimination, while Six Sigma emphasizes statistical rigor to reduce variation and defects (CHERRAFI et al., 2017; SRIJITHESH et al., 2024). In practice, Lean drives efficiency and Six Sigma delivers quality through data-driven problem solving (SINGH and RATHI, 2019; SIM et al., 2022; ASIF, 2021). The integration of these two philosophies results in a powerful methodology for enhancing competitiveness and organizational performance (SINGH and RATHI, 2019; SUNDER et al., 2018), sustaining its relevance across sectors (ASNAASHARI and KHODABANDEHLOU, 2023).

LSS contributes to operational excellence by systematically eliminating non-value-added activities and defects, while promoting speed, accuracy, and continuous improvement (CHERRAFI et al., 2017; BELHADI et al., 2020, 2023; TISSIR et al., 2024). As a data-driven methodology, it relies on robust analytical tools and performs best when supported by accurate and real-time data (ARCIDIACONO and PIERONI, 2018; SKALLI et al., 2024; KUMAR et al., 2024).

LSS enhances quality and productivity by reducing variation and eliminating activities that do not add value (CITYBABU and YAMINI, 2024). Its implementation brings tangible benefits, such as cost reduction, higher quality, improved customer satisfaction, and increased capacity (ABLIWI et al., 2015; PONGBOONCHAI-EMPL et al., 2023). However, handling large volumes of data introduces new challenges, demanding adaptations in LSS practices (PONGBOONCHAI-EMPL et al., 2023).

3.2.2 Big Data Analytics

Big Data refers to large amount of data gathered from various sources characterized by high volume, variety, velocity, and uncertainty, which must be transformed into actionable insights through Big Data Analytics (BDA) (BELHADI et al., 2019; 2023; SAMANTHA et al., 2023). BDA encompasses analytical methods such as statistics, simulations, and optimization to support decision-making (ARUNACHALAM et al., 2018; DENISWARA et al., 2020; BELHADI et al., 2019;

2023). It enables pattern and trend identification beyond the reach of traditional methods (ZULFIQAR et al., 2023), improving resource use and strategic decisions (BELHADI et al., 2020). BDA capability refers to an organization's ability to turn data into strategic insights through tangible (e.g., infrastructure), human (e.g., technical skills), and intangible (e.g., data-oriented culture and organizational learning) resources (AKTER et al., 2016; GUPTA and GEORGE, 2016).

BDA capability can be observed through two major dimensions, technological and management (SUN and LIU, 2021). BDA management capability refers to an organization's competence in carrying out essential activities in managing Big Data Analytics processes, including planning, investment decisions, coordination, and control (AKTER et al., 2016). Companies with high BDA management capability incorporate routines in their tasks, processes, and teams to analyze and process Big Data in decision-making, facilitating a data-driven rational approach (AKTER et al., 2016). While BDA technological capability refers to the ability of infrastructure to provide an integrated platform that ensures data connectivity, compatibility, and flexibility (AKTER et al., 2016; WAMBA et al., 2017). According to Akter et al. (2016), this technological capability provides a flexible platform that allows the BDA team to adjust or recombine existing data modules with ease.

3.2.3 Integration between LSS and BDA

LSS is inherently data-driven (ZWETSLOOT et al., 2018; SKALLI et al., 2024; KUMAR et al., 2024), requiring data collection and analysis throughout the DMAIC cycle making the collection and analysis of large volumes of data highly necessary (GUPTA et al., 2019). Integrating BDA modernizes LSS practices, providing a robust foundation for more assertive decisions (BELHADI et al., 2020). For example, BDA can automate problem identification and reduce analysis time in LSS projects (KOPPEL and CHANG, 2021; PONGBOONCHAI-EMPL et al., 2023).

LSS benefits from BDA, and in some cases, this relationship is mutually beneficial (PONGBOONCHAI-EMPL et al., 2023). The DMAIC method can provide the structure and tools necessary for the successful application of BDA (SHIVAJEE et al., 2019). When combined, large volumes of data and appropriate infrastructure allow for more reliable, robust, and predictable analyses, making BDA an essential element to complement and strengthen LSS (ZWETSLLOT et al., 2018; GUPTA et al., 2019).

This synergy not only improves operational efficiency but also facilitates the implementation of continuous improvement programs, promoting cost reduction and contributing to the sustainable growth of organizations (BEHALDI et al., 2020). The positive and significant impact of BDA on LSS strengths companies' ability to adapt and respond to contemporary operational challenges (REJIKUMAR et al., 2020). Despite the growing relevance of BDA usage, there is still a significant lack of empirical studies on the subject (REJIKUMAR et al., 2018; BELHADI et al., 2020; FAYYAZ et al., 2024), especially in developing countries, which limits the global understanding of its impact on these economies (BEHALDI et al., 2020).

Additionally, to achieve LSS and I4.0 integration, organizations should have adequate infrastructure (ZULFIQAR et al., 2024), a data-driven mindset (SKALLI et al., 2024) and advanced skills to deal with advanced statistical tools and their outputs (GUPTA et al., 2019; CHIARINI and KUMAR, 2021). Therefore, there is a need to understand whether BDA capabilities are impacting LSS efforts in manufacturing firms in a developing country context.

H1a: BDA Management Capability positively affects LSS efforts.

H1b: BDA Technology Capability positively affects LSS efforts.

3.2.4 Impact on Performance

BDA–LSS integration enhances agile and accurate decision-making, impacting financial, operational, and quality performance. In terms of operational performance, it improves production efficiency and reduces downtime (CITYBABU and YAMINI, 2024; BELHADI et al., 2020), Additionally, by providing real-time data, faster recognition of patterns and trends, and more precise root cause analysis, it results in more efficient and effective operations (RAUT et al., 2019; IBRAHIM and KUMAR, 2024).

This relationship is considered highly promising for operational and quality excellence (ANTONY et al., 2019; KOWKOWSKI et al., 2023). BDA can detect defects and analyze their root causes in real time, which improves product and service quality and customer satisfaction, further contributing to the quality performance of the organization (ARCIDIACONO and PIERONI, 2018; BELHADI, 2020; PONGBOONCHAI-EMPL et al., 2023). BDA enables organizations to quickly analyze large volumes of data, identify connections, gain quality insights, implement preventive process changes, reduce waste, and improve quality performance (KOWKOWSKI et al., 2023; CITYBABU and YAMINI, 2024; IBRAHIM and KUMAR, 2024).

The integrated approach offers benefits such as cost savings through waste elimination and timely, data-driven decision-making, ultimately increasing profits (RAUT et al., 2019; PONGBOONCHAI-EMPL et al., 2023). Confirming practices that enhance financial performance is especially relevant for organizations in developing countries, as is understanding the effects of LSS–BDA integration in these contexts (BELHADI et al., 2020; FAYYAZ et al., 2024). Due to the potential impact of BDA and BDA-supported by LSS on organizational performance, the following hypotheses are presented

H2a: BDA mediated by LSS efforts positively impacts financial performance.

H2b: BDA mediated by LSS efforts positively impacts operational performance.

H2c: BDA mediated by LSS efforts positively impacts quality performance.

3.2.5 Moderators Factors

A data-driven culture reflects shared norms, values and behaviors that support data use for decision-making, encouraging learning, knowledge sharing, and openness to change (DUAN et al., 2020). It ensures that decisions are based on analytical insights across all levels of the organization (GUPTA and GEORGE, 2016). The success of BDA is strongly tied to a data-driven culture, which aligns analytics with long-term strategies, supports informed decision-making, and enhances organizational outcomes (SUN et al., 2018; MAROUFKHANI et al., 2020; AL-SAI et al., 2020; GROVER et al., 2018; KARABOGA et al., 2022). Establishing such a culture allows companies to adopt a structured approach to data use and deliver relevant insights to decision-makers (DUAN et al., 2020). To fully leverage BDA, it is essential to foster this culture and base decisions on data-driven insights (KARABOGA et al., 2023).

H3a: A data-driven culture plays a moderate role in the relationship between BDA

Management and LSS efforts.

H3b: A data-driven culture plays a moderate role in the relationship between BDA Technological and LSS efforts.

Top management support is essential for adopting new technologies such as BDA, as leaders define digital strategies and allocate resources for organizational transformation (FINKELSTEIN and HAMBRICK, 2009; ZHANG et al., 2024). Executives play a key role in recognizing BDA's potential to enhance performance in manufacturing firms (RAUT et al., 2019) and should lead efforts to embed BDA across the organization and supply chain (RAUT et al., 2021). Their support is crucial for successful adoption, influencing acceptance and implementation (Jum'A et al., 2022; WAQAR and PARACHA, 2023).

Studies also confirm that top management support is a critical enabler of LSS and Industry 4.0 integration (ZULFIQAR et al., 2023; MACIAS-AGUAYO et al., 2022). A common barrier to this integration is the lack of commitment from leadership, which is needed to provide strategic input and ensure success (SKALLI et al., 2024).

H4a: Top Management Support plays a moderate role in the relationship between BDA Management and LSS efforts.

H4b: Top Management Support plays a moderate role in the relationship between BDA Technological and LSS efforts.

3.3 Research Method

3.3.1 Sampling and Data Collection

The sample consisted of LSS professionals and consultants from manufacturing companies who had also participated in projects involving BDA. Respondents were identified through LinkedIn, which enabled the selection of professionals with verifiable experience in both LSS and Big Data. Social media was chosen as the recruitment strategy due to its ability to filter specific professional experiences efficiently (POTTER, 2021), and has been widely used in surveys on organizational phenomena (E.G., MESQUITA et al., 2023; PSOMAS et al., 2023; LIZARELLI et al., 2023). Participants were contacted directly via LinkedIn, receiving an explanation of the research objectives and a link to the online questionnaire (hosted on Google Forms). Of the 715 professionals contacted, 214 completed the survey.

To ensure data validity and quality (WULFF et al., 2023), several procedures were adopted. Respondents' profiles were screened for knowledge of LSS and Big Data in manufacturing; 8 surveys were removed for not meeting this criterion. All questions included "I don't know how to answer" or "I prefer not to answer" options; these were treated as missing values. Surveys with more than 10% missing data were excluded (19 cases), and for the remaining data (less than 5% per variable), mean imputation was applied, as recommended by Hair et al. (2017). Questionnaires showing suspicious patterns (e.g., straight-lining) were also removed (3 cases). No multivariate outliers were identified. After all procedures, 184 valid responses remained.

Table 1 presents the respondents' profile and the characteristics of their companies. A significant portion of the sample occupies decision-making positions (managers, directors, and supervisors – 43%) or roles related to project execution and data analysis (analysts and consultants – 39%). Respondents work in companies from various sectors, demonstrating sample diversity, with Food and Beverage (10%), Machinery and Equipment (9%), and Agribusiness (8%) as the most represented. Most companies are large, with over 500 employees (Table 8). The respondents are trained in LSS: 69% are at least Green Belts, and 73% have over three years of experience with LSS projects. A similar pattern is observed for Big Data: 71% report moderate or substantial knowledge, and 42% have over three years of project experience. Although 23% have less than one year of experience with Big Data, this may reflect the topic's relative novelty. These results indicate that the sample is adequately qualified to answer the questionnaire.

Table 8. Respondents and companies characteristics

Respondent Position	**Number**	**%**
Manager	46	25%
Analyst (LSS, Big Data)	40	22%
Consultant	32	17%
Supervisor	20	11%
Director	13	7%
Engineer/Coordinator	10	5%
CEO	7	4%
Specialist (LSS, Big data)	4	2%
Other	12	7%

Sector	**Number**	**%**

LSS Training	**Number**	**%**
I have training in LSS	22	12%
White Belt - WB	10	5%
Green Belt - GB	69	38%
Black Belt - BB	50	27%
MasterBlack Belt - MBB	25	14%
I prefer not to answer	8	4%

Experience LSS projects	**Number**	**%**
Less than 1 year	9	5%
Between 1 and 2 years	31	17%
Between 3 and 5 years	54	29%

Consulting	37	20%
Food and beverage	19	10%
Machinery and equipment	17	9%
Agribusiness	15	8%
Chemical or petrochemical	12	7%
Electronics/electronics	12	7%
Pulp and paper	8	4%
Automotive	8	4%
Pharmaceutical	7	4%
Textile or clothing	7	4%
Other	42	23%

Size	**Number**	**%**
Micro (<20)	15	8%
Small (≥20 and <99)	20	11%
Medium (≥100 and <499)	31	17%
Large (> 500)	118	64%

Between 6 and 10 years	34	18%
Over 10 years	47	26%
I prefer not to answer	9	5%

Knowledge about Big Data	**Number**	**%**
Little	40	22%
Moderate	71	39%
Substantial	58	32%
I prefer not to answer	15	8%

Experience in Big Data projects	**Number**	**%**
Less than 1 year	43	23%
Between 1 and 2 years	52	28%
Between 3 and 5 years	51	28%
Between 6 and 10 years	16	9%
Over 10 years	9	5%
I prefer not to answer	13	7%

3.3.2 Research instrument design and variables

The research instrument was a self-administered online questionnaire developed using the Google Forms tool. The development of the research questionnaire underwent validation by experts on the topic to assure content validity and check problems in understanding the statements and presentation, aiming to reduce response bias (FORZA, 2002; HAIR et al., 2019). The questionnaire was validated by three academic experts who research LSS and BDA, 3 experts with experience in LSS and BDA projects and 3 target respondents working in this field. The questionnaire contained four sections, the first contained nominal qualitative questions about the respondent (position, time in the company, training in LSS, experience with LSS and BDA projects) and about the company (size and sector). The second section contained questions about BDA Management Capability and BDA Technology Capability in the company where the respondent works. The third section contains questions about LSS efforts, to understand the perception about the use of LSS practices in the company. The fourth and final section contained questions about financial, organizational and quality performance. These variables were measured as ordinals scale using a 5-point Likert scale (1-“Strongly Disagree”; 5-“Strongly Agree”) (Hair et al. 2017A; FAYYAZ et al., 2024).

Measurement scales for the constructs are based on previous literature and on scales already developed and tested. The constructs, variables, and references are presented in

Table 9.

Table 9: Survey constructs and variables

Construct		Variables	Authors
BDA technology capabilities (BDAT)		All offices (e.g. remote and mobile) are connected to the central for sharing analytics Use of open systems network mechanisms to boost analytics connectivity Software can be used across multiple analytics platforms Interfaces provide access to all platforms Applications can be adapted to the needs of analytics tasks	Sun and Liu (2021); Huang et al. (2022); Akter et al. (2016) and Ferraris et al. (2019)
BDA management capabilities (BDAM)		Continuously examine opportunities for the strategic use of business analytics Systematically planned business analytics processes Estimate the effect business analytics investment decisions will have on the productivity of the employees' Project on how analytics investments improve decision speed for end users Information is widely shared between business analysts and line people to have all available know-how The responsibility for analytics development is clear	
LSS Efforts	**DMAIC methodology (DMAIC)**	DMAIC is fostered for problem-solving DMAIC is perceived as a philosophy Systematic training to DMAIC is provided	Belhadi et al. (2019)
	LSS tools and techniques (TT)	LSS tools are a routine matter LSS tools support the analysts to make real-time decisions Staff is well trained about LSS tools Good results are reached by applying LSS tools	
	Waste elimination (WE)	Wastes are systematically identified Employees have a culture of waste elimination Managers are committed in waste elimination actions Waste elimination is included in our policy	
	Variability reduction (VR)	Stability of key parameters is systematically sought Control charts are well established within process Employees can detect variability within process	
	Measurement metrics (MM)	There is a reliable source of data for LSS metrics Managers monitor the metrics LSS metrics are included in dashboards Reliable methods are used to calculate LSS metrics	
Data-driven culture (DDC)		Data is a tangible asset Decisions are based on data rather than on instinct	Yu et al.(2021); Shamim et al. (2020); Karaboga et al. (2023); Gupta e George

	Intuition is override when data contradict the viewpoints The business rules are improved in response to data insights Employees are coached to make decisions based on data	(2016)
Top Management Support (TMS) to BDA	TM provide the necessary support for BDA adoption TM support the use of BDA TM are enthusiastic about adopting BDA	Waqar and Paracha (2023) utilzou Lian et al. (2014) and Maduku et al. (2016)
	Big data adoption is funded by TM Big data applications are adopted by TM in order to gain a competitive advantage Big data applications are considered strategic by TM	Jum'a et al. (2022); Sun et al., (2020)
Financial Performance (FP)	Increased profits Increase market share Increased return on investment Return on asset Sales growth	Afum et al. (2020); Gaikwas and Sunnapwar (2020)
Quality Performance (QP)	Quality of products and services has been improved Process variability has decreased Delivery of products and services has been improved Cost of scrap and rework as a percentage (%) of sales has decreased Cycle time has decreased Customer satisfaction has increased Equipment downtime has decreased	Patyal and Koilakuntla (2017); Zeng et al. (2015)
Operational Performance (OP)	Decreasing delivery cycle time Rapidly responding to market demand changes Rapidly bringing new products/services to the market Rapidly entering new markets Rapidly confirming customer orders Rapidly handling customer complaints Establishing a strong and continuous bond with customers	Wong and Ngai (2023); Wang et al. (2012)

3.3.3 Response and common method bias

Some procedures were adopted to minimize Common Method Bias. Respondent anonymity was adopted to reduce evaluation apprehension, grouped items from the same construct were avoided, the analysis of the respondents' characteristics aimed to ensure that they had the cognitive ability or experience in dealing with the topic of interest, and the aim was to reduce the difficulty of the questionnaire through pilot testing and the elimination of ambiguous, difficult, or complex language (AS INDICATED BY PODSAKOFF et al., 2012; 2024). An assessment of the presence of Common Method

Bias has often been required for PLS-SEM models (HAIR et al., 2017b). Harman's Single-Factor Test was applied to the present study (PODSAKOFF et al., 2003; HAIR et al., 2017b). The exploratory factor analysis was conducted without factor rotation, and the test showed that the single factor extracted 36.4% of the variance, less than the 50% threshold value. Additionally, the analysis proposed by Kock (2015) to verify Common Method Bias based on full collinearity tests was also carried out. To this end, the inner Variance Inflation Factor (VIF) of the model was analyzed for all constructs, and all values were lower than 3.3, confirming the absence of Common Method Bias (KOCK, 2015; 2023). This indicates that Common Method Bias is not an issue. To test for possible non-response bias, the sample was divided between early and late respondents. Levene's test and a t-test (ARMSTRONG and OVERTON, 1977) were used to verify equality of variances and means between the two groups. No statistically significant differences were found (p-value < 0.05).

3.3.4 Data analysis

PLS-SEM is a variance-based SEM and one of the main SEM techniques used by researchers to analyze complex interrelationships between constructs (HENSELER, 2021). In recent years, the method has been increasingly used in many business and social science disciplines (HAIR et al., 2019; 2020; HENSELER, 2024). PLS-SEM is a suitable approach to deal with composite models and creates construct scores as composite variables, which may involve many constructs and indicators/variables (LATAN et al., 2023). PLS-SEM has the ability to deal with formative or composite variables, complex structural and/or measurement models, nonparametric scales (ordinal or nominal), the use of latent variable scores in subsequent analyses (the structural model will be estimated with a higher-order construct), and non-normally distributed data (MANLEY et al., 2021; LATAN et al., 2023), which are situations present in the current study. The analyses were carried out using Smart PLS 4.0 statistical software.

One of the characteristics of the PLS-SEM method is that it can deliver meaningful results even for small sample sizes (HAIR et al., 2014; 2020). However, some authors indicate that even though it is suitable for small samples, it is important to estimate a minimum sample size, for which different calculation methods exist (KOCK, 2022). One of the most used methods for estimation is the minimum R-squared, which was applied considering a power of 0.95, and the minimum sample size estimated was 107 (HAIR et al., 2017a). As an alternative for minimum sample size estimation in PLS-PM, the inverse square root method was also used (KOCK and HADAYA, 2018), as it is a conservative method that slightly overestimates minimum sample sizes (KOCK, 2022). To apply the method, the minimum absolute significant path coefficient of the model was considered ($\beta = 0.269$; p-value < 0.05) for a retrospective estimation, indicating a minimum sample of 86 respondents. Therefore, considering the two methods applied, the current sample is sufficient for the analysis of the proposed model.

The proposed research model (Figure 9) is composed of five reflective constructs (BDA Management Capability, BDA Technology Capability; Operational, Quality, and Financial Performance), a reflective-reflective second-order construct (LSS Efforts), and two moderating constructs that are also reflective (Data-Driven Culture and Top Management Support). LSS Efforts is a second-order construct (reflective-reflective type), which is evaluated by concrete LSS practices used in companies that encompass efforts for LSS to be in use (Table 9): DMAIC Methodology, Waste Elimination, Variability Reduction, Measurement Metrics, and LSS tools and techniques. Higher-order models require specific approaches for specifying and estimating higher-order constructs (HOC) in PLS-SEM (Hair et al., 2018; Sarstedt et al., 2019).

The HOC enable a complex construct to be modeled in a more abstract dimension (referred to as higher-order component) and in its more concrete subdimensions (referred to as lower-order components), enabling the conceptual dimension of the construct to be effectively captured (Sarstedt et al. 2019; CATALDO et al., 2023). HOCs simplified structural models by reducing the number of path model relationships, thereby achieving model parsimony (Sarstedt et al. 2019; Hair et al. 2021; CATALDO et al., 2023).
Higher-order constructs follow specific PLS-SEM estimation procedures (HAIR et al., 2018; SARSTEDT et al., 2019). In this study, the disjoint two-stage approach was used, which consists in estimating the construct scores of the lower order constructs without the presence of HOC in stage one and, subsequently, in the second stage, the PLS-SEM analysis is performed using the first stage computed scores as indicators of the HOC (CATALDO et al., 2023). All other constructs in the path model are estimated using their standard multi-item measures as in stage one (SARSTEDT et al., 2019). The same assessment criteria for general PLS-SEM measurement models must also be used for higher-order models in stage one and stage two Sarstedt et al., 2019). The choice of method was due the disjoint two-stage approach permits the application of all structural model assessment criteria in both stages (SARSTEDT et al. 2019).

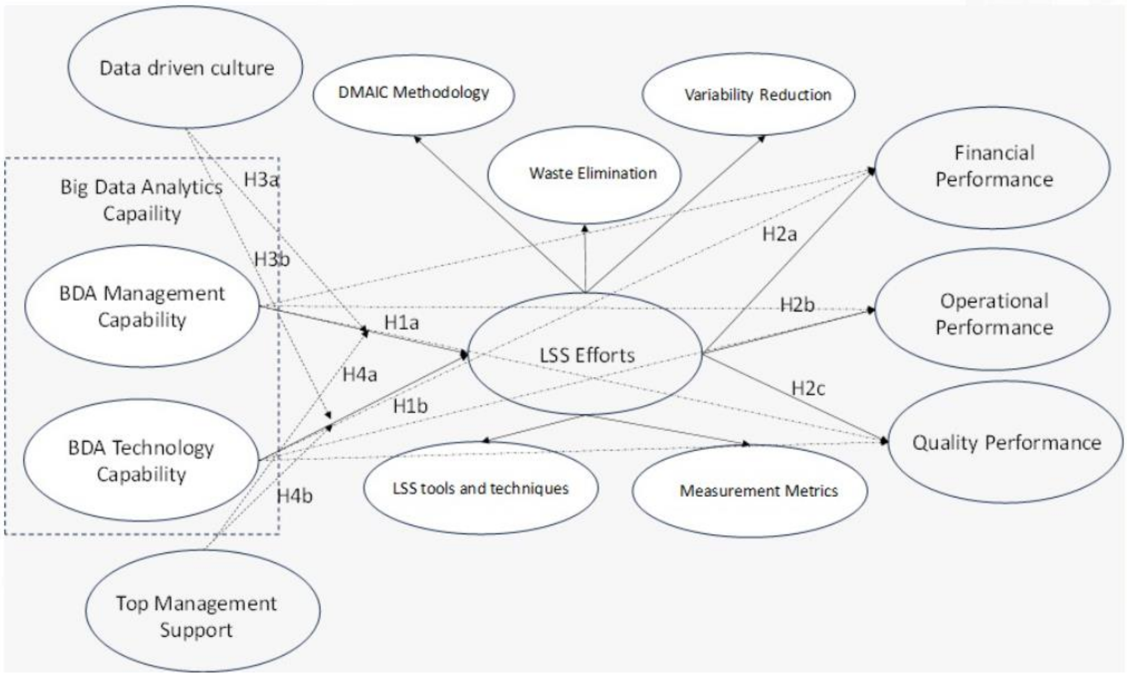


Figure 9. Hypothesised model

3.4 Analysis and Results

3.4.1 Validation of measurement model and hypotheses

The first step of the analysis is to assess whether the measurement model is satisfactory and meets the minimum criteria (Hair et al., 2018). The criteria for reflective constructs in the measurement model encompass (SARSTEDT et al. 2019; HAIR et al., 2020; MANLEY et al., 2021): estimate convergent validity, evaluated by the item reliability (outer loadings for statistically significant and > 0.708) and Average Variance Extracted – AVE (AVE > 0.5); assesses composite reliability of the constructs measured by Cronbach's alpha (CA) and composite reliability (CR) (CA and CR > 0.70); discriminant validity, assessed by heterotrait-monotrait ratio – HTMT (HTMT < 0.90) and evaluate predictive validity (R2, f2, Q2).

Table 3 presents composite reliability, convergent validity, and item reliability and significance for the reflective constructs. As previously described, the disjoint two-stage approach was adopted to analyze the higher-order construct (HOC). Table 10 includes the values for the items that compose both the first- and second-order constructs. Since the reflective measurement model includes two moderator variables (Data-Driven Culture and Top Management Support), they must meet all relevant criteria for internal consistency reliability, convergent validity (HAIR et al., 2017), as presented in Tables 3.

Table 10. Composite reliability and convergent validity

Construct	Code Items	Outer Loading		AC	CR	AVE	R
		Original Sample	p value				
	BDAT1	0.776	<0.001				
	BDAT2	0.806	<0.001				
	BDAT3	0.838	<0.001				
	BDAT4	0.838	<0.001				
BDA technology capabilities (BDAT)	BDAT5	0.802	<0.001	0.872	0.906	0.660	
	BDAM1	0.844	<0.001				
	BDAM2	0.854	<0.001				
	BDAM3	0.821	<0.001				
	BDAM4	0.826	<0.001				
	BDAM5	0.822	<0.001				
BDA management capability (BDAM)	BDAM6	0.799	<0.001	0.909	0.929	0.685	
	DMAIC1	0.914	<0.001				
	DMAIC2	0.915	<0.001				
DMAIC methodology (DMAIC)	DMAIC3	0.895	<0.001	0.894	0.934	0.824	
	TT1	0.926	<0.001				
	TT2	0.932	<0.001				
	TT3	0.909	<0.001				
LSS tools and techniques (TT)	TT4	0.835	<0.001	0.923	0.945	0.813	
	WE1	0.807	<0.001				
	WE2	0.864	<0.001				
	WE3	0.912	<0.001				
Waste Elimination (WE)	WE4	0.923	<0.001	0.900	0.931	0.771	
	VR1	0.889	<0.001				
	VR2	0.882	<0.001				
Variability reduction (VR)	VR3	0.868	<0.001	0.854	0.911	0.774	
	MM1	0.817	<0.001				
	MM2	0.926	<0.001				
	MM3	0.903	<0.001				
Measurement metrics (MM)	MM4	0.921	<0.001	0.914	0.940	0.797	
	FP1	0.871	<0.001				
	FP2	0.800	<0.001				
	FP3	0.916	<0.001				
	FP4	0.912	<0.001				
Financial Performance (FP)	FP5	0.869	<0.001	0.923	0.942	0.765	0.072
	QP1	0.731	<0.001				
	QP2	0.837	<0.001				
	QP3	0.810	<0.001				
	QP4	0.743	<0.001				
	QP5	0.802	<0.001				
	QP6	0.824	<0.001				
Quality Performance (QP)	QP7	0.809	<0.001	0.904	0.924	0.636	0.266
	OP1	0.723	<0.001				
	OP2	0.826	<0.001				
Operational Performance (OP)	OP3	0.808	<0.001	0.904	0.924	0.636	0.184

	OP4	0.793	<0.001				
	OP5	0.859	<0.001				
	OP6	0.736	<0.001				
	OP7	0.827	<0.001				
	DDC1	0.753	<0.001				
	DDC2	0.803	<0.001				
	DDC3	0.776	<0.001				
	DDC4	0.876	<0.001				
Data Driven Culture (DDC)	DDC5	0.818	<0.001	0.866	0.903	0.650	
	TMS1	0.914	<0.001				
	TMS2	0.912	<0.001				
	TMS3	0.900	<0.001				
	TMS4	0.900	<0.001				
	TMS5	0.948	<0.001				
Top Management Support (TMS) to BDA	TMS6	0.940	<0.001	0.963	0.970	0.845	
	DMAIC	0.821	<0.001				
	TT	0.890	<0.001				
	MM	0.915	<0.001				
	VR	0.843	<0.001				
LSS Efforts*	WE	0.877	<0.001	0.919	0.939	0.756	0.267

*Second-order construct calculated in stage two

Table 4 presents the HTMT results used to assess the discriminant validity. HTMT is a robust method for evaluating discriminant validity between constructs and adopts a cutoff value of 0.90 for interpretation (HAIR et al., 2018; 2020). The assessment of discriminant validity between the higher-order construct and its lower-order components is not relevant, as conceptual and empirical redundancies are expected (SARSTEDT et al., 2019). The HTMT results are shown in Table 11. Moderating and second-order constructs were included in the second stage of the analysis.

Table 11. HTMT results

	BDAM	BDAT	DMAIC	TT	MM	VR	FP	OP	QP	LSS Efforts	DDC
BDAM											
BDAT	0.891										
DMAIC	0.412	0.224									
FP	0.397	0.354	0.160								
TT	0.523	0.328	0.856				0.217				
MM	0.549	0.382	0.760	0.857			0.263				
OP	0.460	0.358	0.362	0.366	0.442		0.586				
QP	0.459	0.343	0.406	0.497	0.499		0.563	0.814			
VR	0.485	0.345	0.597	0.644	0.862		0.334	0.422	0.531		
WE	0.413	0.306	0.699	0.790	0.775	0.859	0.262	0.434	0.520		
LSS Efforts*	0.546	0.365					0.284	0.465	0.561		
DDC*	0.616	0.445					0.510	0.606	0.602	0.566	
TMS*	0.576	0.538				0.689	0.351	0.525	0.498	0.442	0.689

* Constructs inserted in the second stage

The evaluation of the structural model follows a structured process (MANLEY et al., 2021). The first step is to verify the absence of multicollinearity between constructs by analyzing the inner VIF values (VIF < 5.0). The second step involves assessing the size and statistical significance of the path coefficients (hypotheses) using the Bootstrapping procedure (p-value < 0.05 and relevance of the coefficients). The effect size (f^2) may also be examined to evaluate the impact of an exogenous construct on an endogenous one (HAIR et al., 2018; 2020). Table 12 presents the VIF results, confirming the absence of collinearity among the constructs and the hypotheses tested.

Table 12. Hypothesis testing (bootstrapping method – 5000 sub-samples)

Hypothesis	**VIF**	**f2**	**Path (β)**	**Stdev**	**p-value**	**Result**
H1a: BDA Management-> LSS Efforts	2.670	0.197	0.621	0.098	0.000	Supported
H1b: BDA Technology -> LSS Efforts	2.670	0.010	-0.142	0.099	0.152	Not supported

*f*2 values of 0.02, 0.15, and 0.35, represent respectively small, medium, and large effects (Cohen 1988)

BDAM has a positive and statistically significant impact on LSS Efforts (β = 0.621; p-value < 0.001). However, no statistical evidence supports a direct impact of BDAT on LSS Efforts. Observing the f^2 effect size to assess the importance of a specific exogenous construct in explaining an endogenous construct (HAIR et al., 2017; 2018), the impact of BDA Management on LSS Efforts shows a medium effect.

It is also essential to assess the explanatory and predictive power of the model (HAIR et al., 2018; 2020). The coefficient of determination (R^2) evaluates in-sample explanatory power by predicting case values using the full sample (SHMUELI et al., 2019). Out-of-sample predictive power is assessed using the PLS-Predict procedure, which involves analyzing Q^2 values (expected to be > 0 for all items) and prediction statistics to assess the model's predictive power. The criterion adopted is that root mean squared error (RMSE) values from PLS-SEM must be lower than those from a linear regression model (LM); the frequency with which this occurs reflects predictive power (SHMUELI et al., 2019; HAIR et al., 2020). In this study, all Q^2 values were above 0, and PLS-SEM yielded lower RMSE values than LM for most items, indicating a medium predictive power for the model.

3.4.2 Mediation effect

One of the objectives of this study is to investigate the mediating role of LSS Efforts in the relationship between BDAM and BDAT and organizational performance (financial, operational, and quality). Although the direct effects of LSS Efforts on performance constructs were not hypothesized, they are reported in Table 6 to support the mediation analysis. LSS Efforts shows positive and statistically significant effects on Financial Performance ($\beta = 0.269$; $p < 0.001$), Operational Performance ($\beta = 0.429$; $p < 0.001$), and Quality Performance ($\beta = 0.515$; $p < 0.001$).

To assess mediation, it is necessary to verify the significance of both the direct effect and the indirect effect via the mediating variable (HAIR et al., 2017). In this study, BDAT shows no significant effect on performance variables, and LSS Efforts does not act as a mediator in these relationships (Table 13), since no indirect effect was found. Thus, there is no-effect nonmediation. If the indirect effect is significant while the direct effect is not, the mediation is classified as indirect-only or full mediation (HAIR et al., 2017). Table 6 indicates full mediation between BDA Management Capabilities and both Quality and Operational Performance. In these cases, BDAM influences performance only indirectly, via LSS Efforts, which connect data usage capabilities with Lean practices to enhance operational and quality outcomes.

Table 13. Specific Direct and indirect effects (bootstrapping method – 5000 sub-samples)

Direct Effect	**Path (β**	**Stdev**	**p-value**	**Result**
LSS Efforts -> FP.	0.269	0.069	0.000	Supported
LSS Efforts -> OP	0.429	0.069	0.000	Supported
LSS Efforts -> QP	0.515	0.065	0.000	Supported
BDAM -> FP	0.222	0.118	0.060	Not Supported
BDAM->OP	0.239	0.124	0.055	Not Supported
BDAM -> QP	0.189	0.118	0.109	Not Supported
BDAT -> FP	0.120	0.099	0.227	Not Supported
BDAT -> OP	0.052	0.110	0.636	Not Supported
BDAT -> QP	0.031	0.112	0.785	Not Supported
Indirect Effect	**Path (β**	**Stdev**	**p-value**	**Result**
H2a: BDAM -> LSS Efforts -> FP	0.075	0.059	0.207	Not Supported
H2b: BDAM -> LSS Efforts -> OP	0.186	0.064	0.004	Supported
H2c: BDAM -> LSS Efforts -> QP	0.263	0.067	0.000	Supported
H2a’: BDAT -> LSS Efforts ->FP	-0.020	0.021	0.331	Not Supported
H2b’: BDAT -> LSS Efforts -> OP	-0.050	0.033	0.136	Not Supported
H2c’: BDAT -> LSS Efforts -> QP	-0.070	0.044	0.111	Not Supported

3.4.3 Moderation effect

The study also aimed to perform a moderation analysis on the effects of two moderating variables—Data-Driven Culture and Top Management Support—on the relationships between BDAM and BDAT and LSS Efforts. Moderation analysis assesses whether a moderating variable alters the strength or direction of a relationship between two constructs in the model (HAIR et al., 2017). To evaluate moderation, the significance of the interaction term must be verified using the bootstrapping procedure (HAIR et al., 2017), as shown in Table 8. However, as presented in Table 14, the moderating effects were not confirmed for either variable in any of the tested relationships. Therefore, neither Data-Driven Culture nor Top Management Support influenced the relationships under analysis.

Table 14. Significance of the interaction term (bootstrapping - 5000 sub-samples)

Interaction term	f2	Path (β)	Stdev	p-value	Result
H3a: DDC x BDAM -> LSS Efforts	0.003	0.081	0.109	0.458	Not Supported
H3b: DDC x BDAT -> LSS Efforts	0.006	-0.111	0.100	0.268	Not Supported
H4a: TMS x BDAM -> LSS Efforts	0.008	-0.130	0.110	0.238	Not Supported
H4b: TMS x BDAT -> LSS Efforts	0.000	0.029	0.106	0.784	Not Supported

f2 values of 0.005, 0.01, and 0.025 represent, respectively, small, medium, and large effect sizes in moderation (HAIR et al., 2017)

3.4.4 Control Variables

The company size variable (measured by the number of employees) was used as a control variable. To perform the analysis, the construct formed by a single variable was connected to all the target variables, however, the path coefficients and effect sizes were not significant (HULT et al., 2018; MANLEY et al., 2022), therefore, there is no effect of company size in the research model.

3.5 Discussion and Implications

This study empirically investigated the relationship between BDA and LSS from a holistic perspective. The findings show that BDA Management Capabilities have a significant impact on LSS efforts, while BDA Technological Capabilities did not present a statistically significant positive relationship. Although the lack of technological feasibility is often cited as a barrier to integrating I4.0 technologies and LSS (MACIAS-AGUAYO et al., 2022; SKALLI et al., 2024), and infrastructure to extract and analyze large volumes of data is seen as a facilitator (MACIAS-AGUAYO et al., 2022; KOMKOWSKI et al., 2023), this was not confirmed in the empirical results of this study

The positive and statistically significant impact of BDAM on LSS aligns with existing literature, indicating that the strategic management of BDA, through extracting valuable insights for resource allocation and strategic decisions and the effective use of data contribute to enhancing LSS benefits (GUPTA et al., 2019; BELHADI et al., 2020). Thus, BDAM acts as a catalyst for LSS, reinforcing the idea that the effectiveness of LSS practices depends on the quality of data-driven decision-making (ANTONY et al., 2018; GUPTA et al., 2020; CITYBABU and YAMINI, 2024).

Although robust technological tools and systems can act as enablers and remove potential barriers to BDA–LSS integration (MACIAS-AGUAYO et al., 2022; SKALLI et al., 2024), they do not guarantee successful integration. This highlights that the effectiveness of BDA technologies depends on the company's managerial maturity in handling data and the quality of its management practices (AKTER et al., 2016; DUBEY et al., 2019). Therefore, technological investments must be paired with efforts to train managers and establish processes that promote a culture of data analysis at all organizational levels. Similarly, the positive effect of BDAM on LSS efforts indicates that, to fully leverage LSS, companies must systematize and integrate data use into their decision-making processes (FAYYAZ et al., 2024). This finding aligns with previous studies showing that BDA–LSS integration enables faster and more accurate root cause analysis and facilitates the identification of improvement opportunities (ZWETSLOOT et al., 2018; IBRAHIM and KUMAR, 2024).

The findings reinforce the importance of integrating BDA and LSS to improve organizational performance, particularly in quality and operational. In the analyzed sample, BDA showed no direct influence on financial performance, diverging from other studies in developing countries (E.G., KARABOGA et al., 2023; THANABALAN et al., 2024). No indirect impact via LSS was found either, such as cost reductions through waste elimination or on-time data-driven decisions, as suggested in other research (RAUT et al., 2019; PONGBOONCHAI-EMPL et al., 2023).

However, although the sample studied did not demonstrate positive and statistically significant direct relationships between BDAM and operational or quality performance, an impact on both was observed when mediated by LSS efforts. The results confirm that the integration of BDA with LSS enhances operational performance by improving efficiency, reducing downtime, enabling real-time data analysis, and supporting faster, data-driven decisions and continuous process improvement (RAUT et al., 2019; BELHADI et al., 2020; CITYBABU and YAMINI, 2024; IBRAHIM and KUMAR, 2024). Additionally, it leads to improved quality, cycle time, customer satisfaction, and more sustainable operations through waste reduction and preventive insights (ARCIDIACONO and PIERONI, 2018; BELHADI, 2020; PONGBOONCHAI-EMPL et al., 2023; CITYBABU and YAMINI, 2024; IBRAHIM and KUMAR, 2024).

Despite the literature emphasizing the relevance of a DDC (GUPTA and GEORGE, 2016; DUAN et al., 2020; KARABOGA et al., 2022) and TPS (ZULFIQAR et al., 2023; RAUT et al., 2021) in the successful adoption of BDA initiatives, the present study found no evidence that these factors significantly moderate the relationship between BDA capabilities and LSS efforts. One possible explanation is that both DDC and TMS may act more as enabling conditions than as moderators that dynamically influence the strength of this relationship. These factors may be necessary to initiate or support BDA and LSS initiatives, influencing strategy formulation and resource allocation, but not sufficient to intensify the connection between them once both are already in place. Additionally, in the context of the studied organizations, especially in a developing country like Brazil, DDC and TMS may still be in a formative or superficial stage, not yet mature enough to significantly shape the interaction between BDA and LSS practices.

3.5.1 Theoretical implications

This research offers important theoretical contributions to existing literature by demonstrating the importance of BDAM capabilities in enhancing LSS efforts. The main theoretical contribution is the confirmation that LSS efforts effectiveness is increased when supported by the strategic and well-structured use of data analytics as pointed out by other authors (E.G. SKALLI et al., 2023). This emphasizes the role of data-driven decision-making in the success of continuous improvement practices (GUPTA et al., 2019; BELHADI et al., 2020; ANTONY et al., 2017; CITYBABU and YAMINI, 2024).

On the other hand, the absence of empirical evidence for the relationship between BDAT capabilities and LSS efforts, shows that although the lack of technological infrastructure is seen as a barrier to integrating technologies and LSS (MACIAS-AGUAYO et al., 2024), infrastructure alone is not enough to enhance LSS outcomes. This suggests that the transformative effect of BDA in LSS contexts depends more on the quality of data management and its integration into analytical routines.

Furthermore, LSS efforts fully mediate the impact of BDAM on operational and quality performance. These findings deepen the theoretical understanding of how BDA capabilities influence performance through their effect on LSS practices. This highlights the relevance of structured improvement in converting analytical capabilities into tangible performance gains, especially in terms of efficiency and operational outcomes (SKALLI et al., 2024; IBRAHIM and KUMAR, 2024). The systematic nature of LSS also supports analytical capabilities for root cause identification, defect reduction, and cycle time optimization, enhancing quality performance (BELHADI et al., 2020; PONGBOONCHAI-EMPL et al., 2023).

The final theoretical contribution concerns the moderating effect of DDC and TMS on the relationship between BDA and LSS. While previous studies have highlighted the strategic relevance of a data-driven culture (DDC) in aligning BDA with long-term organizational goals (GUPTA and GEORGE, 2016; KARABOGA et al., 2023), and the role of top management support (TMS) in facilitating technology adoption within LSS contexts (MACIAS-AGUAYO et al., 2022; ZULFIQAR et al., 2023), the findings of this study suggest that these elements may not exert a dynamic influence in strengthening the connection between BDA capabilities and LSS efforts.

3.5.2 Managerial implications

This study offers valuable practical insights for managers and practitioners seeking to maximize the benefits of integrating BDA with LSS. First, the findings underscore the importance of developing BDAM capabilities. Managers should systematically plan and pursue innovative opportunities for strategic use of analytics, ensuring that investments enhance employee productivity, accelerate decision-making, and promote broad knowledge sharing to strengthen data management.

Another key implication is the need to view BDA not merely as a technology, but as a managerial capability that supports continuous improvement. Organizational processes must enable the transformation of technological resources into actionable improvements. This includes establishing routines for collecting, analyzing, and using data in strategic decisions to generate insights that sustain LSS efforts.

In addition, managers should combine robust data management with strong implementation of LSS practices, such as DMAIC, waste elimination, variability reduction, tool application, and the use of performance metrics, to translate insights into effective improvements. The study shows that BDAM only contributes to performance, particularly in quality and operational performance, when mediated by LSS efforts. Therefore, companies should promote integration strategies that align data analytics with continuous improvement methodologies, enhancing the analytical strength of LSS teams. This approach enables faster responses to operational issues, defect reduction, and greater customer satisfaction.

3.6 Conclusions

Companies face the challenge of integrating innovative technologies like BDA with process improvement methodologies such as LSS to enhance operational efficiency, reduce variability, and achieve sustainable competitive advantage. The present study contributes to the literature and practice by confirming the potential BDAM capability have to bring positive impacts to LSS approach by providing information about process, use advanced analysis tools to understand and solve complex problems and providing information for data-driven decision making (BELHADI et al., 2020; 2023; Gupta et al. 2020). The study also contributes by adding research on the topic, which is scarce and requires empirical studies (BELHADI et al., 2020; FAYYAZ et al., 2024), especially in the context of developing countries (BELHADI et al., 2020). Conceptually, the results also show that the direct impact of BDA infrastructure on LSS efforts is limited, suggesting that BDA for LSS depends on well-established managerial capabilities to transform data into practical insights.

This research advances the field by offering conceptual and practical evidence of the benefits of integrating BDA with LSS to improve operational and quality performance. It addresses a key gap by confirming that this combination can indeed enhance company performance. Moreover, the findings show that LSS is not only complementary but essential—BDA Management capabilities only translate into performance gains when supported by structured LSS practices.

This study has some limitations, particularly related to its methodological approach. Data were collected via an online survey, limiting control over respondents, and the sample was restricted to Brazilian companies, which may face specific challenges in infrastructure and data maturity. Future research should explore whether the findings hold in contexts with different economic and technological conditions. Also, since this is a cross-sectional study, longitudinal analyses are recommended to better capture the evolving impact of BDA and LSS integration over time and across sectors.

Finally, the research suggests avenues for future studies. For instance: (i) the model can be replicated in other contexts (e.g., higher digital maturity), industries (specific service or manufacturing sectors), and countries to assess whether the results differ from those in Brazilian manufacturing firms; (ii) qualitative case studies could complement the survey approach by offering deeper insights into how BDA capabilities are applied in LSS projects and influence decision-making and problem-solving; and (iii) future research could explore additional organizational factors that may mediate or moderate these relationships, such as organizational culture, cross-functional communication, or learning orientation. These paths offer valuable opportunities to expand the understanding of BDA–LSS integration.

4. CONCLUSIONS

This dissertation set out to investigate, in an integrated manner, how Industry 4.0 technologies and Big Data Analytics (BDA) interact with Lean Six Sigma (LSS) to enhance organizational performance. The first article provided a comprehensive mapping of the literature on the relationship between Industry 4.0 and LSS, characterizing the state of research, identifying how specific technologies support LSS goals and DMAIC phases, and highlighting the influence of organizational factors. The second article complemented this theoretical groundwork with empirical evidence, demonstrating how technological and managerial BDA capabilities affect LSS efforts and, through them, operational and quality outcomes.

Together, the two studies advance knowledge about the digital transformation of quality and operational management. The literature review clarified the mechanisms through which Industry 4.0 technologies can reinforce LSS principles of waste reduction, process control, and data-based problem solving. The survey-based analysis further revealed that the managerial capabilities of BDA—such as strategy, governance, and analytical culture—are more decisive than purely technological capacities for enabling LSS and achieving measurable performance gains. These results refine existing conceptual models by showing that the impact of advanced technologies depends on their effective alignment with structured continuous-improvement practices.

From a managerial perspective, the findings stress that merely acquiring advanced digital infrastructure is not enough. Organizations need to invest in managerial analytics capabilities, leadership commitment, and a culture oriented to data-driven decision making in order to transform data into sustained operational and quality improvements. The combined insights of the two articles offer practical guidance for companies seeking to connect LSS with Industry 4.0 and BDA, demonstrating how integrated strategies can enhance efficiency, responsiveness, and competitiveness.

This dissertation also recognizes certain limitations and points to directions for future studies. Although the empirical analysis provides robust quantitative evidence, further research across other industrial sectors and geographic regions would broaden the external validity of the results. Longitudinal designs could capture how the integration of BDA, Industry 4.0 technologies, and LSS evolves over time. In addition, examining other organizational factors—such as employee skills development and interdepartmental collaboration—may deepen understanding of the conditions that sustain successful digital–process integration.

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