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LÍGIA LOBO MESQUITA

INDUSTRY 4.0 AND LEAN FOR SUSTAINABILITY PERFORMANCE

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RESUMO

A atividade industrial é uma das principais responsáveis pelos impactos ambientais, sociais e econômicos, o que leva as indústrias a buscarem novas formas de gerenciar seus processos. Nesse cenário, o Lean tornou-se um forte aliado do setor industrial, uma vez que a aplicação do sistema sociotécnico Lean pode melhorar o desempenho da sustentabilidade. Além disso, o setor está passando por importantes mudanças tecnológicas em meio à Indústria 4.0 (I4.0) e entender como essas abordagens interagem é de grande interesse para acadêmicos e profissionais. Portanto, esta pesquisa se dedica a identificar e propor formas de integrar Lean e I4.0 e analisar o efeito dessas relações no desempenho da sustentabilidade. Para isso, foram realizadas duas Revisões Sistemáticas de Literatura. A primeira teve como objetivo analisar a integração entre os três temas, Lean, Sustentabilidade e I4.0, e a segunda mostra a relação entre Lean e I4.0 para apoiar a sustentabilidade. A segunda análise visa aprofundar como as relações e o apoio podem ocorrer, o que foi fortalecido pelo estudo de casos. Os resultados mostram que as indústrias podem se beneficiar da integração entre tecnologias da Indústria 4.0 e Práticas Lean para explorar o potencial tecnológico e humano e apoiar o sistema operacional na melhoria das medidas de sustentabilidade. A evidência inicial sugere um maior potencial de integração entre tecnologias da Indústria 4.0 como a Internet of Things (IoT) e Big Data Analytics (BDA), com práticas técnicas Lean como Total Preventive Maintenance (TPM) e Just-in-Time (JIT) e práticas sociais Lean, como Melhoria Contínua, Envolvimento do Cliente e Parceria com Fornecedores. Nesse sentido, os indicadores de Desempenho Econômico são os mais favorecidos, com poucas evidências na literatura de melhorias nos indicadores de desempenho ambiental e social decorrentes da integração entre tecnologias da Indústria 4.0 e práticas Lean. O estudo de casos confirma os achados da literatura e acrescenta evidências de como ocorrem as principais relações de apoio em um ambiente industrial, além de abordar aspectos negativos da integração. Os resultados da literatura orientaram a construção de um modelo conceitual testado por meio de survey com a técnica de Partial Least Squares Structural Equation Modeling (PLS-SEM). A survey foi desenvolvida para avaliar os efeitos diretos e indiretos das Big Data Analytics Capabilities (BDAC) no desempenho econômico, ambiental e social, na presença de práticas técnicas e sociais Lean como variáveis mediadoras. Os resultados confirmam a influência direta do BDAC no desempenho social e identificam as práticas técnicas Lean como variáveis mediadoras significativas que atuam como catalisadores para potencializar os impactos indiretos do BDAC no desempenho econômico. Esta pesquisa abrangente pode ajudar pesquisadores e profissionais a entender e se beneficiar totalmente da integração das tecnologias da Indústria 4.0, particularmente BDAC, com práticas Lean ao gerenciar questões de sustentabilidade.

Palavras-chave Tecnologias da Indústria 4.0. Lean Técnico. Lean Social. Desempenho da Sustentabilidade. Revisão Sistemática da Literatura. Estudo de Casos. Survey. Modelagem de Equações Estruturais.

ABSTRACT

Industrial activity is one of the main responsible for environmental, social, and economic impacts, which leads industries to seek new ways to manage their processes. In this scenario, Lean has become a strong ally of the industrial sector since the application of the Lean socio-technical system can improve sustainability performance. In addition, the sector is undergoing important technological changes amid Industry 4.0 (I4.0) and understanding how these approaches interact is of great interest to academics and practitioners. Therefore, this research is dedicated to identifying and proposing ways to integrate Lean and I4.0 and analyze the effect of these relationships on sustainability performance. For this, two Systematic Literature Reviews (SLR) were conducted. The first aimed at analyzing the integration between the three themes, Lean, Sustainability, and I4.0, and the second shows the relationship between Lean and I4.0 to support sustainability. The second analysis aims to deepen how relationships and support can take place, which was strengthened by cases study. The results show that the industries can benefit from the integration between Industry 4.0 Technologies (I4T) and Lean Practices (LP) to exploit the technological and human potential and support the operational system in improving sustainability measures. The initial evidence suggests a greater potential for integration between I4T such as the Internet of Things (IoT) and Big Data Analytics (BDA), with Lean Technical Practices (LTP) such as Total Preventive Maintenance (TPM) and Just-in-Time (JIT), and Lean Social Practices (LSP) such as Continuous Improvement, Customer Involvement, and Supplier Partnership. In this sense, Economic Performance indicators are the most favored, with little evidence in the literature of improvements in environmental and social performance indicators resulting from the integration between I4T and LP. The cases study confirm the findings of the literature and add evidence of how the main support relationships occur in an industrial environment, in addition to addressing negative aspects of integration. The results of the literature guided the construction of a model conceptual model tested through survey research with the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique. The survey research was developed to assess the direct and indirect effects of Big Data Analytics Capabilities (BDAC) on economic, environmental, and social performance, in the presence of Lean Socio-Technical Practices as mediating variables. The results confirm the direct influence of BDAC on Social Performance and identify Lean Technical Practices as significant mediating variables that act as a catalyst to boost the indirect impacts of BDAC on Economic Performance. This comprehensive research can help researchers and practitioners fully understand and benefit from the integration of I4T, particularly BDAC, with the LP while managing sustainability issues.

Keywords Industry 4.0 Technologies. Lean Technical. Lean Social. Sustainability Performance. Systematic Literature Review. Case Study. Survey. Structural Equation Modeling.

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1 INTRODUCTION

This chapter presents the contextualization of the research themes, questions and objectives, importance of the study, stages for the development, and the dissertation structure.

1.1 Contextualization and Motivation

Climate change, environmental degradation, and scarcity of natural resources are some of the biggest challenges that humanity has been facing amidst industrialization (Garza-Reyes *et al*., 2018). Industrial activities are largely responsible for environmental as well as economic and social impacts (Holton *et al*., 2010). In this sense, improving sustainability performance in the industrial sector has become a key objective for countries pursuing sustainable development (Holton *et al*., 2010).

The often-quoted Brundtland report defined sustainable development as "development that meets the needs of the present without compromising the ability of future generations to meet their own needs" (World Commission on Environment and Development, 1987, p. 5). Thus, sustainability concept is based on the creations and maintenance of the conditions under which humans and nature can exist in productive harmony (Cakir *et al*., 2012).

The Triple Bottom Line (TBL) represents the balance between the three dimensions of sustainability (Elkington, 1998) and can be incorporated into industrial strategy as a goal for performance measurement (Henao *et al*., 2018). The concept of sustainability considers the environmental, social, and economic pillars (Elkington, 1998). Sustainability performance groups social and environmental values from business valuations, along with their economic importance (Sajan *et al*., 2017). In this context, industries are expected not to focus solely on maximizing profits (Thanki *et al*., 2016). Additional efforts are required to reduce environmental impacts, as well as the enhancement of the social aspect (McWilliams *et al*., 2014).

To improve sustainability performance in operations, industries are driven to change their management efforts (Wong and Wong, 2014; Garza-Reyes, 2015). A viable path may be to explore beyond the operational potential of continuous improvement initiatives (Garza-Reyes *et al*., 2018; Costa *et al*., 2018). For example, Lean Manufacturing has led industries to go beyond the traditional parameters of quality and productivity, also achieving environmental efficiency in their processes (Garza-Reyes, 2015).

Lean Manufacturing can be described as a management philosophy or strategy using a set of practices to minimize waste (Womack *et al*., 1990). Lean is considered a socio-technical approach, and, as such, it has two pillars of practices, social and technical (e.g., Bortolotti *et al*., 2015; Shah and Ward, 2007). Lean Technical Practices (LTP) refer to the implementation of a group of manufacturing practices that simultaneously focus on the reduction of non-value-added activities and people involvement (Chavez *et al*. 2015, 2020). Lean Social Practices (LSP) relate to behavioral aspects and generally deal with human resource aspects such as training and education, leadership, teamwork, empowerment, customer and supplier participation, and organizational culture (Lewis *et al*., 2006). Implementation of Lean Practices (LP) affects the operational performance dimensions of companies (Khanchanapong *et al*., 2014), in addition to being positively associated with environmental performance (Bai *et al*., 2019) and social performance (Chavez *et al*., 2020b).

The grouping of LP into Lean Socio-Technical practices is expected to promote the development of new processes, procedures, strategies, and work methods that further improve organizational performance and generate long-term competitive advantage (Abdallah *et al*., 2021). Thus, the current research investigates the relationships between the social and technical aspects of LP and their effects on organizational performance outcomes (Arumugam *et al*., 2020; Abdallah *et al*., 2021). For example, Sahoo (2019) argues that LSP can improve the organization's performance. In the same perspective, Chavez *et al*. (2020) claim that LTP can positively affect sustainability performance.

In addition, industrial manufacturing is undergoing important technological changes. Companies are driven to upgrade their manufacturing systems to an intelligent level (Kamble *et al*., 2019), making it necessary to integrate the social and technical elements of Lean using advanced technologies (Mishra *et al*., 2014). Thus, companies worldwide are investigating how they can benefit from the emerging technology-based manufacturing paradigm (Buer *et al*., 2018), namely, Industry 4.0 (I4.0).

I4.0 can be defined as a current trend of automation technologies in the manufacturing industry, and it mainly includes enabling technologies such as the Cyber-Physical Systems (CPS), Internet of Things (IoT), and Cloud Computing (CC) (Hermann *et al*., 2016; Lu, 2017). Furthermore, I4.0 is based on Big Data, and how the data can be gathered, analyzed, and used to make the right decisions has become a competitive factor (Nagy *et al*., 2018).

On the other hand, I4.0 can create direct and indirect impacts on the three dimensions of sustainability (Felsberger *et al*., 2020). In that regard, Ferrera *et al*. (2017) argue that Industry 4.0 Technologies (I4T) carefully adapted and integrated for process monitoring and optimization can improve sustainability performance. Manufacturing companies adopting I4T must be prepared to take responsibility for their digitization process and lead it in a direction for improving economic, environmental, and social performance (Ghobakhloo and Fathi, 2020). Yet, it is still questionable whether the adoption of I4T can result in better environmental performance (Chiarini *et al*., 2020), as well as what impacts they can have on social performance.

However, I4.0 does not replace Lean management practices (Rosin *et al*., 2019). Contrariwise, in the past few years, several papers have investigated how Lean can be matched with I4T to achieve strategic objectives (Chiarini *et al*., 2020). Wagner *et al*. (2017) considered that the features of I4.0 consolidate the Lean gains on processes, once I4.0 allows for the prevention and elimination of defects (Lai *et al*., 2019). In their study, Pagliosa *et al*. (2019) revealed that interactions between I4.0 and Lean were classified as highly synergistic. Their findings point to the existence of a favorable and collaborative relationship between I4T and LP, achieving greater operational performance.

There is evidence that I4T have a direct effect on Lean goals and on sustainability performance (Kamble *et al*., 2019). Thus, the links between Lean, I4.0, and sustainability arouse the interest of academics and practitioners, as well as society in general (Varela *et al*., 2019). Companies must be aware of how the influence of the two production paradigms, Lean and I4.0, occurs on the three pillars of sustainability (Varela *et al*., 2019). A company that implements Lean can reap benefits of achieving goals of sustainability which can further be expedited with I4.0 (Khanzode *et al*., 2021).

Although there is an initial evidence of synergy between Lean, I4.0, and sustainability, some gaps are presented: i) Deepening is needed on how I4.0, Lean, and the three pillars of sustainability interact in manufacturing environments (Duarte *et al*., 2020; Kamble *et al*., 2019; Dubey *et al*. 2017); ii) the organizations may not be able to clearly identify the effect of investments in technologies and Lean on improving financial, environmental, and social performance (Ghobakhloo and Fathi, 2020), and, for this reason, studies on how the companies could use the joint I4.0 and Lean effect to achieve results in different sustainability dimensions, need to be developed (Núñez-Merino *et al*., 2020; Pagliosa *et al*., 2019).

In addition, this dissertation aims to help understand more specific issues regarding the interactions between approaches. In this sense, research is needed to examine the influence of Lean Socio-Technical practices on performance results, i.e., productivity, cost, quality, delivery, flexibility, and employee morale and safety (Sahoo, 2019). Current research should investigate how companies are looking for insights into how and when to combine Lean and I4.0 (Chiarini *et al*., 2020). Earlier studies are not unanimous regarding the nature of the relationship between I4T and Lean and their combined effect on performance (Buer *et al*., 2020), and studies on the relationships between specific LP and specific I4T remain scarce (Buer *et al*., 2018; Ejsmont *et al*., 2020). These gaps are also related to the general scarcity of empirical studies on the topic (Buer *et al*., 2018; Pagliosa *et al*., 2019).

Sadiq *et al*. (2021) point out that studies can be carried out using the innovative concept of I4.0 in conjunction with Lean and environmental sustainability. However, I4.0 and Lean cannot disregard objectives related to social responsibility beyond the environmental and economic aspects (Chiarini and Vagnoni, 2017). Thus, this Dissertation is unprecedented in questioning and answering the following General Research Question (GRQ):

GRQ: What impact do the supportive relationships between Industry 4.0 technologies and Lean socio-technical practices have on sustainability performance?

The main objective of this research is to identify and propose ways to integrate I4.0 and Lean and to analyze the impact of the main relationships between I4T and Lean Socio-Technical practices on sustainability performance. For that, this Dissertation is structured in papers where the specific objectives are pursued that will contribute to achieve the main objective. Thus, the Dissertation will present repetitions of content, since the papers work on similar themes, however, observed from different perspectives that will make up the body of knowledge to draw conclusions about the research question.

This Dissertation contributes to the theory and practice of research in I4.0 and Lean. The gaps presented are filled as this research details what and how the relationships between I4T and LP occur in theory and practice and the impact of them on economic, environmental, and social performance. In addition, the research empirically investigates the mediating effect of Lean Socio-Technical practices on the relationship between Big Data Analytics Capabilities (BDAC) and sustainability performance. The study of the relationship (technology-practices-sustainability performance) and the insights provided in this research can help professionals understand the requirements and anticipate the effects of the integration between I4.0 and Lean. In addition, it can help academics identify directions for future research.

1.2 Research method

This topic summarizes the research methods, which will be detailed in each of the papers. This study is based on the existing literature and uses an empirical-oriented methodological approach. The methods of Systematic Literature Review (SLR), case study and survey research are applied.

The SLR summarizes the field of research and supports the identification of specific issues (Rowley and Slack, 2004), involving a variety of techniques to minimize bias and errors, providing high-quality evidence (Tranfield *et al*., 2003). Your process follows planned steps to gather information on the proposed theme (Gough, 2007), justify and qualify the research question (Tranfield *et al*., 2003).Additionally, the SLR is important in supporting the identification of hypothesis; identifying the theory to which the research will contribute; building an understanding of theoretical concepts and terminology; facilitating the building of a bibliography or list of the sources that have been consulted; suggesting research methods that might be useful; and in, analyzing and interpreting results (Rowley and Slack, 2004). By its nature, SLR demands transparency (Rader *et al*., 2013). Scientific rigor in research reporting minimizes the risk of incomplete or inaccurate results (Rader *et al*., 2013).

The case study contributes to the understanding of complex phenomena through an investigation that preserves the holistic and significant characteristics of the analyzed event (Yin, 2001, p. 21). Furthermore, it can be used to explain causal relationships between variables (Yin, 2001). Thus, it is suitable for investigating the evolution of management strategies and technological advances in an industrial environment (Lewis, 1998).

To fulfill the objectives of this study, two SLR were carried out with complementary objectives. The first SLR makes it possible to know the state of the art, structure the research field, identify gaps and contribute to the evolution of the theme. The second makes it possible to consolidate the understanding of the theme and point out possible directions for future studies. In addition, the case study strengthens the literary findings by improving the validity of the research.

On the other hand, survey research provides preliminary evidence of an association between concepts (Forza, 2002). The survey takes on an exploratory character when it is dedicated to obtaining an initial view of the phenomenon investigated and providing subsidies for future research (Forza, 2002). Typically, there is no defined model in the exploratory survey, and the concepts of interest need to be better understood and measured (Malhotra and Grover, 1998). Thus, survey research data are often analyzed in quantitative units (Yoshikawa *et al*., 2008). Malhotra and Grover (1998) establish that survey research involves: (a) definition of the unit of analysis; (b) collecting data in a structured format; (c) definition of variables and the relationships between them; and (d) specification of the sample, with the ability to generalize findings. Therefore, these steps will be detailed in the papers that follow.

The research variables were used to develop the general research model (Figure 1.1). The theoretical underpinnings of Big Data Analytics (Akter *et al*., 2016; Wamba *et al*., 2017) and of the Lean Socio-Technical System (Shah and Ward, 2003; 2007; Bortolotti *et al*., 2015) support the first hypothesis (H1), which investigates the development of Big Data Analytics Capabilities (BDAC) and application of Lean Socio-Technical System in industries, and the direct effect of the BDAC on Lean technical and social practices. In addition, knowledge about the BDAC (Gupta and George, 2016; Belhadi *et al*., 2019) corroborates hypothesis 2, which analyzes the effect of specific resources, such as tangible resources, human skills, and intangible resources, on the sustainability performance of industries that operationalize their processes in a Lean environment. Finally, the findings of the SLR (Mesquita *et al*., 2021) and of the cases study support the investigation of the mediating effect of Lean technical and social practices on the relationship between BDAC and the sustainability performance (hypothesis H3). To examine the possible non-response bias, responses were compared to three control variables: company size, level of implementation of Lean practices, and knowledge of Industry 4.0 technologies. The methods and hypotheses of the model (Figure 1.1) will be discussed in detail in the chapters (papers) that follow.

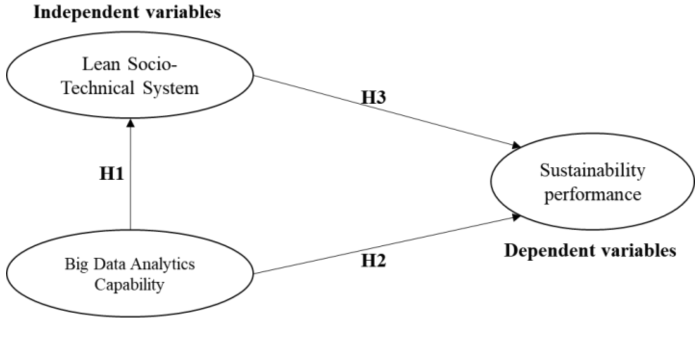

Figure 1.1. Theoretical conceptual model

The general research model (Figure 1.1) was developed specifically for BDA because, through its capabilities, this technology has the potential to integrate with Lean Practices and has a predominantly positive impact on sustainability, according to the SLR and cases study carried out (Chapters 3 and 4). Therefore, in Chapter 5 a model with BDAC, Lean Socio-Technical practices, and economic, environmental and social performances will be presented.

1.3 Dissertation structure

The present Dissertation is divided into 6 chapters (Figure 1.2). Chapter 3 (Paper 1), Chapter 4 (Paper 2), and Chapter 5 (Paper 3) are structured in paper format, so necessarily some information appears more than once in the entire document.

Chapter	Research questions	Objective	Method
Introduction Chapter 1	GRQ: What impact do the supportive relationships between Industry 4.0 technologies and Lean socio-technical practices have on sustainability performance?	Formulate the general research question, present the general objective and general model of the research, and structure the dissertation.	
Conceptual background Chapter 2		Present the theories and main concepts that form the theoretical basis of the research.	
Paper 1 Chapter 3	RQ1. What are the relationships for integration between Lean, Industry 4.0, and environmental sustainability? RQ2. Which are the main paths for future research on this subject?	Identify ways of integrating Lean, Industry 4.0, and environmental sustainability.	Systematic literature review
Paper 2 Chapter 4	RQ1. What are the relationships where Industry 4.0 technologies support Lean socio-technical practices, impacting economic, environmental, or social performance? RQ2. How can Industry 4.0 technologies support Lean socio-technical practices, benefiting economic, social, or environmental performance?	Identify how the Industry 4.0 technologies are supporting Lean technical and social practices and the possible impact of these relationships on sustainability performance.	Systematic literature review and cases study
Paper 3 Chapter 5	RQ: What effect do Lean Social Practices and Lean Technical Practices have on the relationship between Big Data Analytics Capabilities and economic, environmental, and social performance?	Investigate Lean and BDA structures and analyze the mediation effect that Lean technical and social practices can have on the relationship between BDA capabilities and sustainability performance.	Systematic literature review and Survey
Conclusion Chapter 6		Establish conclusions and strengthen academic and managerial contributions.	

Figure 1.2. Dissertation structure

After the contextualization and construction of the theoretical bases that support the study (Chapters 1 and 2), Chapter 3 (Paper 1) is dedicated to identifying what are the main integration relationships between Lean, Industry 4.0, and Environmental Sustainability. Findings indicate that there is a stronger integration between Industry 4.0 technologies and Lean practices to achieve environmental sustainability. Technologies such as Big Data and IoT present themselves as the most promising to support Lean practices related to processes and customers.

In Chapter 4 (Paper 2), the Paper 1 findings contributed to a new SLR and cases study that investigate how Industry 4.0 technologies support Lean technical and social practices and the impact of these relationships on economic, environmental, and social performance. The findings allow us to identify the strengths of the integration between Industry 4.0 and Lean and confirm the results of Paper 1 since IoT (RFID, Sensor, and Actuator) and BDA strengthen the goals of Lean technical and social practices. BDA has relationships with Lean technical practices such as Total Preventive Maintenance (TPM) and Just-in-Time (JIT), and Lean social practices such as Continuous Improvement, Customer Involvement, and Supplier Partnership. The results also point to a more significant impact of relationships on Economic Performance indicators, with few benefits for the environmental and social aspects.

Evidence from papers 1 and 2 shows that BDA can improve Lean system objectives and that the relationships between BDA and Lean technical and social practices can impact sustainability performance. Thus, through survey research, Chapter 5 (Paper 3) investigates the mediating effect of Lean technical and social practices on the relationship between Big Data Analytics Capabilities and economic, environmental, and social performance. The results confirm the direct impact of BDA capabilities on Technical Lean and Social Lean. In addition, Lean technical practices fully mediate the relationship between BDA capabilities and economic performance. Finally, Chapter 6 concludes the dissertation.

2 CONCEPTUAL BACKGROUND

This chapter is a brief conceptual background on Lean and Industry 4.0 approaches and sustainability performance in industrial manufacturing.

2.1 Lean

In 1940, Toyota Motor Company experienced a severe financial crisis that drove a series of revolutionary production innovations focused on eliminating waste and improving the company's core operations (Holweg, 2007). In this context, arise the Toyota Production System (TPS) (Holweg, 2007), by Taichii Ohno's initiatives at Toyota Motor Company (Sanders *et al*., 2016). Then, since the 1950s in Japan, and since the 1980s in the West, under the name Lean Manufacturing, companies have been implementing this approach and its philosophy (Rosin *et al*., 2019).

Lean Manufacturing was understood from different complementary perspectives such as manufacturing system, set of practices, management philosophy, manufacturing paradigm and others (Shah and Ward, 2003, 2007; Treville and Antonakis, 2006; Li *et al*., 2005; Hopp and Spearman, 2004; MacDuffie, 1995; Womack *et al*., 1990). Many manufacturers consider Lean as an industrial strategy that provides the basis for operational excellence through process standardization, propagation of a culture of continuous improvement, and workforce empowerment (Bai *et al*., 2019). Thus, the Lean system is extensively deployed in manufacturing environments, mainly by companies operating under stable production producing large volumes of standardized products (Yadav *et al*., 2017). Lean develops activities such as evaluation, improvement, and performance monitoring (Ejsmont *et al*., 2020).

Lean consists of numerous practices, methods, and tools (Möldner *et al*., 2020), which, of integrated and appropriately implemented, constitute a system for the gradual elimination of waste. Seven waste types are known in Lean Manufacturing: overproduction, inventory, extra processing, motion, waiting for time, defects, and transportation (Hicks, 2007; Amrina and Lubis, 2017). Furthermore, waste can be regarded as any activity that does not add value to the customer, such as unused employee creativity (Liker, 2004). However, the focus of the Lean approach should not just be on eliminating these wastes. Lean should also focus on other waste-generating elements such as mura (process variability) and muri (excessive workload) (Sony, 2018).

Arlbjørn and Freytag (2013) have suggested a division of Lean into three levels, such as i) philosophy level which expresses the idea that Lean basically concerns reducing waste and improving customer value, ii) principles level which comprises five principles deduced from the TPS, and iii) tools level that consists of several well-known tools primarily taken from Just-in-Time, Total Quality Management, and the Theory of Constraints. Furthermore, the Lean system is commonly approached from two points of view (Ciano *et al*., 2020). Theoretically, it is related to guiding principles and general objectives (Womack and Jones, 1996). From a practical point of view, it is defined as a set of practices to achieve the objectives (Shah and Ward, 2003). Principles are the strategic components that refer to the ideals of the system (Souza and Alves, 2018), while practices are the components that operationalize such principles (Tortorella *et al*., 2017).

Womack and Jones (1996) systematized Lean Thinking and brought together five critical principles of Lean implementation such as identifying value, mapping the value stream, creating flow, establishing pull, and seeking perfection. Shah and Ward (2003) group Lean management practices into four groups such as Just-in-Time (JIT), Total Quality Management (TQM), Total Preventive Maintenance (TPM), and Human Resource Management (HRM). Through this set of synergistic practices, Lean focuses on the systematic elimination of wastes and non-value added activities from a company's manufacturing operations to produce products and services at the rate of demand (Womack *et al*., 1990; Shah and Ward, 2007), what gave rise to Lean Thinking (Bevilacqua *et al*., 2015).

The Lean production system seeks to implement streamlined and continuous flow processes based on the adoption of a pull approach (Liker, 2004) to create the finished products at the required pace of customers (Shah and Ward, 2003), clearly identifying customer value and joining efforts to eliminate manufacturing waste (Liker, 2004). Sanders *et al*. (2016) present ten Lean dimensions and group them into four main factors. The supplier factors integrate suppliers into business processes with dimensions of supplier feedback, supplier development, and JIT delivery. The customer factor involves the customer in business processes. The process factors organize operations and process sequencing with the dimensions of pull production, continuous flow, and setup time reduction. The human and control factors structure the control system and motivate employees with the dimensions of Statistical Process Control (SPC), Total Productive Maintenance (TPM), and employee involvement.

It is noticed that the Lean approach focuses on human-centered production systems (Ma *et al*., 2017). The implementation of Lean can be widely recognized when its practices extend to suppliers and customers, and continuous improvement programs are strategically developed throughout the company (Mrugalska and Wyrwicka, 2017). In that regard, Shah and Ward (2007) define Lean as an integrated socio-technical system. The authors conceptualize Lean more holistically by capturing both internal and external practices to better align Lean objectives with its origins and develop an appropriate set of measures. Bortolotti *et al*. (2015) define a set of Lean socio-technical practices (Table 2.1) and argue that Lean hard refers to technical practices introduced to improve production systems, while Lean soft is related to social practices focused on people involvement and human resource management.

Table 2.1. Definition of Lean socio-technical practices

Lean Technical Practices	**Definition**
Continuous flow	Seeks to establish a simplified flow of products without major stops throughout the company (Sanders et al., 2016).
Just-In-Time (JIT)	Seeks to reduce unnecessary stocks by minimizing transport and storage costs, delivering pieces frequently and in small quantities (Goodarzi and Zegordi, 2018).
Kanban	Refers to a physical card that sends the demand signal from a downstream workstation to an upstream workstation preventing the work-in-process (WIP) accumulation between workstations. Kanban strategy is suitable for inventory control (Huang *et al*., 2020).
Setup time reduction	Refers to a set of coordinated activities that keep the time needed to adapt production resources to product variations to a minimum (Sanders et al., 2016).
Statistical Process Control (SPC)	Seeks to ensure that each process will provide defect-free units for the subsequent process (Shah and Ward, 2007).
Autonomous maintenance	Aims to reduce equipment downtime through complementary maintenance methods and techniques with strong human involvement (Tortorella *et al*., 2018; 2021).
Lean Social Practices	**Definition**
Management leadership	It establishes a culture where top managers act as role models to exemplify the desired behavior for Lean implementation, taking initiatives in defining and communicating the vision of change and setting goals (Gaiardelli *et al*., 2018).
Supplier partnership	Seeks long-term relationship between buyer and supplier based on trust, open communication, and close interaction (Gaiardelli *et al*., 2018).
Small group problem solving	Organization of employees in work teams and involvement in problem-solving groups (Gaiardelli *et al*., 2018).
Continuous improvement	Establishes a culture of sustained improvement targeting the elimination of waste in all systems and processes of an organization (Singh and Singh, 2015).
Training employees	Seeks to establish formal job design, job rotation, and cross-functional training programs (Gaiardelli *et al*., 2018).
Customer involvement	Refers to a set of coordinated activities focused on a company's customers and their needs (Shah and Ward, 2007).

Implementation of the Lean system has given rise to significant positive impacts on various industries during the past couple of decades (Shahin *et al*., 2020). Thus, Lean Practices (LP) have been extensively adapted and implemented in several sectors

(Tortorella *et al*., 2020b). There is evidence that LP are positively associated with sustainability performance categorized as economic, environmental, and social performance (Sajan *et al*., 2017). Furthermore, there is a significant positive effect of the simultaneous application of LP and Industry 4.0 Technologies (I4T) in cost reduction, product and process quality improvement, lead time, and flexibility (Khanchanapong *et al*., 2014).

However, Lean is facing several challenges from an integration perspective. For example, more effective integration with suppliers and customers (Moyano-Fuentes *et al*., 2019). The acquisition of exact customer needs is getting more and more complex, pull production must face rapid changes in scheduling, and often the set-up time reduction is based exclusively on human experience (Sanders *et al*., 2016). Successful application of these practices depends primarily on data collection and analysis, which can be time-consuming and costly (Uriarte *et al*., 2018) and requires workers to be highly experienced in increasingly complex and dynamic environments (Longo *et al*., 2017). In this context, attempts have emerged to integrate automation using emerging technologies into the Lean system (Kolberg *et al*., 2016).

There is, therefore, a clear need to pursue the deployment of Lean management using I4T, according to the capability level targeted (Rosin *et al*., 2019). Thus, important questions arise about how a simultaneous implementation of LP and I4T affects the operational performance (Shahin *et al*., 2020) and sustainability performance of organizations (Kościelniak *et al*., 2019).

2.2 Industry 4.0

The term ‘Industry 4.0’, coined in 2011 at the Hannover Fair in Germany, describes an industry whose main characteristics comprehend connected machines, smart products and systems, and inter-related solutions (Tortorella and Fettermann, 2017). Using the Internet of Things (IoT), Big Data, and Cyber-Physical Systems (CPS), among other technologies, Industry 4.0 (I4.0) can reach levels of operational performance that were previously inaccessible (Rosin *et al*., 2019), in addition to defining a different approach to customer value (Kamble *et al*., 2019), as it allows you to dynamically reconfigure manufacturing systems based on your needs (Da and Duan, 2019). However, Ghobakhloo and Fathi (2020) present that there is no literary consensus on the emergence of the fourth industrial revolution or I4.0. Rifkin (2016) argues that the third industrial revolution still has the potential for evolution to be considered complete. For this research, the emergence of Industry 4.0 will be considered.

I4.0 and its international equivalents such as the Chinese movement ("Made in China 2025"), South Korean ("Manufacturing Industry Innovation 3.0") (Li, 2018), North American (“Advanced Manufacturing Partnership”), United Kingdom (“Smart Factory”) and others (Kumar *et al*., 2020), heavily rely on advanced technological innovations (Li, 2018). Therefore, the I4.0 is a technology-driven approach that provides a modular and changeable production environment (Kolberg *et al*., 2016). In the context of I4.0, the physical facilities in an organization, when connected through embedded sensors, processors, and actuators can be controlled and monitored by cyber systems (Sony, 2020).

I4.0 is a generic term for highly complex and automated manufacturing systems, services, and business processes, where devices are self-aware, communicate with one another and with humans and can be remotely accessed, using information available in the network and in the cloud (Kumar *et al*., 2020). Stork (2015, p.21) defines I4.0 as the introduction of technologies in the manufacturing industry to make factories smarter and increase adaptability, resource efficiency, and ergonomics. Furthermore, it refers to greater customer integration in the product definition phase as well as business partners into the value and logistic chains (Stork, 2015, p.21). The success of applying Industry 4.0 technologies (I4T) is linked to a set of factors such as usability, selective provision of information, acceptance of users, consideration of ethical, legal, and social impacts, and profitability (Mayr *et al*., 2018). In this research, the main technologies adopted to compose I4.0 are defined in Table 2.2.

Table 2.2. Definition of Industry 4.0 technologies

Industry 4.0 technologies	**Definition**
Cloud Computing (CC)	Is a technology that offers storage, access, and use of online computing services. It consists of three levels: infrastructure as a service, platform as a service, and software as a service. Moreover, it allows companies to access computing resources in a flexible way with low administrative effort and from different devices, offering agility, interoperability, and scalability (Arredondo-Méndez *et al*., 2021).
Cyber-Physical System (CPS)	System of the embedded computers and networks that monitor and control the physical processes, usually with feedback loops where physical processes affect computations and vice versa (Lee *et al*., 2015).
Internet-of-Things (IoT)	It refers to an Information and communication technology infrastructure with middleware functionality, which facilitates the interoperation of heterogeneous hardware and software components, that can operate inside or outside the industrial environment. IoT forms a broader and more scalable network of generic 'things' (i.e., sensors, actuators, controllers, smart objects, mobile devices, RFID devices, servers, ERP

	and MES systems, third-party systems, cloud services, etc.) (Ferrera *et al*., 2017).
Big Data/ Big Data Analytics (BDA)	Big Data refers to large data sets, varied and complex, that can be difficult to analyze and identify patterns (LaValle *et al*., 2011). For that, BDA is the process of examining large and varied data sets to uncover hidden patterns, unknown correlations, market trends, customer preferences, and other useful information that can help organizations make more-informed business decisions (Abell *et al*., 2017).
Automated guided vehicle (AGV)	Defined as a driverless material handling system with applications in diverse areas such as manufacturing, distribution, transshipment, and external transportation. AGVs can be classified as unit load carrying, forked, mandrel, unit load deck, and load towing (Vlachos *et al*., 2021).
Additive Manufacturing (AM)	Can be called 3D printing, the AM is an umbrella term composed of a set of innovative technologies aimed at manufacturing various 3D objects directly from digital models, depositing and joining layers of polymers, ceramics, or metals (Ford, 2014).
Augmented Reality (AR)	System or set of technological devices that combines the real world with virtual reality through real-time interactions, which apply digital data and images, expanding physical reality by adding an extra layer of computer-generated information to it (Koscielniak *et al*., 2019).

Although it is often characterized by the composition of an extensive portfolio of disruptive digital technologies, the concept and implementation of I4.0 also rely on key design principles (Ghobakhloo, 2018) such as systems integration, decentralized decisions, interconnection, interoperability, modularity, information transparency, virtualization, technical assistance, service orientation (Tortorella *et al*., 2021), and real-time capability (Santos *et al*., 2017). These design principles can support companies in the identification of the most appropriate solutions for their problems (Santos *et al*., 2017). Thus, I4.0 can ensure better cooperation with stakeholders (Sanders *et al*., 2016).

Due to the complexity and scope of the phenomenon, the concept of I4.0 is not unanimous in the literature (Ciano *et al*., 2020). Recent studies have found numerous definitions for I4.0 (Moeuf *et al*., 2017). Thus, there is no consensus among researchers and practitioners on which elements create I4.0, how these elements are interrelated and where I4.0 applies (Ejsmont *et al*., 2020). Pan *et al*. (2015) approach I4.0 by the ability to transmit and interpret information between industrial layers, i.e., effective communication between elements. In this research, it was assumed the definition that I4.0 refers to digital advances where the internet and related technologies serve as a support to connect physical objects, human actors, intelligent machines, production lines, and processes, contributing to an integrated, flexible, and agile value chain (Schumacher *et al*., 2016). Furthermore, it is admitted that the adoption of I4.0 requires a socio-technical transformation that renews different levels and functionalities in industrial organizations (Zheng *et al*., 2020).

I4.0 is the sum of disruptive innovations derived and implemented in a company to address the trends of digitalisation, autonomization, transparency, mobility, modularisation, network collaboration, and socialising of products, processes, and partners (Pfohl *et al*., 2015). Therefore, designing an architecture for I4.0 implementation is a challenge due to technical, social, and organizational complexity (Sony, 2020). In that regard, Prinz *et al*. (2018) argue that an organisation implementing I4.0 without standardised and continuous flow processes will not be productive. On the other hand, I4.0 will bring about a change in work, requiring well-trained employees with different skills (Bittencourt *et al*., 2019).

I4.0 is considered a step forward toward the industrial future of production, with highly connected environments (Ferrera *et al*., 2017). Refers to the digital manufacturing system provided by the successful integration of production processes, information technologies, and techniques (Kamble *et al*., 2019). Furthermore, I4.0 seeks the creation of a network among humans and objects connected through real-time data (Osterrieder *et al*., 2020; Jabbour *et al*., 2018; Wagner *et al*., 2017) that extends to the entire supply chain and results in horizontal integration between all stakeholders (Tortorella *et al*. 2020; Cifone *et al*., 2021), vertical integration between production and manufacturing levels (Tortorella *et al*. 2020), and end-to-end integration among smart machines, products, systems, and operators (Berger *et al*., 2016).

I4.0 presents relationships with technical factors such as robust control system design, optimization of the manufacturing process, real-time feedback system, and monitoring mechanisms (Bhat *et al*., 2020; Cohen *et al*., 2019). Furthermore, socio-cultural requirements such as top management leadership, employee adaptability, organizational strategy, structure, core competencies, priorities, tech-savvy stakeholders, motivation, and budget influence the successful implementation of this industrial approach (Bhat *et al*., 2020; Ghobakhloo, 2018).

The advances achieved with I4.0 have changed the way companies interact with their employees, suppliers, customers, and partners (Reischauer, 2018; Tortorella *et al*., 2021), and these relationships with technical, social, and cultural factors demonstrate synergies between I4.0 and Lean. Furthermore, deploying I4.0 introduces improvements in economic (Moeuf *et al*., 2017), ecological and social performance (Stock *et al*., 2018), impacting sustainability performance.

In this research, in addition to investigating the general context of the integration between Industry 4.0, Lean, and Sustainability, we investigated in depth the relationships between Big Data Analytics (BDA), Lean Socio-Technical Practices, and economic, environmental and social performance. This is because BDA has strong relationships with Lean and Sustainability. BDA is broadly defined as "a holistic process that involves the collection, analysis, use, and interpretation of data for various functional divisions to gain business value, and establish a competitive advantage" (Fosso Wamba et al., 2019). Large volumes of data are not handled with traditional tools, so BDA provides companies with the ability to manage their use of ever-growing databases (Ma et al., 2015).

Yan et al. (2017) proposes the application of intelligent optimization algorithms to reduce total energy consumption with a Big Data processing platform. Jabbour et al. (2017) explored the synergistic relationships between the circular economy and Big Data and how it can enhance social and environmental sustainability, enabling the decoupling of environmental burden and economic growth. Bressanelli et al. (2018) establish that preventive and predictive maintenance promoted by BDA extends the life of machines, minimizing waste. Therefore, BDA can be used to improve economic, environmental, and social performances (Raut et al., 2019), and support Lean.

2.3 Sustainability Performance

In recent decades it has been argued that industries are not just economic units, they are components of society that transmit their role to progress, also from the point of view of sustainability (Tasleem and Athar, 2015). In addition to traditional economic goals, the industrial sector has sought ways to reduce risks and environmental impacts (Duarte *et al.*, 2020). What makes it necessary to manage sustainability in economic, social, and environmental aspects (Garza-Reyes, 2015).

Sustainability has become an invaluable tool for exploring ways to improve performance and promote fundamental internal changes in organizational strategy (Azapagic, 2003). However, failure to measure economic, environmental, and social performance over time can cause practices to become less indicative of what companies are achieving from a sustainability perspective (King *et al.*, 2005). By measuring these performances, industries are better positioned to manage them and thus contribute to sustainable development both within and beyond their boundaries (Hourneaux Jr. *et al.*, 2014).

In this sense, Jayakrishna *et al*. (2015) define that: (i) Economic Performance involves achieving better financial results by ensuring the future availability of scarce resources; (ii) Environmental Performance involves strategies to reduce impacts on the environment caused by, products and processes, as well as initiatives to preserve the system in the future; and (iii) Social Performance measures involve the population, internal and external, in the organizational strategy, that is, it involves contributing to human needs, in addition to meeting other goals.

To meet these expectations, industries are improving the management of sustainability performance indicators (Hourneaux Jr. *et al*., 2017). In this context, Economic Performance reflects the ability of a production unit to obtain maximal output from a given set of inputs and the production technology (Yang and Zhang, 2016). It can be measured through a set of economic indicators characterized by reduced overall production costs and profit maximization (Kamble, *et al*. 2019).

From an environmental perspective, Haffar and Searcy (2018) propose a list with different categories of indicators, such as materials, energy, water consumption, biodiversity, emissions, effluents and waste, transport, products and services, compliance, environmental grievance mechanisms, supplier environmental assessment, and environment-related financial investments. Similarly, Popovic *et al*. (2018) propose a set of quantitative indicators to assess social sustainability in industries. Indicators reflect an organization's social context by evaluating categories such as work practice and human rights.

For this research, we will adopt the economic, social, and environmental performance indicators defined by Kamble et al. (2019) (Table 2.3), used by several authors.

Table 2.3. Sustainability performance indicators

Sustainability Performance	**Performance Indicators**		**Sources** (Authors who reinforce that indicator is part of the performance)
Economic Performance	Reduced overall costs	Reduced inventory	Buer *et al*. (2020); Chavez *et al*. (2020); Hernandez-Matias *et al*. (2020); Baliga *et al*. (2019); Iranmanesh *et al.* (2019); Rossini *et al.* (2019); Tortorella *et al.* (2019); Shrafat and Ismail (2019); Yadav *et al.* (2018); Inman and Green (2018); Panwar *et al.* (2018); Sajan *et al.* (2017)
	Improved profits	Quality	Buer *et al*. (2020); Rossini *et al*. (2019); Tortorella *et al*. (2019); Shrafat and Ismail (2019); Inman and Green (2018)
		Flexibility	Buer *et al*. (2020); Hernandez-Matias *et al*. (2020); Maware and Adetunji (2018)
		Productivity	Chavez *et al*. (2020); Hernandez-Matias *et al.* (2020); Baliga *et al.* (2019); Iranmanesh *et al.* (2019); Rossini *et al.* (2019); Tortorella *et al.* (2019); Shrafat and Ismail (2019); Yadav *et al.* (2018); Panwar *et al.* (2018)

		Efficiency	Baliga *et al*. (2019)
		Reliability	Iranmanesh *et al.* (2019); Maware and Adetunji (2018)
Environmental Performance	Reduced environmental impact		Belhadi *et al*. (2019); Chavez *et al*. (2020); Agyabeng-Mensah *et al.* (2020); Baliga *et al.* (2019); Iranmanesh *et al*. (2019); Inman and Green (2018)
	Reduced gas emissions		Chavez *et al.* (2020); Wong *et al.* (2018); Inman and Green (2018); Sajan *et al.* (2017)
	Reduction of liquid waste		Chavez *et al*. (2020); Baliga *et al*. (2019); Inman and Green (2018)
	Reduction of solid waste		Chavez *et al*. (2020); Agyabeng-Mensah *et al*. (2020); Baliga *et al*. (2019); Wong *et al*. (2018); Inman and Green (2018)
	Resource usage better		Agyabeng-Mensah *et al*. (2020); Iranmanesh *et al*. (2019); Sajan *et al*. (2017)
	Reduced energy waste		Agyabeng-Mensah *et al*. (2020); Wong *et al*. (2018); Sajan *et al*. (2017)
Social Performance	Improved working conditions		Chavez *et al*. (2020); Baliga *et al*. (2019)
	Improved workplace safety		Chavez *et al*. (2020); Iranmanesh *et al*. (2019); Baliga *et al*. (2019); Sajan *et al*. (2017)
	Improved employee health		Chavez *et al*. (2020); Iranmanesh *et al*. (2019); Baliga *et al*. (2019); Sajan *et al*. (2017)
	Improved labor relations		Sajan *et al*. (2017)

3 EXPLORING RELATIONSHIPS FOR INTEGRATING LEAN, ENVIRONMENTAL SUSTAINABILITY, AND INDUSTRY 4.0

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4 RELATIONSHIPS BETWEEN INDUSTRY 4.0 TECHNOLOGIES AND LEAN SOCIO-TECHNICAL PRACTICES

Abstract

A set of enabling technologies has evolved rapidly over the last decade giving rise to Industry 4.0 (I4.0). These technologies have shown support and interactions with the Lean socio-technical system. In addition, both I4.0 and Lean have been shown to encourage sustainability performance improvement, and there is growing interest in understanding the links between these themes. Thus, this paper seeks to identify how the support relationships that integrate Industry 4.0 technologies (I4T) and Lean socio-technical practices occur and the possible impact of these relationships on economic, environmental, and social performance. The proposed objective was achieved through Systematic Literature Review (SLR), where the data obtained were analyzed through descriptive analysis and content analysis. In addition, the literary findings were confirmed and deepened through two cases study in companies that have a consolidated Lean system and Industry 4.0 technologies at different levels of implementation. The findings allow us to identify the strengths of the integration between I4.0 and Lean and how the relationships between the approaches occur, in addition to the impacts of the relationships on sustainability performance. The results demonstrate that the Internet of Things (RFID, Sensor, and Actuator) and Big Data Analytics favor the relationships with Lean Practices (LP). In addition, Big Data Analytics has relationships with Total Preventive Maintenance, Just-in-Time and Customer Involvement. The results also point to a more significant impact of relationships on Economic Performance indicators, with few benefits for the environmental and social aspects. Therefore, this study helps managers and academics to understand ways to integrate I4T and LP aiming the sustainability performance.

Keywords Industry 4.0 Technologies, Lean Technical Practices, Lean Social Practices, Sustainability Performance, Systematic Literature Review, Cases Study.

4.1 Introduction

Lean is a widely applied production system composed of socio-technical practices (Bortolotti *et al*., 2015) aimed at cost efficiency and waste elimination (Tayaksi *et al*., 2020). Lean comprises diversified sets of practices that vary in scope and approach (Tortorella *et al*., 2020), which support the Lean system and direct actions to achieve the intended goals (Iranmanesh *et al*., 2019). Bortolotti *et al*. (2015) present Lean Technical Practices (LTP) related to industrial process management and Lean Social Practices (LSP) related to concepts, principles, and people management. Additionally, Lean can be aligned with environmental methods and social results (Martínez-Jurado and Moyano-Fuentes, 2014), been used by industries to improve the economic, environmental, and social performance of production processes (Souza and Alves, 2018).

On the other hand, companies are being directed towards digital transformation, which has been accelerated recently due to availability of hardware and software solutions realized by cheaper and more effective sensors and actuators, more powerful networking equipment and platforms using wireless and cloud computing and the development of big data analytics and artificial intelligence, giving rise to Industry 4.0 (I4.0) (Shahin *et al*., 2020). I4.0 comprises principles related to the internet and future-oriented technologies and smart systems with improved paradigms of human-machine interaction (Sanders *et al*., 2016).

Industry 4.0 Technologies (I4T) tend to be highly connected to Lean Practices (LP) (Kulinich *et al*., 2021), significantly improving industry results (Tortorella and Fettermann, 2017). Mesquita *et al*. (2021) make it clear that relationships, where I4T support LP in industrial processes, allow more significant benefits for environmental sustainability and good operational results. For example, Roy and Roy (2019) show that IoT is generating Big Data and that these efforts have resulted in significant improvements in streamlining operations, helping industries to achieve Lean and sustainable systems. Big Data generated by sensors and other IoT sources can support LP, fueling autonomous maintenance and continuous improvement projects, identifying excess energy and water consumption, resulting in reduced industrial waste and more efficient use of resources (Dubey *et al*., 2019; Raut *et al*., 2019).

The connection between I4.0 and Lean in production environments have attracted the attention of researchers and practitioners (Shahin *et al*., 2020). This growing interest is driven by studies that indicate that I4.0 is highly and positively correlated with Lean, this occurs through I4.0 assisting LP to be carried out with greater support of data and information (Tortorella *et al*., 2020; Shahin *et al*., 2020; Rosin *et al*., 2019). Tortorella *et al*. (2020) provide evidence of pairwise synergistic relationships between I4T and LP, indicating that the coexistence of both approaches is not conflicting. When used together, I4T and LP have a synergistic effect on performance that is greater than their individual effects added (Buer *et al*., 2020). Evidence suggests that the integration between I4T and LP can also be beneficial for sustainability performance (Kościelniak *et al*., 2019; Bonilla et al., 2018), considering the triple bottom line vision of economic, social, and environmental sustainability (He *et al*., 2019).

Therefore, Lean, I4.0 and sustainability performance are relevant concerns for industries, and in general, for society, and there is a potential impact of Lean and I4.0 on the three dimensions of sustainability (Varela *et al*., 2019). Although some studies point out that there are positive impacts between I4.0 and Lean, there is no in-depth research on how these approaches can be integrated (Belhadi *et al*., 2019; Varela *et al*., 2019) or are being integrated in the real context of industries, since the results of the integration are scarce in the literature with few empirical results (Dubey *et al*., 2019; Kamble *et al*., 2019). Therefore, there is a gap on how these approaches can be integrated (Dubey *et al*., 2019; Kamble *et al*., 2019; Duarte *et al*., 2020). Researches should be conducted to analyze the association between specific relationships of highly synergistic pairs formed by specific I4T and LP (Tortorella *et al*., 2020). In addition to understanding how I4.0 technologies can support LP, it is necessary to highlight the effects of these relationships, that is, to understand exactly how a company's performance is affected by the integration (Tortorella *et al*., 2019), also considering the effect on sustainability performance, which are scarce in the literature (Dubey *et al*., 2019; Kamble *et al*., 2020; Sajan and Shalij, 2021). Thus, one of the main questions that emerged is how to incorporate such disruptive technologies into a well-established management approache, such as Lean, in order to overcome current organizational challenges (Tortorella *et al*., 2020), in this sense, improving economic, social and environmental performances (Yu *et al*., 2020).

In the context of the gaps presented, the research questions (RQ) are the following:

RQ1. What are the relationships where Industry 4.0 technologies support Lean socio-technical practices, impacting economic, environmental, or social performance?

RQ2. How can Industry 4.0 technologies support Lean socio-technical practices, benefiting economic, social, or environmental performance?

The main purpose of this study is to identify, through a Systematic Literature Review (SLR) and cases study, how the I4T are supporting Lean Socio-Technical

Practices, and the possible impact of these relationships on sustainability performance. As an additional contribution, frameworks were proposed that demonstrate the most promising relationships in an industrial environment.

To achieve the objectives, the paper is structured as follows. Section 4.2 defines the variables and presents the research method. Sections 4.3 and 4.4 show the results of the SLR and the cases study respectively. Discussions are presented in Section 4.5 and conclusions, limitations and academic and managerial implications are elaborated in section 4.6.

4.2 Method

To achieve the proposed objectives, the research methods chosen were the Systematic Literature Review (SLR) and the Case Study. The SLR (Figure 4.1) followed the research flow developed by Ferenhof and Fernandes (2016).

Phase	Activity	Results
1. Research protocol	1.1. Search strategy	
	1.2. Database query	2,063 documents found in the databases
	1.3. Document management	
	1.4. Standardization and selection of documents	Removal of duplicate documents (320 documents) Removal of documents by other exclusion criteria (284 documents) Documents approved at first reading (300 documents) Documents approved at second reading (126 documents)
	1.5. Organization of bibliographic portfolio	Documents related to the theme (46 documents)
2. Analysis	2.1. Data consolidation	Documents that respond to RQ1 (46 documents) Documents that respond to RQ2 (39 documents)
3. Synthesis	3.1. Synthesizing information	
4. Writing	4.1. Writing	Tables 4.4, 4.5 and 4.6

Figure 4.1. Phases and activities of the SLR

The search string focused on the search for documents that address the two themes (Lean and Industry 4.0) and their relationships. In order not to restrict the search, only the terms belonging to Lean and I4.0 constituted the string (Table 4.1), and the search for the relationship with sustainability occurred in each selected document. The databases used were Web of Science and Scopus, and the inclusion and exclusion criteria are presented in Table 4.2. The search was carried out in 2022, and there was no time limit for publications, totaling 2,063 documents.

The document management was carried out in the Nvivo software. Retrieved papers were organized and the filtering and analysis processes were performed. In the standardization and selection of documents, after removing documents by exclusion criteria, the exclusion and inclusion criteria were applied first in the content of title, abstract, and keywords, and second including introduction and conclusion. Finally, in the organization of the bibliographic portfolio, the 126 papers selected in Activity 4 were read in full to allow the exclusion of those that were not aligned with the research theme. At this phase, 46 documents presented relationships between I4T and Lean Socio-Technical practices that can contribute to sustainability performance. The snowball technique was applied, but no documents were added to the sample.

Table 4.1. Search string

Themes	Keywords
Lean	Lean manufacturing; lean production; lean management; lean; process improvement; continuous improvement
AND	
Industry 4.0	Industry 4.0; industrie 4.0; internet of things; IoT; cyber-physical systems; cyber physical production system; cyber physical system; cyber physical systems; CPS; big data; cloud computing; augmented reality; additive manufacturing; 3D print; 3D prints; digitalization; digitalisation; digitization; smart factory; smart factories; smart manufacturing; industrial internet of things; cloud manufacturing; smart production; industrial internet; the 4th industrial revolution; the fourth industrial revolution; intelligent factory; factory of the future

Table 4.2. Inclusion and exclusion criteria

Topic	Inclusion Criteria	Exclusion Criteria
Access	Have access to the full paper and not be a duplicate paper.	Not having access to the full paper or be 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, books chapters, editorial, letter).
Theme	Industry 4.0 Technologies Lean Practices Sustainability Performance	Present the technical part (systems operation) of an Industry 4.0 technology. Lean with other meanings (e.g., lean mass). Sustainability with other meanings (e.g., sustainable improvement, in the sense of improvement that is sustained over time).
Focus	The paper deals with the relationships between Industry 4.0 technologies and Lean Practices and the possible impact of these relationships on economic, environmental, or social performance.	The paper does not address the relationships between Industry 4.0 technologies and Lean Practices that impact economic, environmental, or social performance.

In the second phase (Activity 2.1), the 46 papers related to the theme were analyzed to answer the first research question (what are the relationships where Industry 4.0 technologies support Lean socio-technical practices, impacting economic, environmental, or social performance?). Then, an in-depth qualitative analysis was carried out in which 39 papers answered the second research question (i.e., how can Industry 4.0 technologies support Lean socio-technical practices, benefiting economic, social, or environmental performance?).

Qualitative analysis (content analysis) was performed using the NVivo software. Content analysis provides a scientific method to evaluate the collected data (Kondracki *et al*., 2020). For the identification of I4T support relationships to Lean Socio-Technical practices, technologies and practices were codified based on the literature (Table 4.3). The main references for the variables were Bortolotti *et al*. (2015) for Lean Socio-Technical practices and Kamble *et al*. (2019) for I4T. In addition, to analyze the impact on sustainability performance, the economic, environmental, and social indicators defined by Kamble *et al*. (2019) were used.

Table 4.3. Variables for Lean Practices and Industry 4.0 Technologies

Theme	Category	Variables	Code	Source
Lean Practices	Lean Technical Practices	Continuous flow	CF	1; 2; 6
		Just-In-Time	JIT	1; 2; 3; 6
		Kanban	KAB	1; 2; 4; 5
		Setup time reduction	SET	1; 2; 6
		Statistical Process Control	SPC	1; 2; 6
		Autonomous maintenance	AUM	1; 2; 3; 6
	Lean Social Practices	Management leadership	MAL	1; 3; 6
		Supplier partnership	SUP	1; 2; 4; 6
		Small group problem solving	SGPS	1; 2; 6
		Continuous improvement	COI	1; 2; 3; 5; 6
		Training employees	TRE	1; 2; 3; 4; 6
		Customer involvement	CUI	1; 2; 4; 5; 6
Industry 4.0 Technologies	Integration technologies	Cyber-Physical System	CPS	7
		Cyber-Security System	CSS	9
	Data technologies	Big Data	BD	7; 8; 9
		Cloud Computing	CC	7; 8; 9
		Internet of Things (RFID, Sensor, Actuador)	IoT	7; 8; 9
		Simulation/Digital Twins	SIM	7
	Shop floor technologies	Additive Manufacturing	AM	7
		Virtual Reality	VR	7; 8; 9
		Augmented Reality	AR	7; 8; 9
		Robotic System (Collaborative Robot and Automated Guided Vehicle)	RS	7; 8; 9

Table 4.3. (Continued)

Theme	Category	Variables		Source
Sustainability Performance	Economic Performance	Reduction in production costs	-	10; 11
		Improvement in profits	-	10; 11
		Reduction in energy costs	-	11
		Reduction in stock costs	-	11
		Reduction in rejection and rework costs	-	11
		Reduction in raw material purchase costs	-	11
		Reduction in waste treatment costs	-	11
	Environmental Performance	Reduction of atmospheric emissions	-	12; 13
		Reduction of solid waste	-	11; 12; 13
		Reduction of liquid waste	-	11
		Reduction of energy waste	-	11
		Decrease in the consumption of hazardous / harmful / toxic materials	-	12; 13
		Decrease in the frequency of environmental accidents	-	11; 12
		Improvement in the company's environmental performance	-	11; 12; 13
	Social Performance	Improvement in employee morale	-	11; 12
		Work satisfaction	-	12
		Improvement safety in the workplace	-	11; 12
		Improvement in the health of employees	-	11; 12
		Improvement in working relationships	-	11
		Decrease in pressure at work	-	11
		Improvement in working conditions	-	11
		Reduction in health and safety incidents	-	12
		Reduction in injuries and lost days related to injuries	-	12
		Reduction in absenteeism	-	12

Sources for lean practices: 1- Bortolotti *et al*. (2015); 2- Sahoo (2020); 3-Arumugam *et al*. (2020); 4- Malik and Abdallah (2020); 5- Nagaraj and Jeyapaul (2020); 6- Abdallah *et al*. (2021)

Sources for I4.0 technologies: 7- Frank *et al*., (2019); 8- Kamble *et al*., (2019); 9- Ciano *et al*. (2020)

Sources for sustainability performance: 10- Baliga *et al*. (2019); 11- Kamble *et al*. (2019); 12- Chavez *et al*. (2020); 13- Inman and Green (2018)

In the synthesis phase (Activity 3.1) and writing (Activity 4.1), information was compiled and presented through text and tables.

After identifying the relationships in the literature and how they can occur, multiple cases were carried out to verify how companies are carrying out integration in practice. The case study can be used to explain causal relationships between variables (Yin, 2014). It can be part of a broader assessment, complementing and providing explanatory information (Yin, 2014). In this research, the case study was applied to confirm the findings of the theoretical study (Yin, 2014). The steps for the conduction of the case study are shown in Figure 4.2. The phases comprised the Plan, with the selection of research questions, the Design, which comprises the theoretical basis for the case study, the definition of multiple cases and the company as a unit of analysis, since the practices Lean as well as technologies are embedded at the enterprise level. In the Prepare stage, the choice of cases occurred through the investigation of companies that had a high degree of implementation of Lean practices and I4T. The information was identified through websites and news on the internet and 5 companies were selected, two of which agreed to participate in the research.

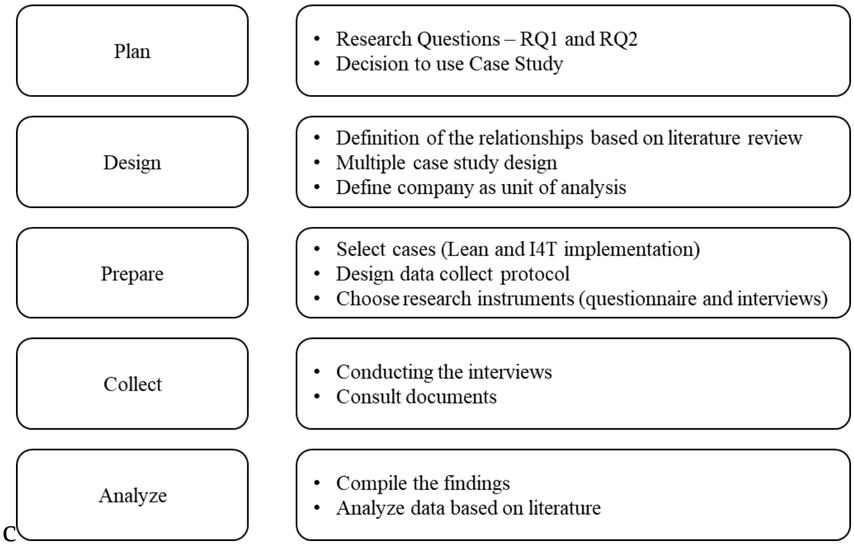

Figure 4.2. Phases and activities of the case study

In each of the companies studied, three key respondents were selected to carry out the interviews. After explaining the research objectives, the company itself indicated the people with the most knowledge on the subject, those responsible for the Lean system and projects related to Industry 4.0, including process, quality, and technology. The interviews were carried out based on a protocol, conducted by at least two researchers and based on a questionnaire with thirty-three open-ended questions. Interviews were conducted from July to August 2022. The interviews were then transcribed for coding purpose, using the same variables as those applied in the Systematic Review. Each interview lasted from 1 to 2 h producing qualitative data that were recorded. The interviews were summarized in a case report reviewed by each company for validation purposes.

Finally, the findings of the SLR and the cases study were synthesized demonstrating how I4T support Lean Socio-Technical practices and, and the impact of the relationships on economic, social, and environmental aspects. A conceptual framework was developed for both perspectives presented.

4.3 Relationships between Industry 4.0 and Lean (SLR)

The relationships identified in the content analysis show a potential to integrate I4T and LP in the industrial environment. The relationships between I4T and Lean Socio-Technical practices are presented in Table 4.4. The numbers in Table 4.4 represent the total of authors that address relationships between I4T and LP, therefore, they represent the strength of these relationships in the literature. Table 4.4 allowed answering RQ1 from the SLR's point of view. To answer the RQ2, Tables 4.5 and 4.6 present an overview of how I4T can support Lean Socio-Technical practices.

Table 4.4. Matrix of the relationships between Industry 4.0 and Lean (what)

	Industry 4.0 Technologies								
Technical Practices	AGV	AM	AR	BDA	CC	CPS	IoT (RFID, Sensor, Actuator)	Simulation (Digital Twin)	**Total**
Continuous flow	[1]		[1]	[1]	[1]	[1]	[4]		[9]
JIT	[4]	[3]	[3]	[5]	[1]	[3]	[7]	[2]	[28]
Kanban	[2]			[2]	[1]	[2]	[7]	[4]	[18]
Setup time reduction						[1]	[7]		[8]
SPC						[1]	[3]		[4]
TPM			[6]	[5]			[9]	[1]	[21]
Social Practices									
Continuous improvement			[1]	[2]	[1]	[3]	[5]	[1]	[13]
Customer involvement		[2]		[4]	[1]	[1]	[6]		[14]
Supplier partnership				[1]	[1]	[1]	[4]		[7]
Training employees			[3]						[3]
Total	[7]	[5]	[14]	[20]	[6]	[13]	[52]	[8]	**[125]**

The results of the contend analysis demonstrated that the I4T are able to support several Lean Technical Practices (LTP) (Table 4.5). In total, 125 supportive relationships were identified (Table 4.4). The most cited relationships in the literature involve IoT support for JIT, TPM, continuous flow, Kanban practices, setup time reduction, and SPC.

Often cited relationships also involve AR and BDA support for TPM and BDA support JIT (Table 4.4). IoT in conjunction with RFID, sensors and actuators can be used to support predictive maintenance (Chiarini and Kumar, 2020). The sensors enable to get information about vibration, noise, and heat, helping operators to detect abnormal conditions, identifying the most favorable moment to carry out maintenance (Satoglu *et al*., 2018). Machines can receive and send information to shop-floor and maintenance personnel about its production performance, indicating the need for maintenance to prevent future failures (Mora *et al*., 2017; Sanders *et al*., 2016). An intelligent information sharing and tracking system based on IoT gives accurate and timely information about the flows and materials throughout the supply chain, decreasing inaccuracies, and long lead times, which are vital to JIT performance (Zelbst *et al*., 2014). The use of IoT technologies in setup time reduction practices allows to reduce downtime whenever an operation change occurs (Tortorella *et al*., 2020), increasing the flexibility and productivity of production processes (Tortorella *et al*., 2019).

The IoT evolve Kanban pull system into an autonomous process over the IoT (Chiarini and Kumar, 2020), where data can be transmitted wirelessly to an inventory control system in real-time (Sanders *et al*., 2016). The AR instructs, train, support, and guide employees during TPM activities (Mora *et al*., 2017; Satoglu *et al*., 2018; Mayr *et al*., 2018), enabling activities to be carried out efficiently and at the correct frequency (Valamede and Akkari, 2020). BDA can be used to predict defects in equipements, which may increase the life expectancy of these instruments (Mayr *et al*., 2018; Valamede and Akkari, 2020). Big data enables be self-aware and self-maintained machines (Sanders *et al*., 2016). Although less numerous in the literature, there are several other supporting relationships between I4T and LTP presented in Table 4.5.

I4T supporting LTP improve economic performance indicators such as quality, flexibility, efficiency, productivity, costs reduction, reduced inventory, and reliability (Valamede and Akkari, 2020; Sanders *et al*., 2016), environmental performance indicators such as responsible use of resources (Núñez-Merino *et al*., 2020), and social performance indicators such as better working conditions and health of workers.

When analyzing the relationships considering the Lean social system, the gains for organizations are increased when there is integration between I4T and Lean Social Practices (LSP) (Ghobakhloo and Fathi, 2020). The strongest relationships found are related to I4.0 support for customer involvement, continuous improvement and supplier partnership, mainly IoT, followed by AR support for employee training (Table 4.4).

The use of IoT technologies supports the implementation of continuous improvement practices by facilitating the identification of errors in the system, enabling the capture, processing, sharing and forwarding of information to stakeholders, and allowing greater involvement of suppliers and customers (Haddud and Khare, 2020). While the incorporation of the CPS provide more accurate data for decision-making in continuous improvement initiatives (Pagliosa *et al*., 2019). BDA incorporates several data analysis tools, which allows the identification of root causes more accurately and quickly, helping continuous improvement (Peças et al., 2021; Valamede and Akkari, 2020).

Several authors propose the use of AR to facilitate employee training (Koscielniak *et al*., 2019; Sordan *et al*., 2021). AR work together with employees, helping them in their manual tasks to avoid possible errors, besides presenting instructions and virtual elements that facilitate the training and performance of activities (Valamede and Akkari, 2020). BDA, on the other hand, can give a better understanding of different customer segments' behavior and needs, enabling a proactive response to customer requirements (Núñez-Merino *et al*., 2020). An information-sharing structure based on Big Data strengthens customer involvement (Raut *et al*., 2019), which becomes even more relevant given the continuous feedback facilitated by the IoT. Despite the identification of a smaller number of citations about I4T support for LSPs, several other relationships were found (Table 4.6).

Some economic, environmental, and social benefits are reported from the integration between I4.0 and LSP. For example, waste and cost reduction and negative environmental externalities (Ghobadian *et al*., 2018), the employees may move into roles with less physical monotony and more intellectual stimulation (Sanders *et al*., 2016), enhanced human learning through intelligent assistance systems as well as human-machine interfaces that lead to increased employee satisfaction in industrial workplaces (Herrmann *et al*., 2014).

Table 4.5. How I4T support LTP

Relationships / How	Sustainability Performance	Authors (Year)
IoT / JIT The application of IoT technologies provides real-time data on product locations and characteristics, which improves traceability and minimizes delays and waiting times, leading to more effective inventory management, and, consequently, reduced lead times. IoT devices as sensors can detect the number of items in kanban baskets and automatically transmit the data to the control system. The system can automatically send orders to suppliers according to production line needs, which reduces stocks and frees up shop floor space. Using IoT technologies, one process can trigger the production of another, introducing a perfect one-piece-flow pull system, which enables JIT. IoT technologies: i) can send employees information if any product changes configuration or if the line balancing finds a new configuration.; ii) can display information corresponding to the precise product and phase of work on virtual work elements sheets; iii) can recognize different orders through barcode scanning devices and inform employees of the right components to assemble, which can dramatically reduce order preparation time. Thus, IoT accelerates work and avoids errors by strengthening JIT.	Economic Performance (quality, stock cost reduction, efficiency, productivity, costs reduction)	Anosike et al. (2021) Raji et al. (2021) Chiarini and Kumar (2020) Ciano et al. (2020) Bittencourt et al. (2019) Mayr et al. (2018) Valamede and Akkari (2020) Zelbst et al. (2014)
IoT / Continuous flow Continuous flow seeks to establish a simplified flow of products without major stops throughout the company (Sanders *et al*., 2016). In this context, sensors can monitor production volumes and help companies reduce unfinished work in the process and resolve issues created by task switching and order reprioritizing, which allows for workflow improvements.		Ghobakhloo and Fathi (2020) Ciano et al. (2020) Raji et al. (2021)
IoT / Kanban IoT technologies can monitor kanban schedule changes and the charge level of the box, and the data can be automatically transmitted to a real-time inventory control system. Furthermore, real-time process monitoring allows minimum batch quantity to be set per workstation. When the workstation reaches minimum stock the information is displayed on the predecessor workstation to forward the material.		Kumar et al. (2018) Sanders et al. (2016)
IoT / TPM An IoT maintenance system allows a quick response to failures. The analysis of collected data can link the occurred failure with past patterns and causes, which can prevent potential failures. In addition, it is possible to request repairs and order spare pieces automatically. Advanced sensors can measure parameters in machines such as times, speed, pressures, vibrations, temperatures, etc.		Anosike et al. (2021) Chiarini and Kumar (2020) Ghobakhloo and Fathi (2020) Tortorella et al. (2021) Raji et al. (2021) Sordan et al. (2021)

Table 4.5. (Continued)

Relationships / How	Sustainability Performance	Authors (Year)
IoT / Setup time reduction Machines-embedded learning enabled by IoT technologies can support setup time reduction practices since machines can perform accurate Single-Minute Exchange of Dies (SMED) procedures followed consistently. IoT technologies can receive material, product, or work phase information and prepare the correct configuration of the machines. Sensors or RFID can recognize the right tool for the right machine or set the parameters corresponding to the new production cycle which results in a faster change of machine parameters according to the instructions read on the piece, reducing setup time.		Anosike et al. (2021) Ciano et al. (2020) Ciano et al. (2020) Sordan et al. (2021) Sanders et al. (2016)
IoT / SPC IoT and Smart sensors for collecting data linked to characteristics of the process permit SPC with autonomous feedback to the machine in case of deviation from the limits and unlikely patterns in the data appear. In addition, communication can be done in real-time through supervisors' smartphones.		Chiarini and Kumar (2020) Sordan et al. (2021)
BDA / JIT Data shared in the cloud between supply chain partners can be processed by BDA, which significantly reduces order execution time, can identify trends and assists in immediate decision-making. Moreover, it helps analyze demand trends, for example, during peak seasons, for proper forecasting and planning purposes, avoiding delays.	Economic Performance (quality, efficiency, stock cost reduction, flexibility)	Raji et al. (2021) Mayr et al. (2018) Valamede and Akkari (2020)
BDA / Kanban BDA increases the transparency of material and process movements and enables the combination of target and actual values to remove excess inventories.		Valamede and Akkari (2020)
BDA / TPM BDA can analyze machine problems and anticipate potential breakdown and identify the root cause. Thus, Big Data capabilities allow to improve preventive maintenance routines, identifying patterns to optimize component life based on current usage conditions.		Li (2019) Tortorella et al. (2021) Sanders et al. (2016)
CPS / JIT CPS can control when the material stock reaches the minimum level and automatically generate a purchase order for the supplier.	Economic Performance (quality, efficiency, stock cost reduction, flexibility, reliability, productivity)	Santos et al. (2021)
CPS / Continuous flow CPS allows the identification of cycle times to find the best solution between the highest possible capacity utilization per working station and a continuous flow of production.		Kolberg and Zuhlke (2015)
CPS / Kanban CPS integrated into the workstations can directly control the production process through the connected actuators and update data automatically. If the stock at a workstation drops under the reorder level, the CPS automatically sends a Kanban to the predecessor, operating on the principle of self-regulation Decentralized data collection and transfer allows full visibility of all processes that are part of the Kanban system.		Kolberg et al. (2016) Pekarcikova et al. (2020)
CPS / Setup time reduction CPS provides a flexible and modular production through its computing capacity and connectable sensors. Working stations or whole production lines can be efficiently reconfigured, significantly reducing setup time.		Kolberg and Zuhlke (2015)

Table 4.5. (Continued)

Relationships / How	Sustainability Performance	Authors (Year)
CPS / SPC CPS can combine historical running data of the system to analyze abnormalities on the basis of mature data statistical analyses and mining algorithms. Moreover, define knowledge rules to predict possible system anomalies and sending pre-alarms production process based on SPC.		Ma et al. (2017)
AGV / Continuous flow The AGVs: i) allow autonomous control in operational functions and promote continuous flow; ii) identify routes and components for specific products, avoiding downtime and improving production flow by adding a sequential component to work in progress.		Ciano et al. (2020) Núñez-Merino et al. (2020) Bittencourt et al. (2019) Mayr et al. (2018)
AGV / JIT The AGV can automatically supply in-process stocks by transporting materials in the exact amount and time they are requested, minimizing stocks and favoring JIT.	Economic Performance (quality, flexibility, productivity, stock cost reduction)	Mayr et al. (2018) Núñez-Merino et al. (2020) Valamede and Akkari (2020)
AGV / Kanban The AGV performs a coordinated supply of kanban boxes in order to avoid excess and lack of materials.		Núñez-Merino et al. (2020) Valamed and Akkari (2020)
AR / JIT AR devices can provide individualized instructions about the tasks required to run and bring information about cycle times into the visual field of employees, supporting JIT processing.	Economic Performance (quality, flexibility), Environmental Performance (reduction of environmental impacts, reduction pollution, reduction use of natural resources), and Social Performance (improvement of working conditions, reduction of the number of accidents at work)	Kolberg and Zuhlke (2015) Ma et al. (2017)
AR / TPM AR devices provide employees with precise instructions to routine maintenance or faulty components/items.		Raji et al. (2021) Koscielniak et al. (2019)
AR / Continuous flow AR provides cycle times information in the visual field of workers, allowing continuous production flow.		Valamede and Akkari (2020)

Table 4.5. (Continued)

Relationships / How	Sustainability Performance	Authors (Year)
AM / JIT AM can offer shorter lead times and reduced inventory, can reduce the time required for tooling and retooling operations and enables the production of pieces and products close to the point of use by further decentralizing and redistributing manufacturing. AM technologies can meet exact customer requests using less raw material and process time as it produces just the amount needed with flexibility when adding layers of material.	Economic Performance (production cost reduction, flexibility)	Raji et al. (2021) Ghobadian et al. (2018) Valamede and Akkari (2020)
AM / Setup time reduction AM equipment can produce a different object by altering the software. Thus, AM can produce varied workpieces with short setup times, i.e., selection, search, and adjustment times for tools and workpieces are technologically reduced to a minimum.		Ghobadian et al. (2018) Mayr et al. (2018)
Simulation / JIT Process simulation allow the visualization of the simulated environment to test if the layout configuration promotes a continuous flow.	Economic Performance (stock cost reduction, productivity)	Ciano et al. (2020)
Simulation / TPM Digital Twin Simulation allow the application of different maintenance solutions and the prediction of future maintenance.		Ciano et al. (2020)
Simulation/ Kanban The simulation ensures the identification of optimal kanban parameters such as lot size, inventory, or delivery frequency. When external changes are required, the system updates the parameters autonomously.		Mayr et al. (2018) Pekarcikova et al. (2020)
CC / Kanban The cloud-based Kanban system has features for entering production data (e.g., number of machines available, number of employees, raw material availability) and a decision support system simulation. Factors such as labor hours, number of bad quality products, and production hours lost due to downtime are also entered to estimate the kanban ideals parameters.	Economic Performance (quality, efficiency, stock cost reduction, flexibility)	Shahin et al. (2020)

Table 4.6. How I4T support LSP

Relationships / How	Sustainability Performance	Authors (Year)
IoT / Continuous improvement		
IoT enables the data collection from machines where a machine learning algorithm can be used in conjunction with a problem-solving database to infer cause-problem relationships, which helps continuous improvement teams. The collected data from IoT can feed a system of indicators to promote continuous improvement projects aiming at more efficient use of resources and energy. Furthermore, IoT sensors on smart products can collect process data during and after production. Thus, it is possible to automatically gather information individualized by product and production line assisting in continuous improvement projects.	Economic Performance (quality, costs reduction, efficiency, productivity) and Environmental Performance (reduction of environmental impacts, reduction of energy consumption)	Peças et al. (2021) Haddud and Khare (2020) Ferrera et al. (2017) Kolberg and Zuhlke (2015)
IoT / Customer involvement Products purchased can be registered using a QR Code to allow the companies to immediately capture user information, establishing greater proximity to customers' needs.		Li (2019)
Sensors and IoT technologies can be applied in products to transform them into smart products (integrated with devices that track usage data and send for smart factories) allowing continuous feedback and usage analysis to understand and serve customers better.		Sanders *et al*. (2016)
IoT / Supplier partnership QR codes can be used for components delivered by suppliers, which will make delivery information clearer, plan changes easier to match, and reduce inventory.		Ciano et al. (2020) Li (2019)
BDA / Continuous improvement Analytics such as machine learning, data mining, root cause analysis, correlation analysis, and predictive analysis performed by BDA contributes to the process of continuous improvement by improving data analysis. Since, the use of advanced analysis tools capable of dealing with a large volume of data automatically collected, for example, from sensors overcomes the limitations of simpler analysis tools. Furthermore, data from stakeholders are collected through IoT devices and shared in a cloud computing environment with speed and variability. These data are processed by BDA and can be used in continuous improvement initiatives.	Economic Performance (quality, efficiency), Environmental Performance (reduction of energy consumption, reduction of water consumption, reduced industrial waste, efficient use of resources)	Peças et al. (2021) Valamede and Akkari (2020)
BDA / Customer involvement Using specific algorithms, the BDA can filter and use a large amount of data from customers, including their requirements (voice of the customer) and perceptions about products and services, strengthening customer involvement strategies.		Sordan et al. (2021) Núñez-Merino et al. (2020) Raut et al. (2019)
CPS / Continuous improvement CPS components on the workstation can provide historical data for fault analysis and continuous improvement processes. The digital information obtained by the physical system can generate a problem-solving mechanism by creating co-creative platforms that guide continuous improvement strategies.	Economic Performance (quality, productivity, efficiency)	Li (2019) Kolberg et al. (2016)
CPS / Customer involvement CPS can transfer customer experience knowledge effectively linking this information to organizational capabilities and solving various problems at the manufacturing site autonomously and flexibly.		Li (2019)

Table 4.6. (Continued)

Relationships / How	Sustainability Performance	Authors (Year)
AR / Training employees AR replaces traditional communication of operational standards on paper. Through tablets, head-mounted displays and three-dimensional holograms, AR can improve training employees' activities, what can decrease time the time to acquire the knowledge. The use of AR in training activities provides more in-depth knowledge about production processes. Thus, employees are empowered to find possible solutions to critical problems.	Social Performance (improvement of worker health)	Sordan et al. (2021) Koscielniak et al. (2019) Valamede and Akkari (2020)
AM / Customer involvement There is greater customer involvement through the analysis of data that can be provided by using smart products and more easily customized products, through AM and the flexibility allowed by technologies, and a better understanding of customer's requirements.		Hadud and Kare (2020) Núñez-Merino et al. (2020)
Simulation / Continuous improvement Simulated models can be used to test improvements in the production system, evaluating their impact in a virtual environment.		Peças et al. (2021)

4.4 Relationships between Industry 4.0 and Lean (cases study)

This section presents the evidence from the cases study. The results were compiled according to the sections established in the research protocol, the characterization of the respondents and company; what and how I4T are supporting Lean Socio-Technical practices to improve sustainability performance and whether there are any negative effects of this integration. Table 4.7 presents the compilation of information about the company and the respondents.

Table 4.7. Characterization of the company and the respondent (Sections A and B)

	Year founded	Industrial sector	Number of employees	Experience in Lean	Experience in I4.0
Company A	1956	Manufacture of automotive pieces	260	Lean was implemented in 2011. As of 2013, there was a process of disseminating the Lean culture and maturing the Lean system.	The two companies began digital acceleration with greater force around 2016.
Company B	1957	Automotive Sector	4000	Lean was implemented in the late 1990s.	

Table 4.7. (Continued)

Results in Lean	Lean is disseminated in all areas and levels of both companies.			
Results in I4.0	The Company A adopted the German model (Alcatech) which comprises six levels of maturity in relation to technologies, the first two being related to the digitalization process (computers and connectivity) and the last four to I4.0 (data visualization, data transparency, prediction, and adaptability). For some technologies, the company is in the digitization phase, for others, in the I4.0 phase. It has 80% in the implementation of the MES system and cloud computing through Oracle, Power Bi, and Dashboards, 50% in the implementation of Big Data, 80% in AM, 70% in IoT, and 90% in CPS.			
	At Company B, many Projects 4.0 were delivered in 2019. The automation engineering sector develops technological solutions for other sectors. Solutions can range from robotics, connecting machines to the industrial network, simulations, Augmented Reality, Virtual Reality, Big Data and analytics, cloud communication, software solutions, cyber security, and manufacturing systems integration.			
	Roles interviewed	**Time in the company**	**Experience with Lean**	**Experience with I4.0**
Company A respondents	(A1) Process and quality engineering manager	10 years	8 years	6 years
	(A2) Quality engineer specialist in process automation	12 years	4 years	6 years
	(A3) Process engineer	10 years	9 years	6 years
Company B respondents	(B1) Engineering manager	8 years	8 years	8 years
	(B2) Quality gate manager	18 years	18 years	10 years
	(B3) Automation engineering manager	20 years	20 years	6 years

The interviews reveal that the participating companies have extensive experience in Lean and have developed strategies for the implementation and consolidation of I4.0 that improve sustainability. At Company A, a set of technologies control shop floor Lean operations, minimizing material waste and reducing gas emissions. LSP are supported by I4T, for example, access to Big Data makes it easier for small group problem-solving.

At Company B, distributed sensors provide data for Kaizen events where Continuous Flow strategies are drawn. The company has AGV connected by IoT sensors that transport pieces from the logistics sector to the production process. AGV pass by delivering the Kanban boxes to each workstation. Company B has many tightening tools in the process that generate real-time data such as applied torque, torque angle, and deviations that occur. Based on this data, the automation team can develop a machine-learning algorithm (Respondent B3). The company also is creating an algorithm to check equipment wear, directing when to intervene (Respondent B2).

Table 4.8 summarizes the collaborative actions between I4.0 and Lean to achieve the sustainability goals revealed in the cases study.

Table 4.8. Support of I4T to LP and the impact on sustainability performance

Company	/Respondents	I4.0 technologies	How relationship occurs	Lean socio practices
Company A	A3	BDA	Big Data promotes analyses and Continuous Improvement. With the data provided by the CNC machine, the company makes improvements in the geometry of the pieces, which avoids unexpected stops in the production line due to the breakage of the piece.	Continuous Improvement
		IoT technologies and BDA	Sensors installed in the process provide data for root cause analysis, which makes problem-solving easier.	Small group problem solving
Company B	B3	AR	The augmented reality glasses project the assembly point of various pieces onto the vehicle, facilitating operator training.	Training employees

Company	/Respondents	I4.0 technologies	How relationship occurs	Lean technical practices
Company A	A2	IoT technologies	The measuring instruments have IoT technologies (RFID and Bluetooth). When measuring a piece, the instrument sends the measurements in real-time to the system, which feeds a control chart. If two yellow dots appear, the system automatically sends an email to the supervisor, and actions must be taken to prevent the piece from arriving in red. That is, to prevent an error from occurring.	SPC
	A3	IoT technologies	IoT technologies in the kanban system allow reducing work in process by supporting JIT. E-Kanban linked to the supplier allows make better use of internal space and internal transport and make better of the route and road resources. Thus, can reduce costs, reduce the emission of polluting gases, and reduce the carbon footprint, which improves economic and environmental sustainability.	Kanban and JIT
Company B	B3	IoT technologies	The operator performs process control via cell phone. The cell phone displays images of the piece and the specific point of the product that the operator must check. If the operator says ‘no ok’, he photographs the product so that the information reaches the support teams in real time. The data automatically goes to the system that generates the KPI to control the defective pieces.	SPC
			Sensors control whether the vehicle's bolts have been tightened, or if they are loosened due to operator forgetfulness. If the screw is loose, the production line does not follow and emits a, not ok, signal displayed on televisions. In addition, it is possible to control the correct force and torque, preventing the screws from being loosened due to vibrations. The company also has some controls in the process that verify if the color of a certain piece is by the customer's specifications. Also, when a vehicle has a deviation in a piece, the system registers it. When another vehicle has the same or similar piece, it is possible to carry out a predictive control of the process, preventing the same deviation from happening again.	

Table 4.8. (Continued)

Company /Respondents		I4.0 technologies	How relationship occurs	Lean technical practices
Company B	B2 / B3	AGV	The AGV supply the Kanbans in the production process, avoiding stoppages in the assembly line due to lack of pieces and controlling the formation of stocks.	Continuous Flow and JIT
	B1 / B3	IoT Technologies	The sensors distributed on workstations provide data for Kaizen events such as operator movement and steps to carry out the work. This information helps improve process flow and achieve JIT goals.	Continuous Flow and JIT
	B1	AM	The company uses 3D Printer to produce prototypes of pieces with standardized fittings for the machine's devices, which reduces setup time.	Setup Time Reduction
Benefits for sustainability				
Company A	Economic benefits (greater efficiency, agile processes, and flexible operations), environmental benefits (reduced consumption of resources), and social benefits (improved worker health and safety and minimization of the monotony of work)			
Company B	Economic benefits (cost savings, reduction of rework, reduction of material waste, shorter development time) and environmental benefits (reduction of solid waste, reduction of compressed air consumption, and reduction of energy consumption)			

Lean and I4.0 bring significant benefits to companies. For example, Company A recognizes that relationships between approaches provide faster and more effective decision-making and improve operational learning. The cases study confirm that these relationships have a synergistic effect that further benefits sustainability performance.

On the other hand, conflicting points were highlighted due to the massive inclusion of technologies in the processes. For example, social impacts such as i) a significant reduction in human coexistence (Respondents A3 and B2) and higher unemployment (Respondent A1); ii) discomfort (Interviewee A2 and B1), operator vertigo and blind spots in the assembly, which generate the risk of accidents (Interviewee B3) due to the use of augmented reality glasses; iii) fatigue and lack of focus to the worker due to the excess of generated data (Respondent B1). In addition to economic impacts such as i) loss of time and productivity due to the use of new technologies (Respondent A2); ii) increase in energy costs due to the increase in the number of TVs in the process (Respondent B1); increase in data security costs (Respondent B1).

Finally, the two companies agree that Industry 4.0 is the natural evolution of Lean. Digitization is not the first step towards Industry 4.0. Lean allows us to move towards digitalization and Industry 4.0. Lean allows the control, standardization, and stability of processes. Therefore, it is the environment through which digitization begins. Lean is the way to reach higher levels of Industry 4.0 (Respondent A3). When a company has the Lean system consolidated, it facilitates the migration to Industry 4.0. Thus, a standardized process becomes necessary to use technologies efficiently (Respondent B1).

4.5 Results

Many relationships reveal that I4T strengthen the goals of LP (Table 4.4) and these relationships impact sustainability. Some relationships found in the SLR were confirmed in the cases study (Table 4.9), additionally, the companies showed that these relationships have potential to improve sustainability in an industrial environment. The letters (A and B) in table 4.9 refer to the cases (Company A and Company B) that confirmed the relationships and impact on sustainability.

Table 4.9. Relationships identified in the SLR and confirmed in the case study

	Industry 4.0 Technologies							
Technical Practices	AGV	AM	AR	BDA	CC	CPS	IoT (RFID, Sensor, Actuator)	Simulation (Digital Twin)
Continuous flow	B/X		X	X	X	X	B/X	
JIT	B/X	X	X	X	X	X	A/B/X	X
Kanban	B/X			X	X	X	A/X	X
Setup time reduction		B/X				X		
SPC						X	A/B/X	
TPM			X	X			A/X	X
Social Practices								
Continuous improvement			X	A/X	X	X	B/X	X
Customer involvement		X		X	X	X	X	
Supplier partnership				X	X	X	X	
Training employees			B/X					

Table 4.9. (Continued)

Benefits for sustainability					
Economic		**Environmental**		**Social**	
Quality		Environmental impact reduction		Improvement in working conditions	
Stock cost reduction		Reducing the use of natural resources	A	Reducing the number of accidents at work	
Reliability		Reducing pollution		Improved worker health	A
Production cost reduction	B	Reduction of energy consumption	B		
Efficiency	A				
Productivity					
Flexibility	A				

A - Evidence found in company A
B – Evidence found in company B
X - Evidence found in SLR

The IoT/JIT and IoT/SPC relationships found in the SLR were confirmed by both cases (Companies A and B). These relationships have strong potential to integrate Industry 4.0 and Lean into an industrial environment. In addition, there is strong evidence that AGV strengthen practices such as continuous flow, JIT and Kanban, which were confirmed by company B. Companies also confirm relationships between BDA and continuous improvement (Company A) and IoT and continuous improvement (Company B). Economic (efficiency, flexibility and production cost reduction), environmental (reduction in the use of natural resources and energy consumption) and social (Improved worker health) benefits found in the literature review were confirmed by company A or company B.

On the other hand, Company A mentions that IoT and BDA reinforce small group problem solving initiatives, as these technologies provide data for root cause analysis. These relationships were not found in the SLR. Furthermore, the relationships between I4.0 and Lean bring sustainability benefits that have been recognized by companies but are not clear in the literature. For example, Company A reveals benefits such as agile processes, minimizing waste material, reducing gas emissions, improved worker safety, and minimization of the monotony of work, and Company B points benefits such as reduction of rework, reduction of material waste, shorter development time, reduction of solid waste, and reduction of compressed air consumption.

All technologies listed in the SLR showed a positive support relationship with TPM. IoT and sensors connected to machines allow the measurement of equipment parameters in real time (e.g., pressure, temperature), its verification enables planned and autonomous maintenance increases machine availability by contributing to TPM

(Chiarini *et al*., 2020; Tortorella *et al*., 2020). The analysis of collected data by IoT, allows the investigation of past patterns and failure causes, which can foster TPM and prevent potential future failures (Chiarini and Kumar, 2020; Chiarini *et al*., 2020; Ghobakhloo and Fathi, 2020). Sensors and IoT provide data for analysis, while BDA effectively allows this data to be analyzed, identifying machine patterns, recurrent problems, and failure causes, improving preventive maintenance (Sanders *et al*., 2016; Li, 2019; Tortorella *et al*., 2021). AR supports TPM activities, ensuring the efficiency of the maintenance steps providing precise instructions to routine maintenance, which reduces the number of work accidents, reduces pollution, and the use of natural resources (Koscielniak *et al*., 2019; Raji *et al*., 2021). While Digital Twin makes it possible to understand the impacts of different preventive maintenance solutions (Ciano *et al*., 2020). The use of technologies for TPM is confirmed in the case study, in which company A has future projects to use historical data and algorithms to predict equipment wear, avoiding downtime.

The application of IoT/RFID for shop floor material management can provide information about delays, material consistency and accuracy, and process waste, improving the JIT (Wang *et al*., 2018). IoT technologies provides real-time data on product locations and quantities, which improves traceability and minimizes delays and waiting times, leading to more effective inventory management, automatic replacement of internal suppliers in pulling systems, and, consequently, reduced lead times (Raji *et al*., 2021; Ciano *et al*., 2020) and costs (Núñez-Merino *et al*., 2020). The system can automatically send orders to suppliers according to production line needs and enables intelligent reallocation of orders, which ensures on-time materials delivery, transport route optimization and reduces stocks (Mayr *et al*., 2018; Núñez-Merino *et al*., 2020). The use of technologies associated with JIT can impact economic performance resulting in increased quality, flexibility, efficiency, productivity, and reduced costs and inventory (Bittencourt *et al*., 2019; Mayr *et al*., 2018; Wang *et al*., 2018; Zelbst *et al*., 2014). Furthermore, in the studied companies, was exposed that IoT technologies (GPS sensors) help map operator movements and the data is used to improve process flow allowing continuous flow and JIT. Confirming the SLR findings, the two companies studied have systems that controls the process in real-time, issuing production alerts at Company A and signaling deviations through points of attention at Company B, which facilitates JIT activities and continuous flow.

Big Data increases the transparency of material and processes information and allows the comparison of target and actual values to remove unnecessary inventory (Valamede and Akkarin, 2020), supporting the JIT system (Bittencourt *et al*., 2019). Additionally, BDA techniques enable improved demand forecasting skills (Nunes-Merino et al., 2020), and help to identify trends, peak seasons and assists in reduce order execution time analyzing data from the supply chain partners (Raji *et al*., 2021; Mayr *et al*., 2018). A JIT system through CPS is highly supported by the integration of big data, data analysis, and vertical integration of machine-to-machine communication (Tortorella *et al*., 2020). CPS can control when the material stock reaches the minimum level and automatically generate a purchase order for the supplier (Santos *et al*., 2021). AM can support JIT, offering shorter lead times and reduced inventory, meet exact customer specifications, in the in the requested amount using less raw material, process time with flexibility when adding layers of material (Raji *et al*., 2021; Ghobadian *et al*., 2018).

AGV can transport products and materials to workstations in accordance with the real-time requirements, automatically, minimizing human mistakes as well as unnecessary trips, favoring JIT replenishment (Mayr *et al*., 2018; Núñez-Merino *et al*., 2020; Valamede and Akkari, 2020). In this sense, the application of AGV can contribute to a JIT delivery to the workplace, since the materials arrive at the exact moment when they are required (Mayr *et al*., 2018), favoring a pull-type flow by promoting timely and automated delivery and logistics (Núñez-Merino *et al*., 2020). These findings were confirmed by company B where the AGV supply the kanban stations in process, facilitating JIT. The economic results generated are related to quality, flexibility, derived from the process integration, increased productivity, and reduced inventory (Valamede and Akkari, 2020; Mayr *et al*., 2018).

The IoT technologies allow real-time stock monitoring, which increases the flexibility of the supply system and provides full visibility of all processes that are part of the pull Kanban system (Pekarcikova *et al*., 2020). IoT technologies monitor when the workstation reaches minimum stock and the information is displayed on the predecessor workstation to forward the material (Sanders *et al*., 2016; Kumar *et al*., 2018). By using sensors, information and communication technologies, an e-kanban system automatically recognizes missing and empty bins, being able to monitor the status, number, and location of material batches and triggers replenishment (Sanders *et al*., 2016; Satoglu *et al*., 2018; Tortorella *et al*., 2019). The integration of IoT and BDA into kanban systems, allows for the immediate detection of production errors, triggering automatic replenishment, and increasing operational efficiency (Tortorella *et al.*, 2019). BDA increases the transparency of material and process movements (Valamede and Akkari, 2020). These relationships were confirmed by company A, where IoT technologies link the kanban system to the supplier, avoiding excess inventory and providing better use of resources such as internal space and road resources, which generates benefits for sustainability.

With the introduction of CPS, the Kanban becomes automated, i.e., intelligent storage tanks operate on the principle of self-regulation, which contributes to the decentralization of the information collection enabling full visibility of all processes that are part of the Kanban system (Pekarcikova *et al.*, 2020). Other technologies can also help the kanban system, such as simulation and digital twin, which allows optimal kanban parameters and new kanban loops to be planned with more foresight and seamlessly integrated into the existing production environment (Mayr *et al.*, 2018; 2019; Pekarcikova *et al.*, 2020). CC based Kanban system has features for entering production data to estimate the kanban ideals parameters (Shahin *et al.*, 2020).

The e-kanban is also assisted by AGV, which can supply workstations according to real needs, reducing inventories, lead times, and unnecessary movements (Valamed and Akkari, 2020). The case study confirms this relationship once a respondent reports the use of the AGV to supply the kanban in process, identifying deviations in the assembly line to regulate the supply automatically. In addition, the e-Kanban in company A linked to the supplier optimizes deliveries, which reduces the emission of polluting gases due to the control of logistics operations. In the context of I4.0, production systems equipped with e-Kanban allow to exchange information, automatic material replenishment monitoring, schedule tracking, and pull system, making the production cycle more efficient (Sanders *et al.*, 2016; Mora *et al.*, 2017). Additionally, stock levels can be minimized, the required space drops which ultimately results in cost savings (Mayr *et al.*, 2019).

Technologies like IoT, sensors, and actuators reduce the time needed to prepare for the next operation, by mitigating the need for machine adjustments after setup (Fatorachian and Kazemi, 2018), minimizing the occurrence of errors. Sensors and actuators indicate the right time to change tools and allow to identify process problems faster, anticipating the change when necessary (Tortorella *et al.*, 2019). AM can contribute to lower setup times due to a reduction in complexity by modularizing production systems (Tortorella *et al.*, 2019). IoT technologies can receive material, product, or work phase information and perform accurate Single-Minute Exchange of

Dies (SMED) and prepare the correct configuration of the machines (Sanders *et al*., 2016; Ciano *et al*., 2020; Sordan *et al*., 2021; Anosika *et al*., 2021). With CPS, working stations or whole production lines can be efficiently reconfigured, significantly reducing setup time (Kolberg and Zuhlke, 2015). The case study reveals that company B uses simulation to design pieces that are produced by AM. The pieces have standardized fittings for machines, which reduces setup time.

The introduction of IoT and sensors gives data about the material distribution real-time tracking of the movements of manufacturing resources and production station status, which provide feedback to employees, helps to eliminate delays, interruption, and waiting in the production line, enabling a continuous streamlined flow (Sanders *et al*., 2016; Fettermann *et al*., 2018; Ren *et al*., 2018b). The data from IoT devices and the production processes are analyzed by BDA and shared CC environment, contributing to achieving results and solutions that provide a continuous flow (Valamedi and Akkari, 2020). Confirming the SLR findings, the two companies studied has systems that controls the process in real-time, issuing production alerts, which facilitates continuous flow.

AGV contribute to achieving Lean objectives since autonomous control in operational functions establishes a continuous flow of materials and favors a pull flow and JIT replenishment (Núñez-Merino *et al*., 2020). CPS also allows the identification of cycle times to find the best solution between the highest possible capacity utilization per working station and a continuous flow of production (Kolberg and Zuhlke, 2015). On the other hand, the use of AR device help employees to solve problems and take better decision quickly, additionally, cycle times information is provided in the workers' visual field for the continuous flow of production (Valamede and Akkari, 2020).

From the data generated by sensors and actuators connected to the production system, it is possible to access data directly out of the machines to identify the instability of the process or avoid deviations related to the quality parameters increased the efficiency of inspection and SPC activities (Sordan *et al*., 2021). In addition, communication can be done in real-time through supervisors' smartphones (Chiarini and Kumar, 2020). CPS can combine historical running data of the system to predict possible system anomalies and sending pre-alarms production process based on SPC (Ma *et al*., 2017). When the technologies such as CC, Big Data, IoT, AM and AGV are implemented together, have a positive impact on the supply chain performance improvement (Tortorella *et al*., 2019b), as well as the possibility of having a new class of SPC with autonomous feedback to the machine (Chiarini and Kumar, 2020) and, consequently, achieve the Lean objectives. This relationship is strongly confirmed in the case study, as both companies have sensors distributed in the process. Company A has IoT technologies installed in work equipment and connected to measuring instruments that can automatically send information to the system, promoting statistical control of the process in real time. At Company B, sensors analyze process parameters and statistical control is performed via cell phone. Therefore, a supply chain that integrates information technologies, data technologies, and shop floor technologies with Lean technical practices will provide more control of operations and activities (Chiarini and Kumar, 2020).

On the other hand, some relationships between I4T and LSP also present strong evidence. For example, IoT and Continuous Improvement (Ferrera *et al*., 2017; Kolberg and Zuhlke, 2015), IoT and Supplier partnership (Ciano *et al*., 2020; Li, 2019), IoT and Customer involvement (Li, 2019), CPS and Continuous improvement (Kolberg *et al*., 2016); CPS and Customer involvement (Li, 2019), BDA and Customer involvement (Sordan *et al*., 2021), and AR and Training employees (Koscielniak *et al*., 2019; Sordan *et al*., 2021).

The SLR results show that continuous improvement is the main LSP supported by I4T, being promoted by IoT, CPS, Simulation, CC, BDA and AR. IoT, as well as RFID, sensors and actuators allow data collection during production, feeding indicators in real time, they also allow data collection after production, making it possible to have more information about product performance, promoting, in both cases, continuous improvement (Kolberg and Zuhlke, 2015; Ferrera *et al*., 2021; Peças *et al*., 2021). BDA contributes to the process of continuous improvement for enabling the use of advanced analysis tools and dealing with a large volume of data, oftentimes collected automatically (Valamede and Akkari, 2020). CPS components on the workstation can provide historical data for fault analysis and continuous improvement (Li, 2019). Therefore, these technologies help the process of continuous improvement by providing available data to define, measure and analyze situations in real time, fostering the continuous improvement process. The SLR results is confirmed by the cases, since at Company A, access to data promotes continuous improvement through incremental improvements in the geometry of manufactured items, in addition to providing correct information to assist in problem-solving in small groups. One respondent emphasizes the importance of data for root cause analysis, which facilitates faster problem resolution promoting continuous improvement.

The relationships between BDA and LSP (continuous improvement, supplier and customer integration) have a potential impact on environmental (e.g., reduction in air pollution, water pollution, and solid pollutants) and economic (e.g., reduced costs, efficiency, and quality) sustainability (Raul *et al*., 2019). This relationship was confirmed in the cases studied. Through data sharing, the BDA ensures that employees, suppliers, and customers are actively involved in sustainability practices (Raut *et al*., 2019; Dubey *et al*., 2016) and top management must invest in training in BDA.

The emerging technologies adoption on the Lean supply chain provides better integration of suppliers and customers (Núñez-Merino *et al*., 2020). IoT and BDA can overcome the bureaucracy of traditional communication channels by obtaining immediate and automatic feedback from customers and suppliers (Tortorella *et al*., 2019b). Sensors and IoT technologies enable smart products that send data to better understand customer behavior and meet their needs (Sanders *et al*., 2016). Through IoT, customers' inputs are collected and have a profound impact on the real-time adjustment of production, tailoring of product design, and providing post-sale feedback (Mesquita *et al*., 2021). Therefore, customer involvement is also supported by several technologies, BDA allows that a large amount of data from customers, including their requirements and perceptions about products and services, be used to increase customer satisfaction (Sordan *et al*., 2021).

Customer involvement practice refers to a set of coordinated activities focused on a company's customers and their needs (Shah and Ward, 2007). Thus, contacts with customer can be reinforced using QR codes in products, increasing the capture of customer needs and perceptions about the product (Li, 2019). While, CPS can transfer customer experience knowledge effectively linking this information to organizational capabilities (Li, 2019). From the customer's point of view, data analytics provides patterns established by using smart products and AM through custom products for greater customer engagement (Hadud and Kare, 2020; Núñez-Merino *et al*., 2020). Sensors can be used for components delivered by suppliers, which will make delivery information clearer, and reduce inventory (Ciano *et al*., 2020). CPS structures a communication platform that allows knowing the status of the suppliers' production and even entering the stock system to remove the pieces, strengthening the bonds (Li, 2019). The introduction of smart technologies allows customers and suppliers to become real-time contributors to the data gathering.

The implementation of networks for horizontal and vertical integration by I4.0 allows a better involvement of customers and suppliers in the process of adding value. IoT enables CPS by connecting all distributed resources in the industry to gain data and in-depth knowledge of the internal and external environment (Ma *et al*., 2017). Data captured by IoT technologies can be treated through BDA and transformed into useful information. With the help of cloud computing, information can be shared internally and with customers and suppliers (Raji *et al*., 2021).

The main technologies to aid employee training are AR and Simulation. In AR displays, virtual and real information, previously acquired with a camera, are digitally merged and represented on a screen, creating an interactive training interface for employees (Mayr *et al*., 2018). These findings coincide with the case study since the two companies do not use AR glasses in the processes due to the discomfort caused to the operator, but Company B uses AR in the operator training to assemble the vehicle. Despite that, designing integrated management frameworks to implement I4T in conjunction with specific Lean Socio-Technical practices becomes a challenge due to technical, social, and organizational complexity (Sony, 2020).

4.6 Conclusions

This study identifies what and how I4T can support Lean Socio-Technical practices, which impact sustainability performance. Through content analysis, it was possible to identify that the technologies such as IoT (RFID, Sensor, and Actuator) and BDA stand out as the greatest facilitators of LTP and LSP. The JIT system and TPM seem to be more likely to be supported by I4T. JIT-related practices such as continuous flow and Kanban minimize waste, reduce inventories and overall production costs, helping with economic performance. TPM modalities such as autonomous maintenance, preventive maintenance and predictive maintenance minimize machine and equipment wear, prevent breakdowns, and improve operations performance. The improvements generated by these practices can have a greater effect from the integration with I4T.

Furthermore, the links of customer involvement, supplier partnership, training employees, and continuous improvement with the technologies show better levels of quality, flexibility, and efficiency as well as present resource usage better and reduced environmental impact.

Confirming the SLR findings, the cases study highlight the benefits of the integration between I4T and Lean in the economic pillar (cost savings, greater efficiency, agile processes, and flexible operations), environmental (reduction of resource consumption, reduction of electrical energy consumption and reduction of solid waste) and social (improvement of workers' health and safety and minimization of monotony at work).

On the other hand, the interviews reveal weaknesses due to the links between I4T and LP in an industrial environment. For example, i) social factors such as the significant reduction of human coexistence, worker fatigue due to exposure to big data, loss of detailed information due to data security, and lack of unskilled jobs; ii) economic factors such as the lost time and productivity due to changes in process and increased costs due to the need for data security; iii) environmental factors such as the increased energy consumption due to the introduction of technological resources on the factory floor. These sustainability issues are pointed out as a consequence of the massification of technologies in the processes.

The analysis of the relationships identified in the SLR and in cases study shows a predominantly positive impact on economic indicators from the integration between I4T and LP, showing an imbalance in efforts to improve sustainability performance. However, it was identified that the impact on environmental and social aspects is not yet fully clarified in literature and in practice.

4.6.1 Academic and managerial implications, limitations and future research

Some researchers have suggested a positive relationship between I4.0 and Lean (Shahin *et al*., 2020; Dubey *et al*., 2019; Sinha and Matharu, 2019; Sanders *et al*., 2016). The present study confirms the results that point to a positive integration between the approaches helping to fill the gap of the need for research to confirm this synergy (Rossini *et al*., 2019), and understanding how the relationships between these approaches can affect the performance of companies (Kamble *et al*., 2020; Tortorella *et al*., 2019; Dubey *et al*., 2019). Furthermore, as proposed by Tortorella *et al*. (2019), this research contributes by including Lean social variables (e.g., employee involvement, and suppliers' and customers' relationship) and the use of I4T to observe the impact of these relationships on sustainability performance.

This research sought evidence both in the literature and in practice, through the use of multiple methods, SLR and case study, to deepen knowledge on the relationships between technologies and Lean social and technical practices. The study identifies viable ways to integrate I4T and Lean Socio-Technical practices through supportive relationships that improve sustainability performance. Based on the findings, conceptual frameworks were proposed that demonstrate the most promising relationships, technical and social, valuing technological and human aspects in the management of industrial processes.

At some points, our findings coincide with the results of Pagliosa *et al*. (2019) that affirm IoT (RFID, Sensor, and Actuator) as the technology that presents the greater synergy with LP. Our analyzes show a strong link between these technologies and the JIT system, similar to the results of Rosin *et al*. (2019). In addition, the study innovates by identifying evidence that BDA can contribute to LTP, such as JIT and TPM, and to LSP such as continuous improvement and customer involvement, improving sustainability performance. From an academic point of view, the study advances by compiling how technologies can help Lean practices and verifying, from an empirical point of view, whether these relationships are evident in companies, as well as identifying the positive and negative empirical impacts.

On the other hand, this study presents implications for practitioners. Additional efforts are needed to meet current internal demands related to sustainability, in addition to government and market requirements. It is important to develop management practices that positively impact economic, environmental, and social performance indicators. In this sense, managers can resort to the findings of this study to guide initiatives to introduce I4T in a Lean environment or even better leverage technologies already introduced by integrating them with Lean practices. For example, IoT, CPS, BDA, and AR can be applied together with the JIT system, and strengthen LP such as customer involvement, supplier partnership, continuous improvement, and training employees to improve the sustainability dimensions. Practitioners should be aware and invest in the integrated use of technologies that capture real-time data, such as the IoT, and large datasets, such as Big Data, to support the supply of production lines at the correct time, inventory reduction, producing the correct quantity of items, among others. Furthermore, AGV can enhance automated delivery of materials on time, minimizing errors and time to JIT.

The results show that industries with a consolidated JIT system that intend to benefit from technologies to improve the flexibility, agility, efficiency, and quality of the processes and simultaneously improve sustainability performance should preferentially invest efforts in the adoption of IoT, BDA and AGV. Furthermore, the findings show that managers should develop continuous improvement practices to value human potential together with technological resources. The are evidences that social aspects and environmental indicators can be improved from the integration between customer, supplier, and employees’ practices with IoT, CPS, AR, and BDA. These practices add value to the customer.

On the other hand, the findings of the cases study reveal that despite the contribution that AR can bring to LP such as TPM, SPC, and employee training, the discomfort caused by glasses with this technology can cause some problems for workers. So, improvements must be made so that augmented reality glasses are applied on a large scale in the industrial environment. In addition, the use of technologies in processes can reduce human contact and the high availability of data can increase security costs. Therefore, managers must pay attention to the negative consequences of integration, which can occur, and the findings help at this point.

In addition, the strongest linkages presented reveal the support that I4T provide to LP and alert the industrial sector to the benefits associated with these integration relationships. Through the cases studied, we concluded that the consolidated Lean system allows companies to move towards digitalization and Industry 4.0. However, the study has limitations, such as the impossibility of generalizing the results obtained with the case study, since only two companies were observed. The study tried to overcome this limitation by looking at the studies already published on the topic. The study also has a partial view, as it focuses on a specific moment in time.

The present study observed a substantial number of relationships between LSP and I4T and LTP and I4T that impact sustainability performance, this allowed a quantitative view of the number of relationships existing in the literature. The study also sought to delve into how these relationships occur, however, more specific empirical studies for each relationship are necessary, to delve into their positive and negative points. Therefore, longitudinal studies are needed to observe the adoption of technology and its evolution, as well as suveys, to measure the impacts generated. Other possibilities for future studies include action research to understand how the integration between Lean technologies and practices can occur at an operational level. Finally, issues such as the influence of the sector and the size of companies on the integration are also variables for future studies.

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5 BIG DATA ANALYTICS AND LEAN PRACTICES: IMPACT ON SUSTAINABILITY PERFORMANCE

Abstract

Academics and practitioners have explored the potential of Big Data Analytics Capabilities (BDAC) to support the Lean Social-Technical System. Despite the pursuit of Big Data initiatives, there is still a limited understanding of how companies translate the potential of BDA to support Lean and can turn this relationship into sustainability benefits, impacting economic, social and environmental performance. Literature findings about BDA capabilities (BDAC) and Lean Social Practices (LSP) and Lean Technical Practices (LTP) were used to develop a comprehensive conceptual model that assesses the mediating effect of LSP and LTP on the relationship between BDAC and economic, environmental, and social performance. Partial Least Squares Structural Equation Modeling (PLS-SEM) was used with a sample of 108 respondents, from companies of different sizes and sectors, at different stages of Lean implementation and BDA adoption. The results show that BDAC positively impact Technical Lean and Social Lean. Statistical evidence supports that BDAC exert a positive effect on Social Performance (SOP), which includes, for example, aspects of work. Furthermore, the results confirm that the relationship between BDAC and Economic Performance (ECP) is completely mediated by Lean Technical Practices. The findings of this research contribute to revealing possible ways that link BDA and Lean and benefit sustainability with these relationships.

Keywords: Big Data Analytics Capabilities; Lean Technical; Lean Social; Sustainability Performance; Systematic Literature Review; Structural Equation Modelling

5.1 Introduction

To be competitive, in addition to concerns about Economic Performance (ECP), companies are concentrating efforts to improve sustainability performance (Garza-Reyes, 2015), including environmental benefits and social equity (Miemczyk and Luzzini, 2018; Yun et al., 2018). In this sense, due to its structured practices and continuous improvement approach, Lean is effective in transforming ideas generated from innovativeness into environmental and social results (Yu et al., 2020) and in improving ECP.

The Lean approach can be defined as a set of methods, tools (Lobo et al., 2018), and practices (Shah and Ward, 2003) that work synergistically to create a streamlined high-quality system that produces at the pace of the customer demand with little or no waste. Lean involves a collection of practices that assist in the process of improving work methods by eliminating waste (Shah and Ward, 2007). In this study, Lean is considered a socio-technical system, and, as such, it has two pillars of practices, social and technical (Bortolotti et al., 2015; Shah and Ward, 2007). Lean Social Practices (LSP) relate to behavioral aspects and usually deal with human resources (Lewis et al., 2006) and continuous improvement strategies (Calvo-Mora et al., 2014). Lean Technical Practices (LTP) are systems-oriented and easier to quantify (Gadenne and Sharma, 2009).

On the other hand, rapid industrialization has contributed to lower levels of health and safety of the workforce and greater environmental degradation (Luthra and Mangla, 2018; Kamble et al., 2018). Industry 4.0 is expected to improve the economic, environmental, and social values using modern technologies and process integration (Stock and Seliger, 2016). For example, Big Data Analytics (BDA) can help companies obtain and suggest better performance measures (Gupta and George, 2016). Big Data and Big Data Analytics (BDA) are some of the key technologies in Industry 4.0 that support Lean and sustainability (Mesquita et al., 2021; Raut et al., 2019; Ren et al., 2018).

BDA refers to the data sets and analytical techniques in applications that are so large and complex that they require advanced and unique storage, management, analysis, and visualization technologies (Chen et al., 2012). BDA is becoming a very popular concept in academia and in the industry (Raut et al., 2019). It helps companies to unveil the hidden patterns, market trends, customer preferences, unknown causality, and correlations between the different parameters (Kwon et al., 2014). Furthermore, Big Data can transform the manufacturing industry to apply practices of sustainability more efficiently (Raut et al., 2019). Dubey et al. (2016) correlate the application of BDA whit performance measures for the environment, social and economic gains.

BDA is becoming important to address unique customer requirements (Grover et al., 2018), making companies increasingly competitive. Côrte-Real et al. (2016) claim that BDA applications can generate value in several ways. However, there is still limited understanding of which Big Data Analytics Capabilities (BDAC) drive performance gains (Mikalef et al. 2019). It is imperative that companies know their actual accounting, economics, finance, and strategic value (Grover et al., 2018), in addition to the sustainability benefits.

On the other hand, BDA presents relationships with Lean Practices such as Just-In-Time (JIT), Kanban, Total Productive Maintenance (TPM), and continuous improvement (Mesquita et al., 2021; Valamede and Akkari, 2020). However, some literary gaps were found, such as i) relationships between Lean Practices and Big Data need to be better analyzed (Sony, 2020); ii) more studies are needed to establish the links between these two approaches (Ciano et al., 2019; Kang et al., 2016). In addition, iii) there are few empirical studies that establish the relationship between BDA and sustainability performance (Belhadi et al., 2019). Future research is highly encouraged to investigate how the dimensions of Lean and the interaction between Lean and new technologies such as BDA influence sustainability performance (Yu et al. 2020). Therefore, this research contributes to the debate forming a body of knowledge on the relationships between Lean Practices, BDAC, and Sustainability Performance, addressing the following research question:

RQ: What effect do Lean Social Practices and Lean Technical Practices have on the relationship between Big Data Analytics Capabilities and economic, environmental, and social performance?

This research is dedicated to investigating Lean and BDA. Furthermore, the objective is to analyze the mediation effect that Lean Socio-Technical Practices can exert on BDAC to improve sustainability performance. For this, a mixed-method approach was used. Section 2 shows the theoretical basis. The set of hypotheses developed is presented in Section 3. The method is presented in Section 4. Analyzes and results, and discussions and implications are presented in Sections 5 and 6, respectively. Section 7 chronicles the conclusions, limitations, and directions of future research.

5.2 Theoretical Background

5.2.1 Big Data Analytics

Notably, companies that digitize their processes can improve their capacity to acquire, analyze, and distribute strategic and operational knowledge. To achieve this digital transformation, the companies adopt enabling technologies, such as information systems and Big Data (Ardito et al., 2018). The term "Big Data" was initially coined to reflect the voluminous size of data generated because of the use of new forms of technology (e.g., social media, radio-frequency identification (RFID) tags, smartphones, and sensors) (Gupta and George, 2016). Big Data can be defined as amounts of various observational data that support different types of decisions, and as non-traditional forms of media data, driven by new technologies (Akter et al., 2016). Thus, Big Data is conceptualized as a significant organizational resource because of its potential to extract quality information from large datasets (Kuo and Kusiak, 2019).

The potential of using Big Data is promising but restricted by the availability of technologies, tools, and skills available for analyzing data (Sivarajah et al., 2016). To meet these needs, Big Data Analytics (BDA) applies statistical, processing, and analytics techniques to Big Data (Grover et al., 2018). The generation of real-time data enables control of the industrial systems, and the analysis of this data can be applied in a vast scope in the companies through BDA (Burmeister et al., 2016). BDA refers to methods used to examine and attain intellect from large datasets and can be considered regarded as a sub-process in the whole process of insight extraction from Big Data (Sivarajah et al., 2016).

A variety of technologies and infrastructure are enabled for BDA such as social media, mobile devices, automatic identification technologies enabling the internet of things, ERP systems, and cloud-enabled platforms (Wamba et al., 2017), and they can be given in text, graphic, audio, and video formats (Choi et al., 2018). To work with this data, Grover et al. (2018) argue that BDA includes all three types of analytics: (1) descriptive analysis that reports on the past; (2) predictive analysis that develops models based on past data for future prediction; and (3) prescriptive analysis that uses models to specify optimal behaviors and actions.

On the other hand, Big Data alone is unlikely to be a source of competitive advantage, the Big Data Analytics Capability (BDAC), which is the organization's ability to handle, process and work with large volumes of data, needs data availability and data processing capacity (Wamba et al., 2017). BDAC include the ability to manage and analyze data to create new insights and can economically generate value from data in a very large volume and variety, enabling high-speed capture, discovery, and/or analysis (Grover et al., 2018). For this, it uses data management (i.e., the ability to manage routines in a structured way), infrastructure (technologies such as applications, hardware, data, and networks), and talent (personnel capability, e.g., skills or knowledge) (Wamba et al., 2017).

In addition, BDA resources are critical in developing BDAC (Mikalef et al. 2019). Gupta and George (2016) propose seven resources that will allow companies to create BDAC such as tangible resources (i.e., data, technology, and basic resources such as time and investments), human resources (i.e., technical and managerial skills), and intangible resources (i.e., data-driven culture and intensity of organizational learning). To develop BDA capabilities, companies need to exploit their technological and human resources (Gawankar et al., 2019).

For this investigation, we assume that BDAC are formed by a structure composed of tangible resources, human skills, and intangible resources (Gupta and George, 2016). The choice is due to the affinities with the Lean structure, composed of the technical and social systems. It is this structure that allows the large volume of structured and unstructured data to be processed and analyzed.

5.2.2 Lean Practices

Lean has evolved from its principles and practices (Marodin and Saurin, 2013). Its main objective is to maintain a production free of waste, in which waste is defined as any process error that adds costs such as overproduction, waiting, poor quality, unnecessary processing, transportation, or inventory and adds no value to the customer (Inman and Green, 2018). Thus, Lean can be considered a collection of practices to organize and improve production sites (Kolberg et al., 2016).

The Lean system can be described from two points of view, that is, through a conceptual perspective related to guiding principles and overarching objectives (Womack and Jones, 1996) and from the practical perspective of a set of management practices, tools, or techniques to improve production processes (Shah and Ward, 2003). Shah and Ward (2007) grouped Lean Practices into bundles with consideration of the socio-technical system. In this context, Paez et al. (2004) proposed a Lean structure in technical (hard practices) and human (soft practices) systems. Hard practices include technical and analytical tools to improve production systems (e.g., statistical process control, kanban, and autonomous maintenance) (Bortolotti et al., 2015; Kariuki and Mburu, 2013), while soft practices are related to principles, managerial concepts, people, and relations (e.g., continuous improvement, top management leadership, customer, and supplier involvement) (Bortolotti et al., 2015).

There is an increasing perception that Lean is a socio-technical phenomenon that emphasizes the importance of people to implement Lean Practices (Hadid et al., 2016). Lean comprises a philosophy of continuous improvement acquired by technical practices and respect for people that encompasses the human or social side (Muraliraj et al., 2019). Adopting Lean Practices in an industrial environment reduces organizational waste, leading to improved levels of sustainability performance (Dey et al., 2019). Thus, an efficient Lean structure can be composed of a set of technical and social practices.

5.2.3 Sustainability Performance

Elkington (1998) introduced the concept of TBL with a focus on three dimensions of performance, i.e., economic, environmental, and social. The pervading environmental issues, such as climate change and gas emissions, and social concerns, such as employee welfare, have forced many companies to integrate a wider set of objectives than just reaching an acceptable level of ECP (Varsei, 2014). However, some authors draw attention to the possible increase in costs due to the implementation of environmental or social initiatives, in the search for balance between the three pillars of sustainability performance (Wu and Pagell, 2011; Ross et al., 2012). Thus, the development of successful and long-term management strategies for sustainability and their performance measurement has attracted the attention of researchers and practitioners over the past two decades (Goyal et al., 2013).

5.3 Hypotheses Development

There is evidence that BDA is related to Lean technical and social practices (Mesquita *et al*., 2021; Valamede and Akkari, 2020). BDA is considered an enabler for process monitoring, supply chain visibility, and industrial automation (Wamba *et al*., 2017). Regarding LTP, the application of Big Data and BDA enables analyze historical and real-time information, providing a huge amount of statistical data directly out from the machines to identify unstable process parameters, avoiding quality issues (Mayr *et al*., 2018; Wagner *et al*., 2017) and enabling continuous flow (Tortorella *et al*., 2019).

Moreover, BDAC contribute to constantly tracking workflow in progress, which provides automated logistics with intelligent inventory control and minimum intermediate material stocks (Valamede and Akkari, 2020), enabling the Kanban System (Tortorella *et al*., 2019), and improving JIT efficiency (Wamba *et al*., 2017).

Big Data increases the transparency of material and processes and allows the comparison of target and actual values to remove unnecessary inventory (Valamede and Akkari, 2020), supporting the JIT System (Bittencourt *et al*., 2019). The advanced analytics capability, inherent in Big Data, allows the production system to anticipate possible failures and identify, in real-time, unusual conditions and the identification of root causes (Stojanovic *et al*., 2015), connecting IoT technologies to machines (Sanders *et al*., 2016). Such machines assess their own operation and degradation and utilise data from other machines to avoid potential maintenance issues (Lee *et al*., 2015). Thus, it is possible to avoid unexpected interruptions in production and minimize errors, enabling continuous flow, JIT, and autonomous maintenance. Tortorella *et al*. (2019) provide arguments to examine the interactions between I4.0 and Lean, and suggest that LTP implementation may, in part, benefit significantly from the adoption of BDA.

Regarding Lean Social Practices, BDA capabilities allow for greater customer involvement (Wamba *et al*., 2017), therefore enabling businesses to provide much more precisely tailored products or services, and substantially improve customer experience (Saggi and Jain, 2018; Grover *et al*., 2018; Choi *et al*., 2018). The use of IoT and Big Data to exchange information in real-time with suppliers overcome bureaucracies and inappropriate communication channels (Dworschak and Zaiser, 2014), reducing a source of waste (Tortorella *et al*., 2019b). One of the most powerful aspects of the Big Data revolution is the unification of large data sets with advanced analytics for problem-solving (Ferraris *et al*., 2019), helping in small group problem solving. BDA talent capability supports employee development and has a positive relationship with learning performance (Bag *et al*., 2020). Thus, the following hypotheses were formulated:

H1a. BDAC positively affect LSP.

H1b. BDAC positively affect LTP.

In fact, few studies exist that empirically establish the relationship between BDA and economic, environmental, and social performance. BDA structure can transform the industrial sector by making the results of sustainability indicators more efficient (Dubey *et al*., 2016). The BDAC is expected to have a significant impact on the economic performance (ECP) of industries (Wamba *et al*., 2017; Akter *et al*., 2016), and can be applied in areas such as demand forecasting, inventory management, marketing, transportation management, supply chain, and risk analysis (Choi *et al*., 2018). Thus, companies can use the insights provided by the BDA techniques to improve economic outcomes through the responsible use of resources (Nunes-Merino *et al*., 2020). BDA supports process integration by better information flow, improving quality, flexibility, and productivity (Müller and Voigt, 2018), impacting economic indicators. The BDA allows better accessibility and availability, creating a competitive advantage (Grover *et al*., 2018).

In addition, the use of BDA optimizes the consumption of materials and energy, improving economic and environmental performance (Bonilla *et al*., 2018). Some authors identify the vast potential of BDA capabilities in the improvement of Environmental Performance (EP) and recommend further studies to empirically validate the relationships between BDA and EP (Belhadi *et al*., 2019; Dubey *et al*., 2019). The previous studies provide limited insights as they analyzed the influence of BDA capabilities only on. For example, Belhadi *et al*. (2019) investigate whether Lean Six Sigma and Green Manufacturing mediate the relationship between BDA capabilities and EP. Dubey *et al*. (2019) analyzed the influence of BDA on EP in the presence of flexible and control orientation.

BDA resources like data-driven culture represent people's beliefs, attitudes, and opinions regarding data-driven decision-making (Arunachalam *et al*., 2017), which improves Social Performance (SOP) through valuing human resources. The increased use of BDA can free up a company's staff to focus on tasks where humans continue to outperform computers, such as judging information, increasing overall productivity (Ferraris *et al*., 2019). The findings by Gupta *et al*. (2019) reveal that companies identify a positive impact of the application of BDA in decision areas such as daily production and maintenance variability, manpower performance, health, safety and environment, and critical raw material availability status. Thus, BDA capabilities can be used to generate insights to integrate processes and people, which can elevate social sustainability performance (Gupta *et al*., 2019).

On the other hand, BDA adoption includes new infrastructure costs, privacy issues, and other challenges in improving economic, environmental, and social performance (Raut *et al*., 2019). Therefore, despite the increasing popularity of this technology, there is ambiguity about how the development of Big Data capabilities can impact the sustainability performance of organizations (Dubey *et al*., 2019). However, future socioeconomic developments rely heavily on Big Data and related information technologies and methods (Choi *et al*., 2018). The large-scale analysis of BDA techniques helps decision-making in complex economic activities, including sustainability issues (Gupta *et al*., 2019). In this sense, BDAC are a potential source of economic, environmental, and social value to gain a company's competitive advantage and human talent (Mikalef *et al*., 2019; Grover *et al*., 2018). Therefore, the hypotheses are proposed:

H2a. BDAC influence the ECP of industries.

H2b. BDAC influence the EP of industries.

H2c. BDAC influence the SOP of industries.

Some authors confirm the effects of Lean socio-technical practices on organisational performance, i.e., operational performance, financial performance, and development of employees (e.g., Abdallah *et al*., 2021; Arumugam *et al*., 2020; Sahoo, 2020). The results of Chavez *et al*. (2020) indicate that LTP exert an effect on economic, environmental, and social performance. This result was reinforced by Chavez *et al*. (2020b) who reveal that LTP are significantly and positively associated with environmental and social performance. In this sense, some authors demonstrate that technical practices such as TPM and JIT positively impact economic measures such as flexibility (Bevilacqua *et al*., 2017), productivity, cost, quality, and flexibility (Jasti and Kodali, 2019; Belekoukias *et al*., 2014), and social measures such as employee morale and safety (Jasti and Kodali, 2019).

However, some authors present controversial results. Studies claim that adopting Lean Practices does not improve emissions (Dieste and Panizzolo, 2018). For example, Amjad *et al*. (2020) state that to improve EP it is necessary to reduce the frequency of delivery, which reduces CO2 emissions, and this is opposed to Lean through the practice of JIT delivery, which can lead to negative impacts on the environment.

On the other hand, social aspects are fundamental to successful Lean implementation as people are an essential element in operations (Arumugam *et al*., 2020). For example, Godinho Filho *et al*. (2016) found that employee engagement is key to organizational change. The commitment and leadership of top management are critical factors for Lean success and social performance improvement (Gelei *et al*., 2015). In addition, leadership, employee involvement, supplier development and partnership, and customer relationship positively impact economic measures such as productivity, cost, quality, delivery, and flexibility (Jasti and Kodali, 2019; Bevilacqua *et al*., 2017), and social measures such as employee morale and safety (Jasti and Kodali, 2019).

Despite the evidence that emphasizes a positive relationship between Lean Practices and sustainability performance, this study intends to compare the impacts of technical and social practices on economic, environmental, and social performance, as well as highlight the contradictory points of these relationships. Thus, the hypotheses are formulated:

H3a. LSP impact the ECP of industries.

H3b. LSP impact the EP of industries.

H3c. LSP impact the SOP of industries.

H4a. LTP impact the ECP of industries.

H4b. LTP impact the EP of industries.

H4c. LTP impact the SOP of industries.

The application of Lean Practices and BDA can lead, to achieving better company's performance (Antony *et al*., 2018; Yang *et al*., 2013). Núñez-Merino *et al*. (2020) present the use of BDA acting in some Lean Practices with a multiplier effect on operational performance. There is evidence of the positive impact of these applications on operational and economic indicators, such as quality, flexibility, derived from the process integration, increased productivity, and reduced inventory (Valamede and Akkari, 2020; Mayr *et al*., 2018).

Some researchers establish links between the BDA and the LSP that impact economic (Haddud and Khare, 2020; Tortorella *et al*., 2019b; Li, 2019; Wamba *et al*., 2019), or environmental performance (Raut *et al*., 2019; Ren *et al*., 2018; Belhadi *et al*., 2019). Sanders *et al*. (2016) point out that through a large set of data, the BDA can help in the development and improvement of products, establishing connections with LSP related to customer engagement. BDA enables an information-sharing structure that strengthens customer engagement (Raut *et al*., 2019; Núñez-Merino *et al*., 2020), and enables the participation of suppliers (Dworschak and Zaiser, 2014). Cochran *et al*. (2016) provide a model that integrates BDA and continuous improvement strategies to identify bottlenecks and improve overall system performance. Adenuga *et al*. (2019) propose an energy efficiency analysis system as a tool to estimate energy costs and provide consumer-oriented analysis. For this, they applied BDA techniques together with continuous improvement practices that improve sustainability performance (Adenuga *et al*., 2019). BDA technologies can support continuous improvement strategies by providing process data (Cochran *et al*., 2016) and consumer-oriented analytics (Adenuga *et al*., 2019), improving product and financial performances.

Technical Practices like Kanban and JIT can incorporate BDA techniques to improve the efficiency of the process (Mayr *et al*., 2018). The development of BDAC impacts the JIT System (Valamede and Akkari, 2020; Bittencourt *et al*., 2019). Big Data provides support to identify trends and deduce rules for the production system, which contributes to a continuous flow and allows for JIT (Mayr *et al*., 2018; Sanders *et al*., 2016), reducing lead time, inventory and costs. By applying BDA, it is possible to guarantee constant monitoring of the work in process for intelligent inventory control (Valamede and Akkarin, 2020), meeting the goals of Kanban (Tortorella *et al*., 2019) and reducing transportation, working in process and costs.

BDA identifies trends, parameter deviation, and correlations, contributing to a defect-free product (Sanders *et al.*, 2016. Chiarini and Kumar, 2020), improving quality performance and environmental sustainability. Using technologies such as BDA, facilitates TPM activities by providing timely information-sharing and real-time data to ensure better inventory management, better maintenance predictions, and shorter downtimes (Haddud and Khare, 2020).. Big Data helps control resources and processes by providing a structure to compare target and actual values (Valamede and Akkarin, 2020), supporting Statistical Process Control (SPC) (Bittencourt *et al*., 2019), and stable process and better products. The use of IoT enables the monitoring and reallocation of orders through a pull system, which assists JIT in the delivery of goods by suppliers (Sanders et al., 2016), presenting greater agility and flexibility to respond to fluctuations in demand, level minimum inventory, and using BDA can improve demand forecasting skills, which leads to more efficient production and responsible use of resources (Núñez-Merino et al., 2020).

Big Data and BDA applications enable real-time and historical data analysis and help identify unstable process parameters by providing large volumes of statistically processed data (Mayr *et al*., 2018; Wagner *et al*., 2017), preventing defects, and improving efficiency (Tortorella *et al*., 2019), which contributes to better the performance of the entire supply chain (Valamede and Akkari, 2020). It is possible to improve demand forecasting techniques by making this process intelligent and efficient through Big Data techniques to define market strategies and reach a responsible use of resources (Núñez-Merino *et al*., 2020). Furthermore, BDA capabilities play a key role in empowering employees, improving decision-making (Bag et al., 2020). Training activities help the employees to optimize resource usage using BDA applications, which drives the sustainability performance of the supply chain (Bag *et al*., 2020).

However, the findings by Raut *et al*. (2019) contradict most studies when they point out that Lean Practices are negatively impacting BDA. Therefore, more studies are needed to investigate how these concepts interact (Belhadi *et al*., 2019). Furthermore, studies should be conducted to help companies develop BDAC to improve Sustainability Performance. Thus, this study is also dedicated to investigating the impact of BDAC on economic, environmental, and social performance in the presence of Lean technical and social practices. This helps companies understand whether Lean System consolidation forms the basis for developing BDAC to improve Sustainability Performance. Thus, the hypotheses are presented:

H5a. LSP mediate the relationship between BDAC and ECP.

H5b. LSP mediate the relationship between BDAC and EP.

H5c. LSP mediate the relationship between BDAC and SOP.

H6a. LTP mediate the relationship between BDAC and ECP.

H6b.LTP mediate the relationship between BDAC and EP.

H6c. LTP mediate the relationship between BDAC and SOP.

5.4 Research Method

5.4.1 Research Design

This research addresses the research question using a mixed-method approach whose structure is composed of a survey and a SLR to improve the conceptual domain of the constructs and variables. The empirical study was carried out through survey research. The survey research provides preliminary evidence of an association between concepts (Forza, 2002), and involves: (a) definition of the unit of analysis and literature domain; (b) collecting data in a structured format; (c) definition of variables and the relationships between them; and (d) specification of the sample, with the ability to generalize findings (Malhotra and Grover, 1998). All these questions are presented in the following topics.

The SLR was used to identify the building blocks of the Lean structure and BDA structure, to better define the conceptual domain of each construct and guide the elaboration of the research questionnaire. In this study, SLR followed the research flow developed by Ferenhof and Fernandes (2016), in which the four-phase procedure was divided into eight activities (Pagliosa et al., 2019), showed in Figure 5.1. The 71 documents (Lean) and 40 documents (BDA) were, respectively, included in the sample of papers that present the Lean Social-Technical and BDA structures that help in the construction of the questionnaire. They were analyzed using content analysis in the NVivo software. Content analysis provides a scientific method to evaluate the collected data (Kondracki et al., 2020). The SLR results will be presented in the 5.4.3 Research instrument design and variables.

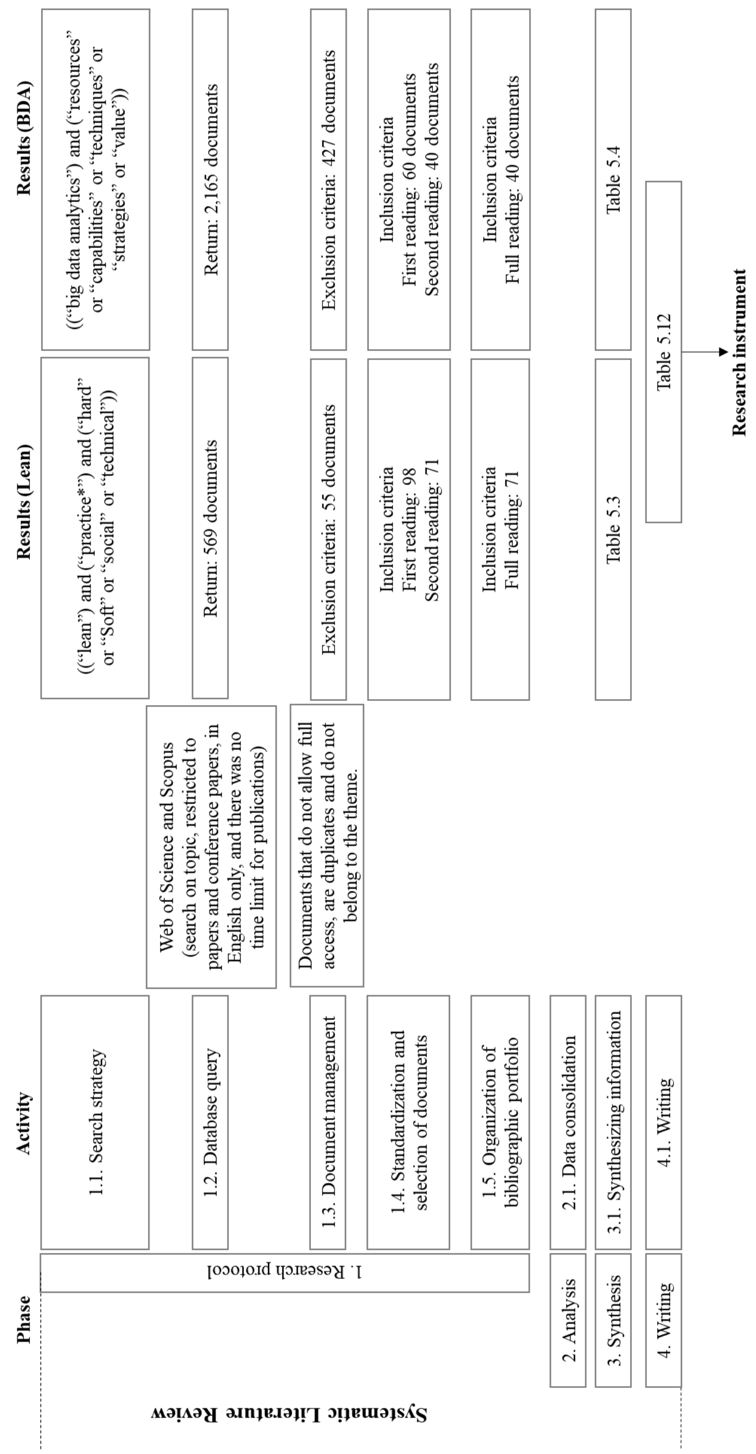

Figure 5.1. SLR research structure

5.4.2 Sampling and Data Collection

The target population of the study were those responsible for the Lean program or Lean consultants from Brazilian manufacturing companies, who also have information about the Big Data Analytics structure in the company. Respondents were found and invited to participate in the survey through corporate social media, selecting professionals with experience in Lean and Big Data. Social media was used for its ease of finding potential target respondents with specific and accurate information about their experiences in management practices and skills, including Lean manufacturing skills (Potter, 2021). Target respondents were contacted via LinkedIn and received an explanation about the survey, those who showed interest in participating voluntarily received the online questionnaire, developed on the Google Forms platform. The questionnaire was sent to 774 potential respondents, obtaining 123 complete questionnaires.

The 123 questionnaires were examined to check if the respondents met the basic requirements (working with Lean in manufacturing companies and knowing the Big Data structure), remove questionnaires with missing data, suspicious response patterns (straight lining or inconsistent answers), and outliers, to ensure data quality (Hair *et al.*, 2017a). A total of 14 questionnaires were removed from the sample because the respondents did not fulfill the basic requirements, mainly related to work in manufacturing companies. There was only one questionnaire with suspicious response pattern, no missing data and outliers were found. The outlier's analysis was performed using the Mahalanobis distance, which is one of the most used approaches for outlier detection in multivariate data (Dai, 2020). Therefore, the final sample consisted of 108 responses from professionals from manufacturing companies from different sectors.

Table 5.1 shows that the positions that the most respondents have in the company are Manager (29%), Analyst (14%) and Director (14%). More than 56% of respondents have participated and 54% of respondents have coordinated more than 10 Lean projects. While 25% of respondents have been working with Lean for more than 15 years. Experience with data is less, but it shows that at least 77% of respondents have already participated in projects with Big Data and 48% have more than 1 year of experience with Big Data. Respondent profiles shows that they are qualified to answer the questions.

Table 5.1. Respondent description

Respondent Position	**Number**	**%**	**Respondent Position**	**Number**	**%**
Manager	31	29%	Coordinator	10	9%
Analyst (Lean, data, R&D)	15	14%	Supervisor	9	8%
Director	15	14%	Owner	7	6%
Specialist (Lean, data)	11	10%	Other	9	8%
Lean projects participation			**Big Data projects participation**		
I never participated	4	4%	I never participated	36	33%
Between 1 and 3 projects	18	17%	Between 1 and 3 projects	45	42%
Between 4 and 6 projects	17	16%	Between 4 and 6 projects	19	18%
Between 7 and 10 projects	8	7%	Between 7 and 10 projects	8	7%
More than 10 projects	61	56%	More than 10 projects	0	0%
Lean coordination			**Big Data coordination**		
I never coordinated	9	8%	I never coordinated	70	65%
Between 1 and 3 projects	25	23%	Between 1 and 3 projects	26	24%
Between 4 and 6 projects	12	11%	Between 4 and 6 projects	6	6%
Between 7 and 10 projects	8	7%	Between 7 and 10 projects	6	6%
More than 10 projects	54	50%	More than 10 projects	0	0%
Time working with Lean			**Time working with Big Data**		
Less than 1 year	8	7%	Less than 1 year	32	30%
Between 1 and 5 years	15	14%	Between 1 and 5 years	42	39%
Between 5 and 10 years	24	22%	Between 5 and 10 years	5	5%
Between 10 and 15 years	24	22%	Between 10 and 15 years	2	2%
Over 15 years	27	25%	Over 15 years	2	2%
Did not answer	10	9%	Did not answer	25	23%

The companies in the sample (Table 5.2) belong mainly to the following manufacturing sectors Automotive (23%), Machines and equipment (17%), Food and drinks (9%), Consultancy in manufacturing industries (9%), and Chemical industry (8%). Most of the sample has Lean implemented for more than 5 years (56%), while 47% of the organizations have been using Big Data for less than 5 years. Most organizations (60%) have more than 500 employees and is considered large companies, while 43 are considered micro, small, and medium companies.

Table 5.2. Companies characteristics

Sector	Number	%
Automotive	25	23%
Machines and equipment	18	17%
Food and drinks	10	9%
Consultancy	10	9%
Chemical industry	9	8%
Aerospace	4	4%
Medical equipment	4	4%
Electrical and electronics	3	3%
Mechanical metal	2	2%
Cellulose products	2	2%
Steel mill	2	2%
Other	19	18%

Size (employees)	Number	%
Micro (<20)	12	11%
Small (≥20 and <99)	7	6%
Medium (≥100 and <499)	24	22%
More than 499	65	60%

Lean implementation	Number	%
Less than 1 year	9	8%
Between 1 and 5 years	29	27%
Between 6 and 10 years	22	20%
More than 10 years	39	36%
Don't know	9	8%

Big Data Implementation	Number	%
Less than 1 year	19	18%
Between 1 and 5 years	31	29%
Between 6 and 10 years	15	14%
More than 10 years	15	14%
Don't know	28	26%

5.4.3 Research instrument design and variables (SLR)

Lean and BDA are widely discussed in the literature and there is no consensus on how to structure these variables. Thus, this SLR justifies the choice of variables and research instrument for Lean and BDA since this study is dedicated to investigating how Lean can influence the relationship between BDA and sustainability performance. It was searched in the literature how the authors structure Lean (Table 5.3) and BDA (Table 5.4) for a company with competitive capacity. The questionnaire was divided into four sections. The first one contains questions about company (size, sector, Lean and Big Data implementation) and respondent (position, experience with Lean and Big Data); while the second one encompasses questions about the use of Lean Social and Technical Practices in the company, followed by the third section about the Big Data Analytics Capability, finally, the last one has questions about sustainability performance (social, economic, and environmental).

Table 5.3. Variables for Lean

Lean Social Practice		Lean Technical Practice	
Management leadership	1; 2; 5; 11; 16; 20; 27; 28	Continuous Flow	5; 8; 11; 12; 14; 15; 17; 22; 23; 24
Supplier partnership	1; 2; 4; 5; 8; 11; 12; 14; 18; 19; 20; 21; 22; 23; 25	Just-in-Time	2; 3; 5; 7; 8; 9; 10; 11; 12; 13; 14; 16; 17; 18; 19; 20; 21; 22; 23
Small group problem solving	1; 2; 5; 11; 15; 18; 19; 21; 22; 24; 25	Setup time reduction	1; 2; 4; 5; 6; 7; 8; 10; 11; 12; 14; 17; 18; 19; 21; 22; 23; 25
Continuous Improvement	2; 5; 11; 16; 27; 28; 29	Total Productive Maintenance	2; 3; 5; 8; 11; 12; 14; 15; 17; 18; 19; 20; 21; 22; 23; 24; 25; 26
Training employees	1; 2; 5; 16; 11; 20; 22; 26; 28	Statistical Process Control	1; 2; 4; 5; 8; 10; 12; 14; 17; 18; 19; 22; 23; 25
Customer involvement	2; 4; 5; 8; 10; 11; 12; 14; 20; 21; 22; 23; 25; 30	Workplace organization	13; 16
Human resource management	10	Process Mapping	13; 16
Reward system	16; 27	Value Stream Mapping	13; 16
Communication system	16; 27	Kaizen or Kaizen Blitzes	13; 16
Employee empowerment	16; 27	Total Quality Management	3; 10; 20
Employee commitment	16; 27	Production scheduling and systemization	20
Employee involvement	4; 8; 12; 14; 16; 17; 20; 22; 23; 25; 27	5S	3
Multifunctional employees	1; 2; 16; 24; 25; 27; 28	Pull System	4; 8; 10; 12; 14; 15; 17; 22; 23; 24; 25
Lean Attitude	3	Cellular manufacturing	7
Lean Leadership	3	Standardized Work	18; 19; 21; 23
Lean Training	3	Production leveling	17; 23
Lean Culture	3	Visual control	18; 19
Top management commitment	28		
Humane orientation	28		
Expert workforce	28		
Financial resources	28		
Skill intensification	28		
Employee commitment	28		
Teamwork	28		
Autonomous workers	28		

Sources: 1- Abdallah et al. (2019); 2- Abdallah et al. (2021); 3- Arumugam et al. (2020); 4- Bevilacqua et al. (2016); 5- Bortolotti et al. (2015); 6- Chavez et al. (2015); 7- Cherrafi et al. (2018); 8- Costa et al. (2020); 9- Cua et al. (2001); 10- Furlan et al. (2011); 11- Gaiardelli et al. (2018); 12- Godinho Filho et al. (2016); 13- Gowen et al. (2012); 14- Inman and Green (2018); 15- Marodin et al. (2018); 16- Muraliraj et al. (2019); 17- Nawanir et al. (2012); 18- Panwar et al. (2017); 19- Panwar et al. (2018); 20- Sahoo (2020); 21- Sajan et al. (2017); 22- Shah and Ward (2007); 23- Tortorella and Fetterman (2017); 24- Tortorella et al. (2019); 25- Yadav et al. (2019); 26- Zeng et al. (2015); 27-Hadid et al., 2016); 28- Hernandez-Matias et al. (2020); 29-Peng et al. (2011); 30-Rahman and Bullock (2005)

Table 5.4. Variables for Big Data Analytics

Big Data Analytics Capabilities			
Wamba et al. (2017)		**Gupta and George (2016)**	
Infrastructure	1; 2; 3; 4; 6; 7; 8; 9; 11; 12; 14; 16; 17; 18; 19; 20; 21	Tangible resources	22; 23; 24; 25; 26; 27; 28; 29
Management	1; 3; 4; 5; 6; 9; 10; 11; 12; 13; 14; 15; 16; 17; 18; 19; 21	Intangible resources	22; 23; 24; 25; 26; 27; 28; 29
Personnel	1; 2; 3; 4; 5; 10; 11; 13; 14; 16; 17; 19; 20; 21	Human skills	22; 23; 24; 25; 26; 27; 28; 29

Sources: 1- Akter et al. (2016); 2- AlNuaimi et al. (2021); 3- Arunachalam et al. (2017); 4- Awan et al. (2021); 5- Bag et al. (2020); 6- Belhadi et al. (2019); 7- Corte-Real et al. (2016); 8- Dubey et al. (2019); 9- Ferraris et al. (2019); 10- Grover et al. (2018); 11- Jha et al. (2020); 12- Pathak et al. (2021); 13- Popovic et al. (2016); 14- Rialti et al. (2019); 15- Saggi and Jain (2018); 16- Shamim et al. (2020); 17- Shokouhyar et al. (2020); 18- Sun and Liu (2020); 19- Wamba and Akter (2019); 20- Xiao et al. (2020); 21- Yasmin et al. (2020); 22- Ciampi et al. (2021); 23- Lozada et al. (2019); 24- Mikalef and Krogstie (2018); 25- Mikalef and Krogstie (2020); 26- Mikalef et al. (2019); 27- Mikalef et al. (2019b); 28- Mikalef et al. (2019c); 29- Wetering et al. (2019)

The Lean and BDA measurement scales were based on the SLR. Lean practices were divided into social and technical to better represent the concept of socio-technical system (Shah and Ward, 2007). The SLR findings (Table 5.3) identify that 66.33% of the authors studied based the Lean structure on the variables of Bortolotti *et al*. (2015). In addition, Bortolotti *et al*. (2015) based their Lean questionnaire on Shah and Ward (2003; 2007) who are widely validated authors in the literature for having developed the basis of the Lean social and technical structure. Therefore, this research instrument was based on mainly on the validated measurement scale proposed by Bortolotti *et al*. (2015), the Lean Social Practices was represented by a second-order reflective construct composed of six first-order reflective constructs, while the Lean Technical Practices was structured as a second-order reflective construct composed of five also reflective first-order constructs.

Furthermore, SLR identified that authors investigating BDA capabilities base their studies on two main authors, namely, Wamba *et al*. (2017) and Gupta and George

(2016) (Table 5.4), forming two important lines of research. Wamba *et al*. (2017) structure the BDAC in infrastructure, management, and personnel. Gupta and George (2016) structure the BDAC in tangible resources, intangible resources, and human skills. BDA resources are critical in developing BDA (Mikalef *et al*. 2019), so allow companies to create BDAC (Gupta and George, 2016). Thus, the Big Data Analytics Capability measurement scale was based mainly on Gupta and George (2016), where the Big Data Analytics Capability construct was considered as a multidimensional third-order formative construct composed of three second-order formative constructs; big data-specific tangible, human skills, and intangible resources constructs, which in turn comprises seven first-order constructs.

The sustainability performance was measured by three reflective constructs, to highlight the three dimensions of the triple bottom line, economic, social, and environmental. The constructs were based on the measurement scale developed by Kamble et al. (2019).

The questionnaire used a five-point Likert scale, varying from 1 (“strongly disagree”) to 5 (“strongly agree”) (Hair *et al*., 2017a). The constructs, variables and references are presented in Appendix I (Table 5.12). Before the application of the questionnaire, the pre-test was carried out, which was developed following the recommendation of Forza (2002), the questionnaire was sent to 3 academic experts, who research Lean and Industry 4.0, 2 experts with experience in implementing Lean in the manufacturing sector of and 3 target respondents to verify the clarity of the questions, the questionnaire format, and the scale.

5.4.4 Response and common method bias

To avoid Common method variance (CMV), some recommendations were applied: the respondents were anonymous, there were explanations about each section and that there were no correct or wrong answers, there was a concern that the respondents had the knowledge to answer the questions, there were different sections and with different visual formats for the dependent and independent variables, in addition , the measurement scale was based on multi-item constructs to ensure the conceptual domain (Podsakf *et al*., 2003). The Harman's Single Factor Test were performed to verify the existence of CMV in the data analyzed, and the test showed that less than 50% of all variance (threshold value) was explained by one single factor (29.5%), ensuring that CMV was not present. Additionally, to test for possible non-response bias Levene’s test and a t-test (to check equality of variance and means) was used to verify if the answers of the early and late respondents are similar. No differences were found in any variable (p-value<0.05).

5.4.5 Data analysis

In recent years, there has been a large dissemination Partial Least Squares - Structural Equation Modeling (PLS-SEM), mainly in business research, but also in engineering and various fields of natural sciences (Ringle *et al*., 2018; Shiau *et al*., 2019). Many methodological developments have emerged for PLS-SEM in recent years, strengthening some reasons for choosing the method, especially when the structural and/or measurement models are complex (many constructs and/or items), formatively measured constructs are specified in the research, it is necessary to use latent variable scores in subsequent analyses, sample size is small, the scaling of responses is ordinal or nominal and the structural model will be estimated with a higher order construct (Hair *et al*., 2017b; Ringle *et al*., 2018). All these issues are present in the proposed model, and, for this reason, the PLS-SEM was chosen.

Although the PLS-SEM is suitable for analysis with small samples, some rules of thumb were observed to ensure that the sample size of 108 respondents was adequate. Two rules for minimum suitable size were observed to verify the adequacy of the sample size: (i) the ten times rule (minimum sample size of 30), (ii) the minimum R-squared method with power of 0.90 (minimum sample size of 99) (Hair *et al*., 2017a).

Models with higher-order constructs, as the one chosen for this research, allow researchers to model a concept in a more abstract dimension (higher-order components) and its more concrete sub-dimensions (lower-order components), increasing the chance of capturing the correct conceptual dimension of the abstract concept (Sarstedt *et al*., 2019; Hair *et al*., 2021). Each lower-order component is a separate construct in a PLS path model and is measured by multiple items (Hair *et al*., 2021). In the present model, the Big Data Analytics Capability is a third-order formative construct, composed of three second-order constructs; Tangible Resources (formative-formative), Human Skills Resources (reflective-formative) and Intangible Resources (reflective-formative). Social and Lean Technical Practices are second-order constructs (reflective-reflective type), which are evaluated by concrete practices used in companies. Environmental, social and economic performance are first-order reflective constructs, with the objective of capturing sustainability performance in the three dimensions. Higher order models require specific approaches for specifying and estimating higher-order constructs in PLS-SEM (Hair *et al*., 2018; Sarstedt *et al*., 2019). The disjoint two-stage approach was used, which consists in considering only the lower-order components of the higher-order constructs in stage one, generating construct scores that will be used in the second stage to evaluate the structural model (Sarstedt *et al*., 2019). The same evaluation criteria for general measurement PLS-SEM models must also be used for higher-order models and the disjoint two-stage approach permits the application of all structural model assessment criteria and (Sarstedt *et al*., 2019).

The hypothesised model is presented in Figure 5.2.

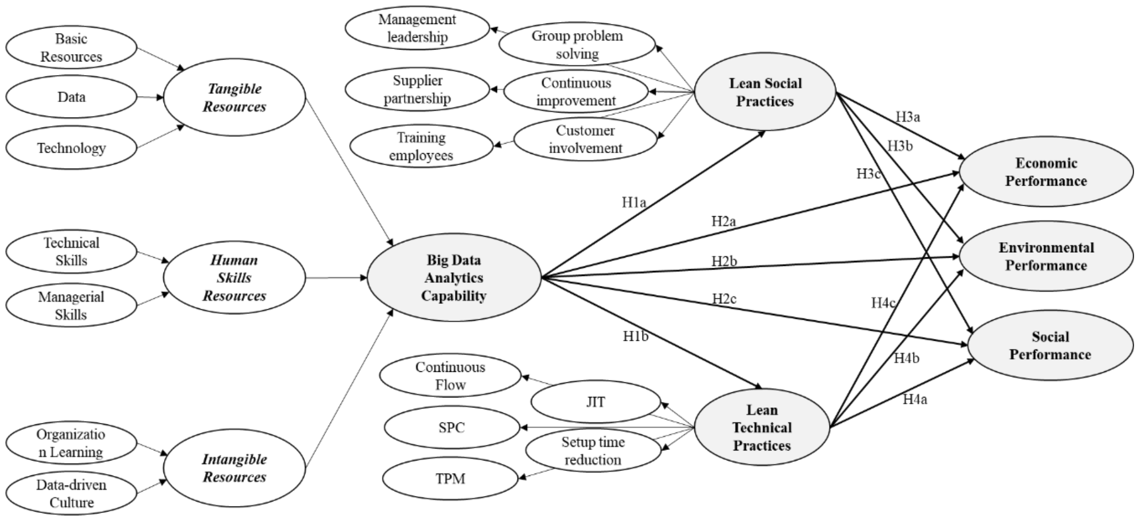

Figure 5.2. Hypothesised model

5.5 Analysis and Results

5.5.1 Validation of measurement model and hypotheses

The present model has low-order and second-order reflective and formative constructs and a third-order formative construct. Each type of measurement model (i.e., reflective or formative) has specific evaluation criteria (Hair *et al*., 2017; Sarstedt *et al*., 2019). Satisfactory for the measurement model are a judgment for evaluating the relationships in the structural model (Hair *et al*., 2018).

The criteria for reflective constructs in the measurement model encompass internal consistency, measured by Cronbach's alpha (CA) and composite reliability (CR) (CA and CR > 0.70); convergent validity, evaluated by the item reliability (outer loadings for statistically significant and > 0.708) and Average Variance Extracted – AVE (AVE >

0.5); and discriminant validity, assessed by heterotrait-monotrait ratio – HTMT (HTMT < 0.90) (Hair *et al*., 2018; 2020; Sarstedt *et al*., 2019). In contrast, evaluation of formative measurement models involves testing the construct collinearity (VIF<5), measures' convergent validity (CV) (path coefficient with a magnitude at a minimum 0.70) and the significance of the item outer weight (OW) (p-value<0.05) and relevance (outer loading is ¬> 0.5). Hair *et al*. (2017a) indicates that if the outer weights of formative items are not significant, outer loadings (OL) should be observed, if greater than 0.5, the items should be kept in the model.

The model assessment first focuses on the reflective and formative models of the lower-order components, and in stage two, the latent variable scores of the lower order components obtained from stage one to create and estimate the stage two model (Sarstedt *et al*., 2019). As the model has a third-order construct, the same was done for the second-order components, the measurement model was validated and the generated score was used in a new stage (Hair *et al*., 2018). One item in lower-order constructs (MS1) were removed because it did not meet the threshold for discriminant validity. Table 5.5 presents the item reliability (OL) assessment for the reflective constructs and the significance and relevance of the items for the formative constructs. Table 5.5 presents the values for the items that comprise the second and third order constructs. Table 5.6 shows the results of the measurement model for first, second and third-order constructs. All lower-order and higher-order constructs meet the reflective and formative measurement models criteria (Table 5.6).

Table 5.5. Item reliability, relevance and significance

High order construct	Low order construct	OL	OL p-value	OW	OW p-value
Lean Technical Practices (reflective)	Continuous Flow	0.236	<0.001		
	JIT	0.198	<0.001		
	Setup time reduction	0.269	<0.001		
	Statistical Process Control	0.279	<0.001		
	TPM	0.270	<0.001		
Lean Social Practices (reflective)	Management Leadership	0.212	<0.001		
	Supplier Partnership	0.208	<0.001		
	Small group problem solving	0.216	<0.001		
	Continuous Improvement	0.198	<0.001		
	Customer Involvement	0.170	<0.001		
	Training Employees	0.244	<0.001		
Tangible resources (formative)	Rasic Resources	0.741	<0.001	-0.373	0.124
	Data	0.894	<0.001	0.691	0.000
	Technology	0.908	<0.001	0.726	0.003

Human skills (formative)	Managerial Skills	0.999	<0.001	0.100	0.531
	Technical Skills	0.854	<0.001	-0.071	0.864
Intangible resources (formative)	Data-Driven Culture	0.997	<0.001	0.936	0.000
	Organizational Learning	0.672	<0.001	0.100	0.531
Big Data Analytics Capability (formative)	Tangible Resources	0.849	<0.001	0.533	0.000
	Human Skills	0.626	<0.001	-0.164	0.270
	Intangible Resources	0.933	<0.001	0.697	0.000

Table 5.6. Convergent validity, reliability and collinearity results

Constructs	**CA**	**CR**	**AVE**	**CV**	**VIF**	**R2**
Continuous Flow	0.93	0.95	0.84			
JIT	0.87	0.91	0.66			
SPC	0.95	0.96	0.87			
Setup time reduction	0.92	0.94	0.80			
TPM	0.92	0.95	0.81			
Continuous Improvement	0.91	0.93	0.73			
Customer Involvement	0.87	0.91	0.72			
Supplier Partnership	0.92	0.94	0.81			
Training Employees	0.90	0.93	0.76			
Small group problem solving	0.94	0.95	0.79			
Management Leadership	0.92	0.94	0.76			
Basic Resources				0.9	3.69	
Data				0.8	4.07	
Technology				0.7	3.57	
Data Driven Culture	0.93	0.95	0.78			
Organization Learning	0.97	0.98	0.89			
Managerial Skills	0.98	0.99	0.94			
Technical Skills	0.97	0.97	0.86			
Economic Performance	0.91	0.93	0.66			0.37
Environmental Performance	0.96	0.97	0.82			0.27
Social Performance	0.96	0.97	0.76			0.46
Lean Technical Practices *	0.89	0.91	0.64			0.41
Lean Social Practices*	0.85	0.90	0.63			0.39
Tangibles resources*				0.7	3.76	
Intangibles resources*				0.7	1.60	
Human Skills*				0.8	4.16	
Big Data Analytics Capability **				0.7	2.38	

*Second-order constructs, calculated in stage two; **Third-order constructs, calculated in stage two; VIF is calculated for each item, the highest value of the construct items was presented, which did not exceed the threshold value

For reflective constructs, other criterion for the measurement model is the discriminant validity, which can be verified, even for a higher order construct, based on the HTMT, it is as a method more accurately to assess discriminant validity between constructs and has a 0.90 cutoff score for interpreting the results (Hair et al., 2018; 2020).

The discriminant validity between the higher-order construct and its lower-order construct is not relevant and meaningless, since conceptual and empirical redundancies are expected (Sarstedt *et al*., 2019). The HTMT results are shown in Table 5.7.

Table 5.7. HTMT results

	FLOW	CI	CUI	DD	ECP	EP	JIT	ML	MS	OL	SPC	SETUP	SGPS	SOP	SP	TPM	TS	LSP
FLOW	0.41																	
CI	0.37	0.58																
DD	0.46	0.54	0.47															
ECP	0.52	0.28	0.27	0.47														
EP	0.32	0.44	0.31	0.36	0.63													
JIT	0.58	0.43	0.37	0.48	0.38	0.28												
ML	0.62	0.70	0.56	0.44	0.48	0.46	0.43											
MS	0.32	0.24	0.26	0.59	0.39	0.24	0.34	0.18										
OL	0.24	0.35	0.31	0.65	0.39	0.24	0.42	0.21	0.75									
SPC	0.56	0.37	0.28	0.61	0.51	0.35	0.51	0.45	0.40	0.34								
SETUP	0.75	0.54	0.37	0.53	0.52	0.48	0.60	0.62	0.31	0.26	0.66							
SGPS	0.39	0.80	0.59	0.56	0.39	0.43	0.49	0.67	0.29	0.30	0.53	0.51						
SOP	0.40	0.50	0.45	0.62	0.72	0.73	0.30	0.50	0.40	0.43	0.51	0.47	0.52					
SP	0.61	0.52	0.54	0.54	0.46	0.37	0.60	0.60	0.45	0.44	0.48	0.58	0.51	0.44				
TPM	0.55	0.50	0.35	0.47	0.59	0.47	0.46	0.62	0.26	0.27	0.55	0.64	0.60	0.46	0.59			
TS	0.25	0.21	0.24	0.55	0.33	0.19	0.35	0.12	0.89	0.80	0.37	0.26	0.22	0.33	0.43	0.25		
TE	0.56	0.66	0.60	0.59	0.53	0.45	0.47	0.66	0.40	0.40	0.56	0.61	0.69	0.58	0.62	0.61	0.36	
LSP					0.51	0.52								0.64				
LTP					0.66	0.50								0.56				0.83

The structural model assessment starts with analyzing the relationships between the constructs (Sarstedt *et al*., 2019; Hair *et al*., 2018). The assessment of the stage two results addresses the structural model considering the latent variable scores of the lower-order constructs (Sarstedt *et al*., 2019; Hair *et al*., 2018). The structural assessment encompasses the collinearity between constructs (via the inner VIF values, that should be less than 5.0), significance and relevance of the path coefficients, explanatory (R2) and predictive power (Hair *et al*., 2018; 2020; Sarstedt *et al*., 2019). Other criteria can be observed, such as the effect size ($f2$). The path coefficient significance and relevance was verified by the bootstrapping procedure (Table 5.8) (Hair *et al*., 2018; 2020).

Table 5.8. Hypothesis testing (bootstrapping method - 5000 sub-samples)

Hypothesis	VIF	f2	Path (β)	Stdev	p-value	Result
H1a: Big Data Analytics Capability -> Lean Social Practices	1.00	0.63	0.623	0.072	<0.001	Supported
H1b: Big Data Analytics Capability -> Lean Technical Practices	1.00	0.70	0.642	0.065	<0.001	Supported
H2a: Big Data Analytics Capability -> Economic Performance	1.86	0.02	0.162	0.157	0.302	Not Supported
H2b: Big Data Analytics Capability -> Environmental Performance	1.86	0.01	0.134	0.158	0.396	Not Supported
H2c: Big Data Analytics Capability -> Social Performance	1.86	0.17	0.419	0.126	0.001	Supported
H3a: Lean Social Practices -> Economic Performance	2.34	0.00	0.021	0.133	0.876	Not Supported
H3b: Lean Social Practices -> Environmental Performance	2.34	0.05	0.281	0.172	0.102	Not Supported
H3c: Lean Social Practices -> Social Performance	2.34	0.08	0.314	0.154	0.042	Supported
H4a: Lean Technical Practices -> Economic Performance	2.43	0.15	0.481	0.161	0.003	Supported
H4b: Lean Technical Practices -> Environmental Performance	2.43	0.02	0.167	0.208	0.423	Not Supported
H4c: Lean Technical Practices -> Social Performance	2.43	0.00	0.024	0.162	0.882	Not Supported

The results in Table 5.8 show that five hypotheses (H1a, H1b, H2c, H3c, H4a) proposed in the research model are statistically supported. The Big Data Analytics Capability have a positive and statistically significant impact on Lean Social ($\beta = 0.623$; p-value = <0.001) and Technical Practices ($\beta = 0.642$; p-value = <0.001). This demonstrates that the development of tangible and intangible factors and human skills for Big Data Analytics enables a better development of the social and technical practices of Lean. There is no statistical evidence to support that Big Data Analytics Capability directly impacts Environmental and Economic Performance, however, the results demonstrate that an investment in Big Data capacity positively impacts the Social Performance and aspects of work ($\beta = 0.419$; p-value = 0.001).

Lean Social Practices impacts directly and positively affects Social Performance ($\beta = 0.314$; p-value = 0.042), that is, the presence of Lean Social Practices, such as incentives for continuous improvement, group problem solving, and employee training, have a positive impact on Social Performance such as absenteeism, health and safety, and worker satisfaction. However, the results did not demonstrate statistically significant relationships between Lean Social Practices and Economic and Environmental Performance. While Lean Technical Practices had a positive and significant impact only with the Economic Performance ($\beta = 0.481$; p-value = 0.003). The greater use of technical practices such as JIT, continuous flow, TPM, SPC and Setup time reduction, help to obtain better financial results, such as greater profit and reduction of production costs.

The path coefficients and f2 effect size allows comparing the intensities of the relationships between the constructs and the importance (f2) of a specific construct to explain other endogenous latent variables (Hair et al., 2017a; 2018). $f2$ values of 0.02, 0.15, and 0.35, represent respectively small, medium, and large effects (Cohen, 1988).

The results show that the impact of Big Data Analytics Capability has a similar effect on Social and Lean Technical Practices, observing the magnitude of the path coefficient and $f2$. As in the other cases only one relationship was statistically validated, comparisons are not possible, but the f2 effect size demonstrates that the impacts of Big Data Analytics Capability on Social Performance and of Lean Technical Practices on Economic Performance are medium, while the effect of Lean Social Practices on Social Performance is small, confirmed by the path coefficient, which is the lowest statistically significant of the analyzed model.

Another important assessment for the structural model is the predictive power and generalizable findings, which requires assessing whether the results apply to in-sample and out-of-sample data sets (Shmueli *et al*., 2019; Hair *et al*., 2020). The coefficient of determination (R2) measures the in-sample predictive power (Hair *et al*., 2017; Shmueli *et al*., 2019), presented in Table 5.5. To assess the statistical model's out-of-sample predictive power, we used the PLS predict procedure, in which Q2predict values are higher than 0 for all items; and the mean absolute error (MAE) values from the PLS-SEM analysis was smaller than the linear regression model (LM) results for all items (Shmueli *et al*., 2019; Hair *et al*., 2020). This suggests that the model has high predictive power (Shmueli *et al*., 2019).

5.5.2 Mediation effect

The model was also intended to investigate the mediating role of Lean technical and social practices in the relationship between Big Data Analytics Capability and Environmental, Social and Economic Performance. To verify the existence of the effect and the type of mediation, the first step addresses the significance of the indirect effect via the mediator variable (Hair *et al*., 2017a). If the indirect effect is not significant, the construct (Lean technical or social practices), does not function as a mediator in the tested relationship. If the indirect effect exists, it is necessary to verify the direct effect between the constructs to classify the type of mediation (Hair *et al*., 2017a). Table 5.9 shows the specific indirect effects considering the two mediators, Lean technical and social practices.

Table 5.9. Specific indirect effects (bootstrapping method - 5000 sub-samples)

Indirect Effect	**Path (β)**	**Stdev**	**p-value**	**Result**
BDAC -> LTP -> SOP	0.015	0.107	0.886	Not Supported
BDAC -> LSP -> ECP	0.013	0.084	0.878	Not Supported
BDAC -> LTP -> ECP	0.309	0.115	0.007	Supported
BDAC -> LSP -> SOP	0.196	0.104	0.060	Not Supported
BDAC -> LSP -> EP	0.175	0.115	0.129	Not Supported
BDAC -> LTP -> EP	0.107	0.137	0.433	Not Supported

Only the relationship between Big Data Analytics Capability and Economic Performance mediated with Lean Technical Practices showed statistical significance. As the direct relationship between Big Data Analytics Capability and Economic Performance was not statistically significant (Table 5.8), it is possible to state that the type of mediation that occurs in this case is full mediation. Where Big Data Analytics Capability affects Economic Performance only indirectly, through Lean practices, which manage to associate data usage capabilities with techniques to reduce waste from operational activities.

5.5.3 Multigroup analysis

Lean implementation maturity and company size were considered as variables that could imply heterogeneity and differences in the model. Company size considered the number of employees, less than 500 was considered micro, small, or medium companies, and large companies are those with 500 or more employees. Maturity considered the implementation time, level of dissemination of Lean practices and the perception of Lean level on implementation. Companies with more than 5 years of implementation, high level of practices dissemination and high implementation were classified as high maturity. The companies that did not show this evolution were considered as low maturity. As the variables were considered binary, the sample was separated into two groups, which allows greater consistency in the analyses due to the size of each group. The multigroup test was applied to verify the differences between groups in the relationships of the model (Hair *et al*., 2018). Multigroup test was applied via permutation, after confirmed the configural and compositional invariance based on the MICOM test (Henseler *et al*., 2016; Hair *et al*., 2018), was verified the differences in the path coefficients in the permutation test (Hair *et al*., 2018). The only difference found was for the relationship between Lean Technical Practices and Economic Performance (Table 5.10), which the relationship has greater magnitude for smaller companies than for large companies. Therefore, the adoption of Lean Technical Practices is more important for micro, small and medium-sized companies to achieve economic results.

Table 5.10. Multigroup analysis (Permutation)

Relationships	Maturity (Time and implementation)				Size (employees)			
	Low maturity	High maturity	Path Difference	p-value	Up to 499	More than 499	Path Difference	p-value
H1a: BDAC -> LSP	0.650	0.463	0.187	0.219	0.675	0.613	0.062	0.697
H1b: BDAC -> LTP	0.672	0.548	0.124	0.349	0.673	0.620	0.054	0.686
H2a: BDAC -> ECP	0.248	0.163	0.085	0.817	0.049	0.228	-0.179	0.627
H2b: BDAC -> EP	0.135	0.214	-0.079	0.837	0.245	0.041	0.204	0.586
H2c: BDAC -> SOP	0.399	0.430	-0.031	0.910	0.445	0.396	0.049	0.844
H3a: LSP -> ECP	0.007	0.262	-0.255	0.359	-0.136	0.371	-0.508	0.069
H3b: LSP -> EP	0.358	0.250	0.108	0.804	0.093	0.601	-0.508	0.196
H3c: LSP -> SOP	0.324	0.301	0.023	0.966	0.217	0.527	-0.310	0.414
H4a: LTP -> ECP	0.328	0.421	-0.093	0.774	0.789	0.038	0.751	0.040
H4b: LTP -> EP	0.014	0.238	-0.223	0.614	0.289	-0.119	0.408	0.397
H4c: LTP -> SOP	0.032	-0.036	0.068	0.860	0.122	-0.191	0.312	0.374

n Group low maturity – 56; n Group high maturity – 52
n Group up to 499 – 43; n Group more than 500 – 65

5.6 Discussion and implications

5.6.1 *Theoretical implications*

This study empirically investigates the integration between BDAC, Lean Practices and sustainability performance holistically. Through a survey the study investigates i) the direct impacts of BDAC on Lean technical and social practices, ii) the direct impacts of BDAC on economic, environmental, and social performance, iii) the direct impacts of Lean technical and social practices on sustainability performance, and iv) Impacts of BDAC on the sustainability performance in the presence of Lean technical and social practices. We validate the relations between BDAC and Lean, BDAC and Social Performance, Social Lean and Social Performance, Lean Technical and Economic Performance, and the support relationship between BDAC and LTP to achieve higher economic performance.

The findings of the present study had points of convergence and divergence with previous studies. In fact, BDAC has been found to have a positive and direct impact on Technical Lean and Social Lean. Large volumes of structured and unstructured data are captured and transformed into useful information by the BDA. The quality information feeds the Lean System for fast and accurate decision making, which strengthens Lean technical and social practices. The targeted use of BDA resources improves the quality of products and processes (Mayr *et al*., 2018; Wagner *et al*., 2017) and helps achieve continuous flow and JIT goals (Bittencourt *et al*., 2019; Tortorella *et al*., 2019), as well as enables better reach of customer needs (Mesquita *et al*., 2021; Valamede and Akkari, 2020; Saggi and Jain, 2018; Grover *et al*., 2018; Choi *et al*., 2018). BDA in conjunction with IoT technologies constantly monitors the process enabling inventory control, which allows for effective Kanban (Valamede and Akkari, 2020; Tortorella *et al*., 2019). Connecting machines and equipment via IoT allows BDA to unify large datasets for advanced analysis and help identify the root cause in problem solving in small groups (Ferraris *et al*., 2019; Sanders *et al*., 2016), and even allows you to identify patterns to avoid future errors (Lee *et al*., 2015).

Although there is evidence in literature of a positive relationship between BDA and sustainability performance (Mikalef *et al*., 2019; Grover *et al*., 2018; Bonilla *et al*., 2018; Gupta *et al*., 2019; Dubey *et al*., 2016), the results of this research do not confirm the direct impact of BDA on environmental and economic performance. The study found evidence that only social performance is directly impacted by the use of BDA in the industrial environment. This result contrasts with the findings of Belhadi *et al*. (2019) who identify that BDA resources can be used to analyze environmental data overcoming complex environmental issues. The authors confirm a positive and direct impact of BDA on environmental performance. Furthermore, some authors argue that BDA outputs can generate economic value while providing insights to reduce costs and improve productivity (Nunes-Merino *et al*., 2020; Valamede and Akkari, 2020; Mayr *et al*., 2018; Grover *et al*., 2018; Müller and Voigt, 2018; Chen *et al*., 2012). Brazilian companies may be at an initial level of insertion of BDA technology, which affects performance relationships. Many technologies only have a long-term payoff. On the other hand, the use of BDA quickly changes the style and quality of work, facilitating the worker's routine, which may have contributed to a positive perception of the impact of BDA on social performance. Having access to data can enable more consistent decision-making, reducing work pressure and improving working conditions. However, the findings of this research find support in Raut *et al*. (2019) who point to new organizational challenges and additional costs due to the adoption of BDA. Kamble *et al*. (2019) demonstrate that Industry 4.0 Technologies, including BDA, have a positive and direct effect on Lean Practices, but a negative and insignificant effect on Sustainability Performance.

Therefore, more research is needed to understand, from different points of view, how BDA can impact economic, environmental, and social performance.

The findings of this research also indicate that the Lean Social System (continuous improvement, supplier partnership, customer involvement, and small group problem solving) directly and positively impacts Social Performance, while the Lean Technical System (Continuous Flow, JIT, TPM, Setup time reduction, and SPC) has a direct and positive effect on Economic Performance. It is clear that LTP improve the Economic Performance of companies (Jasti and Kodali, 2019; Bevilacqua *et al*., 2017; Belekoukias *et al*., 2014), and that LSP value people's participation (Arumugam *et al*., 2020; Godinho Filho *et al*., 2016), favor employee morale and safety (Jasti and Kodali, 2019). In addition, it is not uncommon to find results in which the coordinated use of Lean Practices does not favor Environmental Performance (Dieste and Panizzolo, 2018), since, for example, the JIT system requires a high frequency of deliveries, increasing CO2 emissions (Amjad *et al*., 2020). This point is consistent with our findings which did not confirm a positive relationship between Lean Practices and Environmental Performance. The results of this research also do not confirm hypotheses in which LTP favors social measures and LSP favors economic measures. In isolation, Lean Practices tend to directly favor only the pillar of sustainability that share the same goals, that is, LTP favor ECP and LSP favor SOP.

Therefore, the findings of this research contradict evidence that STP, as TPM and JIT, affect social measures (Jasti and Kodali, 2019) and some LSP improve productivity, cost, quality, delivery, and flexibility (Jasti and Kodali, 2019; Bevilacqua *et al*., 2017). In addition, our results contradict Chavez *et al*. (2020) when they point out that LTP directly and positively affects sustainability performance, especially on the social and environmental side (Chavez *et al*., 2020b). One of the reasons that the relationship may not have been statistically supported is that the companies analyzed may not have incorporated environmental objectives into the LP, since when environmental measures are integrated into Lean strategies, improvements in environmental performance are noticeable (Inman and Green, 2018).

Finally, this research confirms a full mediating effect of LTP on the relationship between BDAC and ECP, did not confirm the mediation of LTP in the relationships between BDAC and EP and BDAC and SOP, and did not confirm the mediation of LSP in the relationship between BDAC and economic, environmental and social performance. Thus, our findings are not consistent with Belhadi *et al*. (2019) and Kamble *et al*. (2019).

Due to the complexity of environmental measures, Belhadi *et al*. (2019) suggest that Lean improves Environmental Performance only through mediation between BDA resources and Environmental Performance. Kamble *et al*. (2019) found that Lean Practices have a significant mediating effect (full mediation) on the relationship between Industry 4.0 Technologies, including BDA, and economic, environmental, and social performance. In Table 5.11 we synthesized the comparison of our results with the previous literature.

Table 5.11. Comparison of the results with the literature

Hypothesis	**Supported**	**Consistent with**	**Inconsistent with**
H1a. BDAC positively affect LSP.	Yes	2; 6; 8; 16; 17; 20; 21; 24; 26; 29;30; 32; 34; 37; 39; 40; 41; 44; 49; 50; 52	-
H1b. BDAC positively affect LTP.	Yes	10; 15; 29; 30; 33; 34; 44; 47; 48; 50; 51; 52	-
H2a. BDAC influence the ECP of industries.	Not	29; 39	11; 14; 16; 19; 24; 25; 33; 35; 36; 37; 38; 50;
H2b. BDAC influence the EP of industries.	Not	29	8; 11; 19; 24; 25; 29; 34; 35; 39; 40
H2c. BDAC influence the SOP of industries.	Yes	5; 11; 19; 21; 24; 25; 34; 35; 38; 39; 40	29
H3a. LSP impact the ECP of industries.	Not	-	1; 4; 9; 19; 28; 34; 39; 40; 42; 53
H3b. LSP impact the EP of industries.	Not	3; 18	27
H3b. LSP impact the SOP of industries.	Yes	4; 22; 23; 28; 53	-
H4a. LTP impact the ECP of industries.	Yes	1; 4; 7; 9; 12; 28; 42	-
H4b. LTP impact the EP of industries.	Not	3; 18	12; 13; 27; 53
H4c. LTP impact the SOP of industries.	Not	-	12; 13; 28; 53
H5a. LSP mediate the relationship between BDAC and ECP.	Not	-	29
H5b. LSP mediate the relationship between BDAC and EP.	Not	-	29
H5c. LSP mediate the relationship between BDAC and SOP.	Not	-	29
H6a. LTP mediate the relationship between BDAC and ECP.	Full	29	-
H6b.LTP mediate the relationship between BDAC and EP.	Not	-	29
H6c. LTP mediate the relationship between BDAC and SOP.	Not	-	29

Authors: 1- Abdallah et al. (2021); 2- Adenuga et al. (2019); 3- Amjad et al. (2020); 4- Arumugam et al. (2020); 5- Arunachalam et al. (2017); 6- Bag et al. (2020); 7- Belekoukias et al. (2014); 8- Belhadi et al. (2019); 9- Bevilacqua et al. (2017); 10- Bittencourt et al. (2019); 11- Bonilla et al. (2018); 12- Chavez et al. (2020); 13- Chavez et al. (2020b); 14- Chen et al. (2012); 15- Chiarini and Kumar (2020); 16- Choi et al. (2018); 17- Cochran et al. (2016); 18-

Dieste and Panizzolo (2018); 19- Dubey et al. (2016); 20- Dworschak and Zaiser (2014); 21- Ferraris et al. (2019); 22- Gelei et al. (2015); 23- Godinho Filho et al. (2016); 24- Grover et al. (2018); 25- Gupta et al. (2019); 26- Haddud and Khare (2020); 27- Inman and Green (2018); 28- Jasti and Kodali (2019); 29- Kamble et al. (2019); 30- Lee et al. (2015); 32- Li (2019); 33- Mayr et al. (2018); 34- Mesquita et al. (2021); 35- Mikalef et al. (2019); 36- Müller and Voigt, (2018); 37- Nunes-Merino et al. (2020); 38- Popovic et al. (2016); 39- Raut et al. (2019); 40- Ren et al. (2018); 41- Saggi and Jain (2018); 42- Sahoo (2020); 44- Sanders et al. (2016); 47- Stojanovic et al. (2015); 48- Tortorella et al. (2019); 49- Tortorella et al. (2019b); 50- Valamede and Akkari (2020); 51- Wagner et al. (2017); 52- Wamba et al. (2019); 53- Yu et al. (2020).

5.6.2 Practical implications

This study provides managers and practitioners with conceptual and practical evidence that BDAC, when well developed in companies, can improve the results of applying Lean technical and social practices. The research model (Figure 5.2) establishes a flow where the tangible resources, intangible resources, and human skills of BDA support Lean practices to improve sustainability performance. The model shows that BDA managers must support other company managers, suppliers, and customers in achieving their goals. The company must be able to develop BDA projects to improve shop floor operations through a JIT system and continuous flow strategies (related to Kanban, setup time reduction, TPM, and SPC). BDA teams must receive training in BDA technologies to properly support the industrial production system. The company must have access to data to conduct its operations effectively. In addition, engagement with suppliers and customers and continuous improvement strategies must be supported by BDAC. Companies interested in improving economic, environmental, and social results in a coordinated way can invest in technologies for efficiently collecting, processing, analyzing, and disseminating Big Data.

The expensive investment and short-term view often make companies reluctant to implement BDAC and Lean initiatives (Belhadi *et al*., 2019; Kamble *et al.*, 2019). However, our practical results confirm that BDAC directly and positively impact social performance and economic performance in the presence of the Lean system. . In addition, through the empirical research findings, top management that isolated Lean practices do not fully benefit sustainability. It is necessary to develop technical and social practices to improve economic, environmental, and social measures.

Finally, the results guide decision makers to mobilize for a Big Data-driven decision. Therefore, the results of the present study motivate executives and top managers, to consider adopting Lean socio-technical practices and developing BDA capabilities to achieve improved economic, environmental, and social performance.

5.7 Conclusions

BDA is emerging as a promising theme among academics and practitioners (Wamba *et al*., 2017). In addition, the challenge of remaining competitive with Lean and sustainable processes has been motivating companies to develop new forms of management. Thus, literature has evolved to point out ways to integrate innovative technologies, such as BDA, with continuous improvement approaches, such as Lean, to further improve economic performance (Haddud and Khare, 2020; Tortorella *et al*., 2019b; Li, 2019; Wamba *et al*., 2019), environmental performance (Raut *et al*., 2019; Ren *et al*., 2018; Belhadi *et al*., 2019), and social responsibility.

Studies suggest that companies with high BDA capabilities result in improved sustainable performance (Kamble *et al*., 2020; Belhadi *et al*., 2019). BDA will make great strides possible when companies are able to build BDA resources for data-driven decision-making, as well as leverage BDA insights to build predictive capability avoiding economic, environmental, and social negative impacts. In addition, the use of BDA resources in the Lean system also presents a high potential for integration with suppliers and customers. BDA capabilities can develop the full human potential, achieving one of the main goals of Lean.

However, current literature provides limited possibilities to integrate BDA and Lean with conflicting and inconsistent results to improve sustainability (Belhadi *et al*., 2019). This research goes one step further by providing conceptual and practical evidence of the benefits of this relationship. The present research aimed to understand how BDA capabilities can support the Lean socio-technical system to help the manufacturer achieve improved economic, environmental, and social performance. The objective was achieved by conceptually investigating a BDA structure and a Lean structure and the strengths of each of them that form the basis for the integration. A conceptual model points out ways in which BDA capabilities support Lean technical and social practices in the industrial production system. Finally, survey research evaluates the vision of 108 respondents, mostly Lean managers and BDA managers, to statistically validate these relationships.

The conceptual results show that tangible resources, intangible resources, and human skills of BDA (Gupta and George, 2016) support the JIT System (Kanban) and Continuous Flow (reduction of setup time, TPM, SPC), and these relationships facilitate direct supplier contact and customer engagement, meeting their unique needs faster. Furthermore, the practical results show that the Lean socio-technical system improves economic and social performance and needs information (Big Data) to be more efficient and achieve sustainability goals, also environmental. BDA capabilities can transform Lean into a data-driven system capable of achieving significant gains in sustainability. Overall, our practical results demonstrate that BDA capabilities reach their full potential to improve the economic performance of companies in the presence of Lean technical practices. Thus, more research is needed to empirically demonstrate that a data-driven Lean system can further improve sustainability performance.

Finally, this study directs many opportunities for future research. For example, i) it is possible to confirm the validated hypotheses and/or investigate the hypotheses not statistically supported by applying the research with larger samples and/or in other countries, ii) it is possible to go into the detailed level of BDAC to investigate through a case study how each capability is developed in an industrial environment, and iii) it is feasible to investigate how specific relationships between BDAC and Lean Practices occur to support sustainability through a case study or survey research. These are some paths for future studies; however, researchers may have several other insights through this research.

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5 Appendix I

Table 5.12

High order construct	Low order construct	Authors	Code	Item	OL	OL p-value	OW	OW p-value
Lean Technical Practices (Reflective)	Continuous flow (Reflective)	7, 18, 19, 21	FLOW1	Processes and/or machines stay close to each other.	0.894	<0.001		
			FLOW2	Shop floor layout facilitates inventory reduction and production pace.	0.947	<0.001		
			FLOW3	Processes are located close to each other, so that material handling and pieces storage are minimized.	0.896	<0.001		
			FLOW4	Machines are located to support a Just-in-Time production flow.	0.928	<0.001		
	Just-in-time (Reflective)	1, 3, 7, 17, 18, 19, 21	JIT1	The kanban system is used for production control.	0.735	<0.001		
			JIT2	Suppliers make frequent deliveries of materials.	0.825	<0.001		
			JIT3	Supplier deliveries are based on Just-in-Time.	0.875	<0.001		
			JIT4	Suppliers deliver in a short time.	0.851	<0.001		
			JIT5	We rely on punctual delivery from suppliers.	0.765	<0.001		
	Setup time reduction (Reflective)	1, 7, 19, 21	SETUP1	We seek to reduce setup times in our factory.	0.888	<0.001		
			SETUP2	The next operation is prepared while the machine is running.	0.883	<0.001		
			SETUP3	Equipment setup time is reduced in our factory.	0.902	<0.001		
			SETUP4	Our teams are constantly looking to reduce setup times.	0.908	<0.001		
	Statistical process control (Reflective)	7, 19, 21	SPC1	Most shop floor processes are under statistical process control.	0.895	<0.001		
			SPC2	We make extensive use of statistical techniques to reduce variation in processes.	0.922	<0.001		
			SPC3	We use charts to determine if our manufacturing processes are in control.	0.934	<0.001		
			SPC4	We monitor our processes using statistical process control.	0.837	<0.001		
	Total Productive Maintenance (Reflective)	1, 3, 7, 18, 19, 21	TPM1	Our employees understand the cause and effect of equipment deterioration.	0.862	<0.001		
			TPM2	Our employees perform the cleaning and lubrication basic of the equipment.	0.911	<0.001		
			TPM3	Our employees inspect and monitor the performance of their own equipment.	0.947	<0.001		
			TPM4	Our employees are able to detect and treat abnormal operating conditions of your equipment.	0.889	<0.001		
Lean Social Practices (Reflective)	Management leadership (Reflective)		ML1	Department heads within the factory accept their responsibility for quality.	0.815	<0.001		
			ML2	Our factory manager strives to promote quality improvement and quality products.	0.910	<0.001		

	1, 7, 17, 21	ML3	Our top management strongly encourages employee involvement in the quality improvement process.	0.812	<0.001
		ML4	Our factory management reinforces and communicates a vision focused on quality improvement.	0.930	<0.001
		ML5	Our factory management is personally involved in quality improvement projects.	0.892	<0.001
Supplier partnership (Reflective)	1, 7, 18, 19, 21	SP1	We maintain cooperative relationships with our suppliers.	0.895	<0.001
		SP2	We contribute with our suppliers to improve the quality of their processes.	0.922	<0.001
		SP3	We help our suppliers to improve their quality.	0.934	<0.001
		SP4	Our main suppliers contribute to our product development projects.	0.837	<0.001
Small group problem solving (Reflective)	1, 7, 19, 21	SGPS1	During problem-solving sessions, we make an effort to get the opinions and ideas of all team members before making a decision.	0.848	<0.001
		SGPS2	We form teams to solve problems.	0.903	<0.001
		SGPS3	In the last three years, many problems have been solved through small group activities.	0.902	<0.001
		SGPS4	Problem solving teams helped improve manufacturing processes at this plant.	0.906	<0.001
		SGPS5	Improvement teams are encouraged to try to solve their own problems as much as possible.	0.899	<0.001
Continuous improvement (Reflective)	7, 17, 21	CI1	We strive to continually improve aspects of products and processes, rather than taking a static approach.	0.801	<0.001
		CI2	Our performance will be affected in the long term by the process of improvement and constant learning.	0.836	<0.001
		CI3	Continuous improvement constantly affects our performance measures, putting us ahead of our competitors.	0.908	<0.001
		CI4	We believe that process improvement is never complete; there is always room for incremental improvement.	0.840	<0.001
		CI5	Our company is not a static entity, but engages in continuous improvement processes to better serve its customers.	0.876	<0.001
Training employees (Reflective)	1, 7, 17, 18, 19, 21	TE1	Our employees receive training to carry out various operations.	0.827	<0.001
		TE2	Our employees learn how to perform a variety of tasks.	0.931	<0.001
		TE3	The longer an employee stays at the factory, the more operations he learns to perform.	0.836	<0.001

			TE4	Our employees are trained in multiple operations at this plant so that they can replace others if necessary.	0.899	<0.001		
	Customer involvement (Reflective)	1, 7, 18, 19, 21	CUI1	We are in frequent contact with our customers.	0.866	<0.001		
			CUI2	Our customers give us feedback on our overall quality.	0.848	<0.001		
			CUI3	We strive to be highly responsive to our customers' needs.	0.853	<0.001		
			CUI4	We regularly research our customers' needs.	0.818	<0.001		
Tangible Resources (TR) (Formative)	Basic Resources (Formative)	6, 10, 12, 13, 14, 15, 16, 20, 22	BR1	Our company adequately invests in BDA projects.	0.958	<0.001	0.487	0.190
			BR2	Our company has the resources to manage Big Data projects.	0.967	<0.001	0.551	0.130
			BR3	Top management and the teams involved dedicate enough time for BDA projects to achieve their goals.*				
	Data (Formative)	6, 10, 12, 13, 14, 15, 16, 20, 22	D1	We have access to large databases or unstructured data, for analysis.	0.783	<0.001	0.056	0.815
			D2	We integrate data from multiple sources into software such as a data warehouse for easy access.	0.892	<0.001	0.166	0.580
			D3	We integrate external data (e.g., customer data) with internal data (e.g., process data) to facilitate analysis of our business environment.	0.994	<0.001	0.813	0.001
			D4	We have access to data that allows a positive return for our company. *				
	Technology (Formative)	6, 10, 12, 13, 14, 15, 16, 20, 22	T1	We explore or adopt computing approaches where multiple calculations are performed at the same time, i.e., parallel computing, for Big Data processing (e.g., Hadoop).	0.852	<0.001	0.463	0.116
			T2	We explore or adopt different data visualization tools.	0.855	<0.001	0.608	0.010
			T3	We explore or adopt cloud analytics capability services.	0.726	<0.001	0.106	0.656
			T4	We explore or adopt open source software for BDA.	0.507	<0.001	-0.595	0.038
			T5	We explore or adopt new forms of databases, such as Not Only SQL (NoSQL), for data storage.	0.737	<0.001	0.421	0.196
			T6	Our company performs data management. *				
			TR	Big Data resources are well structured in the company**				
Human Skills (HS) (Formative)	Technical Skills (Reflective)		TS1	We provide BDA training for our employees.	0.844	<0.001		
			TS2	We hire new employees who already have BDA skills.	0.861	<0.001		

		6, 10, 12, 13, 14, 15, 16, 20, 22	TS3	Our BDA team has the right skills to do their jobs successfully.	0.959	<0.001
			TS4	Our BDA team has adequate training to carry out her jobs.	0.968	<0.001
			TS5	Our BDA team has adequate work experience to do their jobs successfully.	0.961	<0.001
			TS6	Our BDA team is well trained.	0.973	<0.001
	Managerial Skills (Reflective)	6, 10, 12, 13, 14, 15, 16, 20, 22	MS 1	Our BDA managers understand and appreciate the needs of our company's other functional managers, suppliers, and customers.	0.914	<0.001
			MS 2	Our BDA managers can work with other functional managers, suppliers, and customers within our company to determine the opportunities that big data can bring to our business.	0.966	<0.001
			MS 3	Our BDA managers are able to coordinate big data related activities in order to support our company's other functional managers, suppliers, and customers.	0.974	<0.001
			MS 4	Our BDA managers are able to anticipate the future business needs of our company's other functional managers, suppliers, and customers.	0.976	<0.001
			MS 5	Our BDA managers have a good sense of where to apply the output extracted from big data.	0.963	<0.001
			MS 6	Our BDA managers are able to understand and evaluate the output extracted from big data.	0.979	<0.001
			HS	The company presents maturity of knowledge and application of Big Data analysis**		
Intangible Resources (Formative)	Organization Learning (Reflective)	6, 10, 12, 13, 14, 15, 16, 20, 22	OL1	We are able to seek out new and relevant knowledge about BDA.	0.953	<0.001
			OL2	We are able to acquire new and relevant knowledge about BDA.	0.968	<0.001
			OL3	We are able to assimilate relevant knowledge about BDA.	0.967	<0.001
			OL4	We are able to apply the relevant knowledge of BDA.	0.961	<0.001
			OL5	We have been striving to improve the exploitation of existing, new knowledge and skills from BDA.	0.873	<0.001
	Data-driven Culture (Reflective)	6, 10, 12, 13, 14, 15,	DD1	We consider data a tangible asset.	0.783	<0.001
			DD2	We base our decisions on data, not instinct.	0.917	<0.001
			DD3	We are willing to ignore our own intuition when the data contradict our views.	0.907	<0.001

		16, 20, 22				
			DD4	We continually evaluate and improve the company's strategic planning in response to insights extracted from the data.	0.919	<0.001
			DD5	We continually train our employees to make data-driven decisions.	0.875	<0.001
			IR	Big Data resources have already generated positive results by being disseminated across the various sectors of the company**		
BDAC			BDAC	The company implements Big Data analytics***		
	Environmental Performance (Reflective)	5, 8	EP1	There was an improvement in the reduction of atmospheric emissions.	0.883	<0.001
		5, 8, 9	EP2	There was an improvement in the reduction of solid waste.	0.920	<0.001
		9	EP3	There was an improvement in the reduction of liquid waste.	0.925	<0.001
		9	EP4	There was an improvement in the reduction of energy waste.	0.921	<0.001
		5, 8, 9	EP5	There was a decrease in the consumption of hazardous / harmful / toxic materials.	0.882	<0.001
		2, 5	EP6	There was a decrease in the frequency of environmental accidents.	0.895	<0.001
		2, 5, 8, 9	EP7	There was an improvement in the company's environmental performance.	0.915	<0.001
	Economic Performance (Reflective)	4, 9	ECP1	There was a reduction in production costs.	0.768	<0.001
		4, 9	ECP2	There was an improvement in profits.	0.747	<0.001
		9	ECP3	There was a reduction in energy costs.	0.834	<0.001
		9	ECP4	There was a reduction in stock costs.	0.874	<0.001
		9	ECP5	There was a reduction in rejection and rework costs.	0.846	<0.001
		9	ECP6	There was a reduction in raw material purchase costs.	0.760	<0.001
		9	ECP7	There was a reduction in waste treatment costs.	0.834	<0.001
	Social Performance (Reflective)	5, 9	SP1	There was an improvement in employee morale.	0.883	<0.001
		5	SP2	In general, our employees are satisfied with their work.	0.855	<0.001
		5, 9	SP3	There has been improved safety in the workplace.	0.849	<0.001
		5, 9	SP4	There was an improvement in the health of employees.	0.861	<0.001
		9	SP5	There was improvement in working relationships.	0.890	<0.001
		9	SP6	There was a decrease in pressure at work.	0.883	<0.001
		9	SP7	There was improvement in working conditions.	0.885	<0.001
		5	SP8	There was a reduction in health and safety incidents.	0.818	<0.001
		5	SP9	There was a reduction in injuries and lost days related to injuries.	0.901	<0.001

	5	SP10	There was a reduction in absenteeism.	0.864	<0.001

*question to assess convergent validity in a first-order construct; **question to assess convergent validity in a second-order construct; ***question for evaluating convergent validity in a third-order construct

Authors: 1- Abdallah et al. (2021); 2- Agyabeng-Mensah et al. (2020); 3- Arumugam et al. (2020); 4- Baliga et al. (2019); 5- Chavez et al. (2020); 6- Ciampi et al. (2021); 7- Gaiardelli et al. (2018); 8- Inman and Green (2018); 9- Kamble et al. (2019); 10- Lozada et al. (2019); 12- Mikalef and Krogstie (2018); 13- Mikalef and Krogstie (2020); 14- Mikalef et al. (2019); 15- Mikalef et al. (2019b); 16- Mikalef et al. (2019c); 17- Muraliraj et al. (2019); 18- Sahoo (2020); 19- Shah and Ward (2007); 20- Wetering et al. (2019); 21- Bortolotti et al. (2015); 22- Gupta and George (2016)

6 CONCLUSION

Sustainability, constituted by the economic, social, and environmental pillars, is increasingly recognized as a mandatory and competitive criterion. Therefore, industries are looking for ways to manage and operationalize their processes incorporating environmental and social aspects without discarding the strategic objectives of profitability and efficiency. Lean has been an ally of the industrial sector by promoting recognized improvements in sustainability performance. Lean is a socio-technical system with technical practices, aimed at improving processes, and social practices, aimed at human resource management. Furthermore, new technological challenges are emerging in the fourth industrial revolution. Additional efforts are needed to meet market pressures such as high variety, speed, and flexibility in mass-production processes. For that, Industry 4.0 brings together a set of integration technologies, data technologies, and shop floor technologies. Thus, this study aimed to identify and propose ways to integrate Industry 4.0 and Lean and to analyze the impact of the main relationships between Industry 4.0 technologies, mostly Big Data Analytics, and Lean socio-technical practices on sustainability performance.

To achieve the proposed objectives, this Dissertation followed a path that begins with two Systematic Literature Reviews (SLR). The first (Paper 1) identified the pillars of Industry 4.0, Lean and Sustainability, that is, 'what' most facilitates integration, in addition to identifying the direction of support between the approaches. The second (Paper 2) explained 'how' the relationships that integrate Industry 4.0 technologies and Lean socio-technical practices occur to improve sustainability performance. Paper 2 also has two cases study to demonstrate how the interactions between Industry 4.0 and Lean occur, in practice, which reinforces the conceptual findings. In addition, this Dissertation presents, in Paper 3, an SLR to identify a Lean structure and a Big Data Analytics structure, technology with great integration potential, which served as the basis for the development of a tested path model through Structural Equation Modeling in a Survey Research.

The results of this study show that this is a new and little explored theme, with some conceptual research (e.g., Valamede and Akkari, 2020; Pagliosa et al., 2019; Rosin et al., 2019), and little empirical research that generically addresses Industry 4.0 technologies (e.g., Tortorella et al., 2019b;2020; Kamble et al., 2019; Lugert et al., 2018) and specifically addresses Big Data Analytics (Belhadi et al., 2019; Gupta and George, 2016). Some empirical studies indicate that Industry 4.0 and Lean can coexist in an industrial environment and their synergistic effect presents improvements in operational performance (e.g., Tortorella et al., 2019; Haddud and Khare, 2020), and economic, environmental, and social performance (e.g., Kamble et al., 2019). In this context, the conceptual evidence of this Dissertation adds to the literature when they indicate that the synergies between Industry 4.0 technologies and Lean Practices positively influence economic performance indicators and, to a lesser extent, environmental and social performance indicators. The results of Paper 1 add to the literature by bringing specific relationships between Industry 4.0, Lean, and sustainability. Paper 1 shows that 29.1% of identified relationships are between Industry 4.0 technologies in support of Lean practices to improve environmental sustainability. Paper 2 shows that technologies such as Big Data and IoT facilitate integration with Lean socio-technical system to make industrial systems intelligent and connected, adding value to the customer. Furthermore, Lean technical practices such as JIT, Kanban, and Continuous Flow, some Lean tools such as VSM and Poka-Yoke, and the Jidoka principle are the most promising for integration with Industry 4.0 technologies to improve Economic Performance. Evidence also suggests that the JIT system integrated with integration technologies (CPS), data technologies (Big Data and IoT), and shop floor technologies (AGV) support the operating system and enable horizontal, vertical, and end-to-end integration improving the performance of the supply chain. On the other hand, Lean social practices such as customer engagement, supplier participation, and employee training also demonstrate adherence to Industry 4.0 technologies such as AM, Big Data, CC, CPS, IoT, and Simulation. These peer relations of the industry 4.0 technology categories and Lean socio-technical system create a dynamic industrial environment driven by real-time information. The integration between Industry 4.0 and Lean provides for the harmonization of technological and human aspects, extracting the potential benefits of these connections. In Paper 2, the cases study findings confirm and reinforce the support that Industry 4.0 provides for Lean and the remarkable improvement that this relationship presents in sustainability performance. These data guide future research.

New research opportunities arise from the connections between these approaches and the synergistic effect of the integration between specific Industry 4.0 technologies, mostly Big Data Analytics, and Lean socio-technical practices on economic, environmental, and social performance. Some studies have identified the potential of Big Data Analytics in improving Environmental Performance (Belhadi et al., 2019; Dubey et al., 2019). Furthermore, improvement approaches such as Lean appear to be more successful in achieving better performance in a Big Data Analytics environment (Belhadi et al., 2019). Therefore, Paper 3 analyzed the mediation effect that Lean Socio-Technical Practices can exert on Big Data Analytics Capabilities to improve sustainability performance. The results of Paper 3 confirm that the relationship between Big Data Analytics Capabilities and Economic Performance is fully mediated by Lean Technical Practices. Likewise, the Lean socio-technical system needs the information provided by Big Data Analytics Resources to achieve higher economic, environmental, and social performance.

All this research trajectory has brought relevant findings that benefit academics and professionals. The results of this study present conceptual and empirical data that form a robust theoretical basis for academics to delve deeper into the topic and explore new lines of research. The specific links between Industry 4.0 and Lean, presented conceptually in Paper 2, can inspire future research. For example, very strong supporting relationships (Strong +) such as IoT and JIT, IoT and Continuous flow, IoT and TPM, IoT and Setup Time Reduction, IoT and SPC, BDA and JIT, and BDA and TPM can be empirically investigated through Survey Research. In addition, new research can be developed to confirm or refute the Paper 3 hypotheses, with a larger sample, in Brazil or in other countries. To know, H1. Big Data Analytics capabilities positively affect Lean socio-technical practices (supported hypothesis); H2. Big Data Analytics capabilities influence the economic, environmental, and social performance of industries (supported hypothesis for social performance). H3. Lean socio-technical practices impact the economic, environmental, and social performance of industries (supported hypothesis for the relationships between social Lean and social performance and technical Lean and economic performance); H5. Lean social practices mediate the relationship between Big Data Analytics capabilities and economic, environmental, and social performance (not supported hypothesis); H6. Lean technical practices mediate the relationship between Big Data Analytics capabilities and economic, environmental, and social performance (supported hypothesis for the mediation effect that Lean technical practices exert on the relationship between Big Data Analysis capabilities and economic performance).

In addition, the findings of this Dissertation guide management decisions about investing in innovative technologies. Industries now have a solid parameter of what results to expect from Industry 4.0 technologies and their coexistence with the Lean system to improve sustainability performance. Managers can also use the results of this research to develop a production system based on technologies and Lean.

However, some limiting factors of this study can be pointed out. For example, i) there is a limited literary collection on the theme studied; ii) Brazilian companies are starting to introduce technologies in production and management processes; therefore iii) Lean managers and technology managers have a partial and incomplete view of the potential that Industry 4.0 technologies integrated into the Lean system have for improving sustainability performance. Therefore, more dissertations can explore the interactions between Lean, Industry 4.0, and Sustainability as companies continue to advance in this perspective and new results can be expected. Finally, it is concluded that improvements can be achieved from the support that Industry 4.0 technologies provide to the Lean socio-technical system. Lean and Industry 4.0 form the basis for a production system with high economic, environmental, and social performance.

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