Lean Six Sigma practices supported by Industry 4.0 technologies: Evidence from heavy vehicle manufacturers

ABSTRACT

Purpose - This paper aims to provide empirical evidence regarding Lean Six Sigma (LSS) practices supported by Industry 4.0 (I4.0) technologies in heavy vehicle manufacturing processes.

Design/methodology/approach - A two-case study was performed involving LSS specialists, leaders, and managers of two heavy vehicle manufacturers in Brazil. The data analysis procedure combined content analysis techniques, conceptual maps and network analysis.

Findings - The results provide consistent evidence of synergies between LSS and I4.0, including digital mistake-proofing, digital *andon*, *e-kanban*, statistical monitoring, as well as process mapping aided by cyber-physical systems (CPS) and Big Data Analytics (BDA). To enable such interactions, companies need to invest in automation architectures, system integration, human-machine interfaces, and analytical skills.

Research limitations/implications – This study relies on data from a two-case study carried out in two companies from a single manufacturing sector in Brazil. For this reason, the findings cannot be generalized to the entire automotive industry.

Originality/value – There is still a lack of comprehensive research on the application of digital technologies in LSS practices. This is the first study which provides empirical evidence regarding the LSS practices supported by I4.0 technologies used by heavy vehicle manufacturers.

Keywords: Lean Six Sigma; Industry 4.0; Quality 4.0, Operational Excellence, Case study.

Paper type: Research paper

Quick value overview

Interesting because - To ensure competitiveness in the digital era, manufacturing companies need to understand how Industry 4.0 (I4.0) can expand and support operational excellence (OPEX) initiatives, including Lean Manufacturing and Lean Six Sigma (LSS) approaches. Since this blending remains empirically under-researched, this paper aims to shed new light on digital practices that arise from integrating I4.0 technologies into LSS in the automotive industry.

Theoretical value –Previous research has addressed the integration between I4.0 and LSS, focusing on theoretical reviews, survey research or single case studies. However, field studies and multiple cases performed in the same industrial sector are needed to understand the similarities or dissimilarities of digitalization strategies of LSS practices. This study confidently presents and compares innovative examples that effectively combine LSS practices with I4.0 technologies, highlighting the technical requirements needed, the results from this seamless integration and assumptions that can expand the current literature.

Practical value – To effectively merge I4.0 technologies with LSS practices, heavy vehicle manufacturers must adopt a top-down approach regarding digital transformation, with pilot projects and proof of concepts performed by cross-functional teams. Additionally, such symbiosis requires system integration and a high level of automation that goes beyond connectivity and data conversion. The cases analyzed have shown advanced levels of automation, including networks and optimization algorithms. Furthermore, LSS practitioners, including green belts and black belts must expand their traditional skills to encompass data science and new techniques, such as predictive analytics and machine learning.

1. Introduction

Nowadays, a deluge of scientific papers regarding Industry 4.0 (I4.0) has advocated the use of digital technologies to support a new manufacturing model. This paradigm, referred to as the fourth industrial revolution, is strongly related to the Industrial Internet of Things (IIoT), which is still explorative (Belli et al. 2019). After a decade of discussion on the topic, only a few large companies have evidenced high levels of process digitization by combining advanced technologies such as IIoT, Big Data Analytics (BDA), advanced robotics and augmented reality (Rüßmann et al. 2015; Küpper et al. 2019).

Cyber-physical Systems (CPS) and smart factories are complementary ideas of I4.0. These systems encompass collaborating computational entities that are highly connected to the physical world, providing and using data-accessing and data-processing services available on the internet simultaneously (Monostori et al. 2016). The I4.0 paradigm has generated new concepts and branches such as Quality 4.0 (Q4.0), Industry 5.0 (I5.0), operator 4.0 (Peruzzini et al. 2020), Supply Chain Management 4.0 (Zekhnini et al. 2020), I4.0 integrated with circular economy (Akkad et al., 2022), and so forth. However, our study focuses on the impact of I4.0 on LSS practices from an operational and technological perspective rather than I5.0, which complements and extends I4.0 through the economic, environmental, social, and fundamental rights dimensions (Enang et al., 2023).

The Q4.0 concept emerges as an evolution of previous quality eras through the new applications of digital technologies and BDA in quality activities. Sony et al. (2020) argue that Q4.0 is concerned with managing quality in the context of I4.0, where CPS and cloud computing are applied to enhance an organization's ability to give customers high-quality products reliably. The research on Q4.0 developed so far has addressed mainly inspection automation and quality control activities rather than the use of I4.0 technologies in Lean Six Sigma (LSS) projects (Jacob, 2017; Ma et al., 2021; Tercan et al., 2022; Zhou et al., 2022). Our research, on the other hand, focuses strictly on the use of I4.0-enabled technologies in LSS projects rather than Q4.0-related practices.

The traditional LSS approach is a business strategy focused on increasing performance to enhance customer satisfaction and improve bottom-line financial results (McAdam and Hazlett, 2010; Albliwi et al. 2015; Null et al., 2020). The integration of digital technologies into LSS practices can optimize the data collection and analysis process with high accuracy and speed, increasing the possibilities of improving business performance (Agarwal and Brem, 2015). In addition, companies using LSS may be able to adopt I4.0 technologies to achieve higher operational performance improvements (Tortorella and Fettermann, 2017).

Considering that I4.0 may play an important role in the effectiveness of LSS, this study can shed light on the innovations provided by such integration, since it is still under-researched (Osterrieder et al. 2020; Maia et al., 2023). Empirical research, which is based on practical evidence, has helped in elaborating and verifying proposed theories (Vamsi Krishna Jasti and Kodali, 2014). Some case studies on the topic have discussed only single-use cases on the operative level (Mayr et al., 2018; Powell et al., 2018). Furthermore, many literature review papers have focused on organizational theories instead of digital solutions for LSS (Pongboonchai-Empl et al., 2023). Some of these articles have reviewed the existing knowledge on I4.0 and its adoption barriers.

In contrast to developed countries, which have established national strategies for digitalizing industrial sectors, developing countries have only witnessed initiatives to transition to I4.0 at the corporate level (Bogoviz et al., 2019). Therefore, it is important to gather empirical evidence on the advancements and benefits of incorporating I4.0 into LSS implementation (Tortorella and Fettermann, 2017; Raj et al., 2020). Given this scenario, field studies and comparative analyses of cases performed in the same industrial sectors are necessary to understand how and why companies undergoing digital transformation in emerging economies have combined I4.0 technologies with LSS. Therefore, this study was guided by the following research questions (RQs):

(RQ1) *How can I4.0 technologies be used to support LSS practices in heavy vehicle manufacturing?*

(RQ2) *What requirements are needed to enable this integration?*

(RQ3) *How does such integration impact LSS performance?*

Our study aims to provide empirical evidence regarding the LSS practices supported by I4.0 technologies in heavy vehicle manufacturing Brazilian companies. On the other hand, the research is also theory-building, *i.e*., it proposes to investigate the key concepts about the contact points between LSS and I4.0, their interrelationships, and why such interaction exists (Corley and Gioia, 2011). The results were obtained through a two-case study, which is an established method of empirical research in operations management (Eisenhardt, 1989; Lameijer et al., 2021). The disclosure of the practice-technology relationship and the insights given by comparative analysis between two real cases can support practitioners in understanding the key requirements and anticipating the effects of the LSS-I4.0 transformation (Ciano et al., 2021).

The remainder of this paper is organized as follows. Section 2 provides a literature review on LSS and I4.0, and outlines the contact points between these concepts. Section 3 describes the research methodology. Section 4 provides the findings and results, followed by a detailed discussion, while Section 5 summarizes and concludes the article.

2. Literature Review

2.1 Lean Six Sigma

LSS is a continuous improvement strategy which aims to improve, quality, speed, cost and customer satisfaction (Albliwi et al. 2015). The Lean Manufacturing principles became globally known after the publication of the book *The Machine that Changed the World* (Womack et al. 1990), whose purpose was to present the Toyota Production System (TPS) later known as "lean production" (Akbulut-Bailey et al. 2012). On the other hand, the Six Sigma program was developed at Motorola by Bill Smith in 1986 to reduce defects and improve quality (Montgomery and Woodall, 2008). Although these two approaches have different origins, they are complementary (Antony et al., 2003; Sordan et al. 2020).

Lean manufacturing is based on removing waste by implementing *Just-in-time* (JIT) and *Jidoka* principles (Womack and Jones, 1996). Six Sigma, in its turn, aims to reduce variability and defects through the Define-Measure-Analyze-Improve-Control (DMAIC) and Define-Measure-Analyze-Design-Verify (DMADV) methods (George, 2002; Snee and Hoerl, 2003). LSS projects are performed by specialists, including champions, Master Black Belts, Black Belts, and Green Belts (Eckes, 2002; Albliwi et al. 2015).

While Six Sigma is conducted in a wide range of areas at different levels of complexity to reduce variation, in the lean production approach, project groups are usually established to perform continuous improvements (Andersson et al. 2006). Effective implementation of LSS can contribute to the development of an "aversion to waste" culture on the shop floor (Alnajem et al. 2019) as well as provide analytical skills for specialists, *e.g.*, green belts and black belts (Pyzdek and Keller, 2010; Snee, 2010). Management commitment, investment in training, change management, resource availability, proper application of statistical tools and data analysis are examples of critical success factors for the effective implementation of LSS (Albliwi et al., 2015).

To implement OPEX strategies in the automotive sector it is important to understand some specifics. Firstly, Shop Floor Management (SFM) is an alternative approach for implementing lean manufacturing because it defines the organizational structure present on the shop floor through standardized processes and has been widely implemented in automotive plants to systematize continuous improvement (Gaspar and Leal, 2020). Secondly, the performance of an assembly workstation can be defined by complexity sources, including (1) task complexity, (2) equipment and facilities complexity, e.g., robotics and material handling equipment, and (3) management coordination complexity (Johansson et al., 2020). Finally, the repetitive activities observed in the truck manufacturing industry are difficult to analyze because disruption based on unforeseen factors fluctuates and leads to big losses in time and productivity (Poswa et al., 2022).

2.2 Industry 4.0

The expression "*Industry 4.0"* was coined by the German government at the Hannover fair in 2011, reflecting a high-tech strategy to stimulate businesses around the CPS and smart factories (Kagermann et al. 2013). This term has evolved into an overall label for describing a new manufacturing era, becoming a buzzword for the future of production (Lasi et al. 2014). The I4.0 concept refers to a set of tools and methods able to change the industry radically through the integration and use of technologies such as RFID, cloud computing, 3D printing, IIoT, BDA, robotics and artificial intelligence, among others (Zheng et al. 2018; Osterrieder et al. 2020). In the manufacturing environment, the integration between Information Technologies (IT) and industrial automation has evolved into complex systems that combine hardware, software, sensors, microprocessors, databases, and connectivity, forcing companies to rethink how they do everything internally to face new threats and opportunities (Porter and Heppelmann, 2014).

As mentioned before, CPS and Smart Factory are related concepts within I4.0. While CPS involves smart machines, storage systems and production facilities capable of exchanging information, triggering corrective actions, and controlling each other independently (Kagermann et al. 2013), Smart Manufacturing is defined as an emerging form of production that integrates manufacturing assets with sensors, computing, communication technology, control, simulation, data-intensive modeling, and predictive engineering (Kusiak, 2018).

2.3 Contact Points between Lean Six Sigma and Industry 4.0

The research developed under this topic refers to the symbiosis between LSS and I4.0 to expand the possibilities of performance improvement. Kolberg et al. (2017) explain that contrary to popular belief, lean manufacturing does not exclude automation. These authors provide examples of an interface for digitizing lean production methods using CPS. According to Sony (2020), BDA and I4.0 can effectively support LSS through variability analysis and data-driven methodology since the physical facilities are connected by embedded sensors, processors and actuators operating in a CPS environment.

The results from a survey conducted by Tortorella and Fettermann (2017) suggest that most companies with a higher adoption level of I4.0 technologies also stated a higher implementation level of lean manufacturing. However, as stated by Rüttimann and Stockli (2016), when not put into the proper context of fundamental manufacturing laws (*e.g.*, variability and cycle time), the I4.0 initiative as a whole *"has a high probability to fail"* (p.499).

Table 1 summarizes part of the literature regarding the Contact Points (CPs) addressed in this paper. Although several models and frameworks on the topic have been released in the last years (Kolberg and Zühlke, 2015; Dombrowski et al., 2017; Gupta et al., 2020), this research is an extension of a previous study (Sordan et al., 2021), which sought to identify the key elements for the integration of I4.0 technologies into LSS practices through an in-depth systematic literature review. Figure 1 shows the conceptual framework covering the 13 CPs (RQ1), the technical requirements (RQ2), including information technology, automation, and competencies, and the outcomes expected from this integration (RQ3).

**** TABLE 1 ABOUT HERE ****

**** FIGURE 1 ABOUT HERE ****

3 Research methodology

The type of research questions plays a significant role in determining whether an extensive or an intensive approach is needed. This study is descriptive, exploratory, qualitative, and intensive. It focuses on a contemporary phenomenon and aims to answer the RQs (how and what) through a descriptive approach without the researcher interfering with the object of study. Moreover, our research utilized an intensive approach by conducting a deep investigation of the phenomenon through a two-case study to address all RQs effectively.

To achieve literal replications, researchers need multiple cases to determine if the theory can withstand varying conditions or if it needs adjustments (Swanborn, 2010). For this reason, our study does not aim to generalize conclusions but to obtain an analytical validation consisting of comparative cross-case analysis in order to provide comparisons of similarity or contrast information (Yin, 2009; Lameijer et al. 2021). 'Reputation' and examples of cases identified on social media comprised the list of companies with potential eligibility. The cases were then selected through the mandatory criteria detailed in Table 2. To ensure their privacy, such companies will be referred to as "CoA" (company A) and "CoB" (company B). Table 3 summarizes the main characteristics of the surveyed companies.

**** TABLE 2 ABOUT HERE ****

**** TABLE 3 ABOUT HERE ****

Primary data were gathered through interviews with managers, leaders, and specialists who participated in digital transformation projects in their respective companies. Data collection was performed between May and December 2019, following a case study protocol and interview script (Appendix A). The profile of the respondents is shown in Table 4. *In loco* interviews were conducted to facilitate access to the facilities and data collection. The empirical research resorted to a triangulation approach, including documents, interviews and *in loco* observations.

**** TABLE 4 ABOUT HERE ****

Following the sequence shown in Appendix A, the interviews were carried out in two stages, lasting approximately 50 minutes. The representativeness and consistency of the sample in qualitative studies depend more on the concepts extracted than on the number of people interviewed (Corbin and Strauss, 1990). Thus, while mapping questions were designed to open research territory and identify the dimensions and aspects relevant to the participant, mining questions were used to explore the details within each dimension or interview section (Legard et al. 2013). Many case studies resort to broad, orienting questions through an exploratory approach. However, new research topics need not start with broad questions but with a series of closed, precise questions (Swanborn, 2010). Therefore, closed-ended mapping questions were used in the first stage of the interview to capture the respondents' perceptions regarding the level of implementation of each CP through a scale from (1) "totally disagree" to (5) "totally agree."

To prioritize the CPs for in-depth investigation in this study, the authors used the Favorable Response Index (FRI), which indicates the percentage of the sum of the "4" and "5" answers on the scales. The questions with FRI $> 50\%$ and median ≥ 4.0 were then selected for in-depth investigation through open-ended mining questions. The interviews were recorded and transcribed using N-Vivo software. Next, the primary author classified and coded the data in a spreadsheet based on the framework depicted in Figure 1.

A spreadsheet was structured in columns containing an identification of the interviewee, transcription of the recording, codes and their respective categories (*i.e.*, CPs, technical requirements and results), For example, the statement *"We have a vision system that scans the cutout geometries in real-time. In case of deviations, this system automatically blocks the process, and an alert is triggered through MES"* was coded as computer vision - automatic controls - real-time information – MES – CP12.

As recommended by Corbin and Strauss (1990), Bardin (2008), and Yin (2009), the data coding procedure was carried out as a data reduction strategy. Thus, open and axial coding techniques were used to summarize the collected information to retrieve information from the narratives and link it to the conceptual framework and research questions. Then, conceptual maps were designed to compare the evidence observed in each case with the framework and identify similarities or dissimilarities between the perceptions of both groups of professionals involved. The conceptual maps graphically reflect the main variables, the key factors of the studied phenomenon and the causal relationships between them (Voss et al., 2002).

Finally, a complementary cross-case analysis was performed using Network Analysis (NA). A spreadsheet containing the frequency of codes was processed in the Gephi software. The primary elements (CPs, technologies, technical requirements, and results) were represented by the nodes, where their associations (frequency) were represented by the edges, in order to provide a graphical view of the relationships between such elements.

The perspective of networks involves theories, models, and applications that express relationships between units, conceptualizing a structure as patterns of relations between actors or concepts (Wasserman and Faust, 1993). In this analysis, the following metrics were used: (1) *degree*, which refers to the number of links for a given node; (2) *eccentricity*, which informs the maximum distance to the other nodes or the farthest node from it in the network; (3) *closeness*, which is a measure of proximity (average of the shortest path to reach another node); and (4) *betweenness*, which quantifies the number of times a node acts as a bridge between two other nodes along the shortest path.

4. Findings and results

4.1 Case overview (CoA)

In 2018, CoA implemented a truck assembly line in the metropolitan region of São Paulo, designed and adapted for the I4.0 concept. An integrated management system supports the company's continuous improvement strategy through nine lean principles. As an OPEX strategy, production supervisors must implement at least two kaizens per year, covering five levels. At the 1st level (*quick wins*), simple ideas proposed by the operators are implemented in a short time. The 2nd level is called "*quick kaizen*" and involves implementing two-day kaizen events. In the 3rd level, *traditional kaizens* are accomplished through 5-day workshops. At the 4th level, projects with greater scope and duration (*six-week projects*) are carried out by specialists. Lastly, at the 5th level, the "*expert projects*" are assigned to specialists, including green belts and black belts, who are proficient in advanced LSS techniques.

Since 2019, the CoA has been implementing Proof of Concepts (PoCs) based on ten I4.0 pillars. According to the interviewees' perception, the technologies with the most adherence to the manufacturing processes and supply chain operations include (1) BDA and (2) IIoT, which were implemented before the PoCs; (3) cloud computing and (4) cybersecurity, which are understood as critical technologies for vertical integration; (5) AGVs "Automated Guided Vehicles" and (6) AIVs "Autonomous Intelligent Vehicles," implemented to support internal logistics through (7) RFID communication; and (8) collaborative robotics (COBOTs) used for applying glue and silicone in the assembly of panels. Table 5 shows the frequencies of scores assigned to the questions referring to the 13 CPs. As explained before, only the CPs with FRI > 50% and median ≥ 4.0 were selected for in-depth investigation. The evidence obtained for CPs 3, 8, 11, and 13 was insufficient for this analysis. Table 6 summarizes the CPs evidenced in the CoA.

**** TABLE 5 ABOUT HERE ****

**** TABLE 6 ABOUT HERE ****

The *IT architecture* required to implement the CPs involved the integration of mobile devices (handheld), touch monitors, WiFi, and cloud (MM1; SM1). Interviewees TA1 and MM1 also mentioned system integration operating systems. On the other hand, among the most cited *Automation Requirements*, the following stand out (PC1; MM1; PA1; QM1; OM1; SM1): Network automation, communication protocols, sensors and actuators, RFID, AVGs/AIVs, and Man Machine Interface (MMI). Regarding the *competence requirements*, some interviewees highlighted the importance of people's participation in PoCs (TA1; IM1; PM1; LP1; LM1). According to them, this practice generally covers agile and ideation methodologies, training through a "learn by doing" approach, and actions to promote a "digital culture". One of the interviewees made the following observation:

> We are performing several PoCs in partnership with technology providers and startups. Some of them are successful, and some are not. However, we have learned a lot from these outcomes (TA1).

To fill some skill gaps, CoA has developed on-the-job training and hired IT professionals. It is also worth noting that a project to test the use of an exoskeleton on the assembly line was cited as a requirement for people to improve ergonomics and safety in the workstation (PC1). The survey pointed to gains in terms of cost reduction, waste elimination, efficiency, quality, bottleneck management, real-time information, paperless management, and increased competitiveness. The conceptual map shown in Figure 2 summarizes the evidence collected in CoA. From a bottom-up perspective and following the logical sequence of RQs, the concept map illustrates the most reported CPs, the necessary technical requirements, and the results obtained.

**** FIGURE 2 ABOUT HERE ****

4.2 Case overview (CoB)

CoB supplies structural components for commercial vehicle markets, including frames, suspension and transmission modules, chassis and stringers for heavy trucks and buses. Cross-functional teams have promoted the digital transformation at CoB through experimental projects emphasizing vertical integration, and computer vision systems. The production process of chassis and stringers represents the company's highest level of digitization.

The operational excellence strategy at CoB has emphasized Lean Manufacturing practices. However, some experts (including yellow, green, and black belts) have implemented "Advanced Statistics Projects" through the DMAIC framework. The company developed a Direct Communication Card (DCC) practice, which promotes daily kaizens involving all operators. Additionally, lean practitioners have implemented kaizen events covering topics such as Material Information Flow Chart (MIFC), which replaces the traditional Value Stream Mapping (VSM), standardization, 5S, and SMED.

The I4.0 strategy at CoB is part of a "high-level plan" established by the corporation over a six-year horizon. The company has implemented some projects involving suppliers and development agencies (QM2). Among the I4.0 technologies mentioned by respondents, the following stand out: (1) BDA; (2) vertical integration; (3) IIoT; (4) cybersecurity; (5) cloud; (6) additive manufacturing for prototypes; and (7) RFID. The responses obtained for the level of implementation of the 13 CPs with their respective FRI are shown in Table 7. The evidence and statements regarding the CPs with FRI > 50% and median ≥ 4.0 are shown in Table 8.

**** TABLE 7 ABOUT HERE ****

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The *IT architecture* required to implement the seven CPs reported covers system integration (sensors, Programmable Logic Controller - PLC, Manufacturing Execution System - MES, Supervisory Control and Data Acquisition (SCADA), ERP, and Microsoft Power BI), out-tasking services, database architecture, and computer vision systems. Information security is managed through a hierarchy with permissions levels (MA1). Inquiries into *automation requirements* revealed that the elements most cited by respondents cover technologies such as PLC, RFID, sensors and actuators, wireless, Bluetooth, and M2M communication.

Regarding *competence requirements* at CoB, knowledge of software engineering and network architecture, proficiency in data science and analytics as well as online training were mentioned by three respondents as necessary skills for the implementation of CPs. Competence development actions have included participation in workshops, conferences and international fairs, where several questions were clarified, and insights were generated (EA1; TD1). The company's human resources strategy also covered programming language workshops, promoting a digital culture, and hiring IT experts to support digitization projects. The budget for training actions is established *ad hoc*, based on the percentage of the company's budget approved for the project (MA1; QA2).

> We need many IT skills, but when the IT experts joined our teams, it became a revolution. The projects would not have evolved if these people had not been hired (QM2).

Finally, the results most reported by the interviewees include competitiveness, quality, reliability, waste elimination, cost reduction, and real-time information. According to two respondents, competitiveness in the automotive industry means offering a faster development of more complex and customized products. This advantage can be achieved by cost reduction and eliminating waste (QA1 and QA2). Figure 3 depicts the conceptual map of CoB.

**** FIGURE 3 ABOUT HERE ****

4.3 Cross-case analysis

Aiming to achieve literal replications, we contrast the evidence of the second case based on the initial case study's findings. In all cases, the implementation of CPs followed a top-down approach, with pilot projects and PoCs performed by cross-functional teams assisted by IT professionals and technology providers. However, the characterization of CPS and BDA differs between the companies. The automation level analysis (see item 8.2.1 of Appendix A) reveals that 57% of interviewees from CoA possess a clear understanding of the plant's “network” configuration, while 50% of respondents from CoB perceive the automation of the process as an “optimization” level. At CoA, data captured by the physical world is used for maintenance purposes and computer vision in the engine assembly line. However, at CoB, data from machines and equipment is extensively analyzed using machine learning algorithms to identify cause-and-effect relationships. Table 9 compares some managerial and technological aspects observed in the two companies.

Data from the two cases were grouped to generate an overall perspective concerning the adherence to the research framework. The CPs classified as non-adherent were excluded from this analysis. Figure 4 shows the network with 71 nodes and 84 edges. These nodes were colored according to the categories of analysis. For instance, nodes indicating the CPs were highlighted in red. Node metrics of degree, eccentricity, closeness and betweenness were calculated and summarized in Appendix B. The measurements associated with the node's IT, automation, competencies and results were not considered because they refer to categories of analysis.

Among the IT and automation requirements (highlighted in blue), MES, RFID, and AGVs/AIVs (degree = 4) stand out. Conversely, Data Science has the highest degree regarding competence requirements (degree = 3). Regarding *eccentricity*, 95% of the nodes are relatively far from other nodes (eccentricity ≥ 5), except for CP7, which connects 'intuitive programming' with 'COBOTs' (eccentricity = 2). This result confirms that there is heterogeneity among the components of the network.

As shown in Figure 4, the thickness of the edges provides information about the technical requirements. System integration (weight = 11.0), database and IIoT (weight = 6.0) stand out among the IT requirements, indicating a strong association of these elements as fundamental IT requirements for the implementation of CPs. Regarding automation requirements (highlighted in purple), RFID (weight = 10), communication protocols (weight = 8) as well as sensors-actuators and PLC (weight = 6.0) were reported more often. The competence requirements (highlighted in yellow) emphasize Data Science (weight = 9.0), on-the-job training (weight = 8.0) and digital culture (weight = 6.0).

The results perceived by respondents (highlighted in green) are more expressive in terms of productivity (weight = 11.0), competitiveness (weight = 9.0), cost reduction (weight = 8.0), real-time control, waste elimination, and quality (both with weight = 7.0). This network also reveals direct connections between CPs and technical requirements. For example, implementing CP9 requires the integration of MES, WiFi buttons, and sensors/actuators, while CP7 involves intuitive programming and collaborative robotics. Based on the data summarized in Tables 5 and 6, we established the degree of implementation of the CPs as follows:

- *Adherent CPs*. This category includes CPs implemented in both companies, with FRI > 50% (CP1, CP2, CP4, CP9, CP10, and CP12).
- *Partially adherent CPs*. Encompasses CPs with FRI > 50% observed in only one company (CP3, CP5, CP6, and CP7).
- *Non-adherent CPs.* This category covers CPs not evidenced in the companies, with FRI < 50% (CP8, CP11, and CP13).

5. Discussion

The study's findings demonstrate how I4.0 technologies can support LSS practices by systematically addressing the research questions. We used the concept of 'contact points' from intensive and in-depth research to approach this phenomenon. The studied cases have provided insights and assumptions that can expand the current literature. As recommended by Swanborn (2010), we confront the existing literature with bridge assumptions to effectively tailor the theory to the specific situation. By contrasting the cases, we found similarities and dissimilarities between the perceptions of both professional groups. In both companies, the interplay between I4.0 and LSS has required system integration and a high level of automation, covering networks and optimization algorithms. The most adherent practices include digital mistake-proofing, digital *andon*, *e-kanban*, statistical monitoring, and process mapping aided by CPS and BDA.

Psarommatis et al. (2021) and Villalba-Diez et al. (2021) brought potential links between process control and digital technologies. According to them, digital technologies provide "intelligence" to machines through checking systems to block any defective part automatically. In the cases studied, process control was operationalized through a zero defect approach (Poka-yoke/ Jidoka) observed through CPs 2 and 12. These processes were efficiently supported by AI and system integration, operationalized with RFID, IMM, MES and computer vision systems. This specific approach has provided automatic error blocking and failure reduction. Thus, we assume that:

> ***Assumption 1****: Digital mistake-proofing solutions require communication protocols, connectivity, computer vision, simulation, and artificial intelligence to enable the automatic blocking of machines and reduce internal failure costs.*

The idea regarding the 'digital andon' was presented by Ma et al. (2017). This solution combines IoT, SOA, cloud, and real-time function blocks to trigger scenes based on real-time data. As discussed in the previous section, this CP has required systems integration (BI-MES-SCADA), M2M technologies (e.g., RFID, sensors, actuators, and AGVs or AIVs), and hardware resources, including handheld and touch screens for real-time visualization and control of production. As a result of this integration, the interviewees pointed out paperless management, real-time information, and increased productivity on the shop floor. Therefore, we assume that:

> ***Assumption 2****: Real-time production monitoring through "digital andon" requires system integration, M2M technologies, condition monitoring, and handheld devices to enable data visualization in real-time, promote paperless management, and increase productivity on the shop floor.*

In the context of digital manufacturing, physical cards could be replaced by *e-kanban* via sensors to avoid supply mistakes and empty bins (Kolberg and Zühlke, 2015; Romero et al., 2018). The research results showed that the automation of the inventory control and digital kanban relies on system integration (ERP-MES) and communication technologies (i.e., WiFi push button, pick by light, barcode, and sensing). The outcomes of "*e-kanban* projects" were associated with the elimination of waste (inventory and overproduction). This empirical evidence complements the previous literature (Romero et al. 2018; Eleftheriadis and Myklebust, 2016) and suggests that the implementation of an *e-kanban* system requires the integration of production planning and control systems and communication technologies. Thus, we assume that:

> ***Assumption 3:*** *Digital kanban (e-kanban system) requires the integration of production planning and control (PPC) systems and communication technologies,*

such as WiFi push button switches, barcodes, QR-Code, scanners, sensors, smart tags, smart bins, and pick by light technologies, in order to reduce inventory levels, overproduction, and material costs.

From the BDA perspective, new database architectures, combined with real-time data analytics and SPC systems, can take place in real-time error corrections to reduce rework and scrap (Romero et al. 2018). Additionally, capability analysis and SPC through CPS and BDA rely on database management and specific skills to deal with new analytics techniques (Eleftheriadis and Myklebust, 2016). As shown in Tables 6 and 8, both cases indicated a readiness to handle databases and offer real-time statistical control (CP4). However, there is no standardized approach to predictive analysis across the organization. Thus, we assume that:

Assumption 4: *Statistical process monitoring in CPS requires vertical integration, proper database infrastructure, and predictive analytics skills to predict process deviations, as well as promote real-time controls and defect reduction*.

The literature related to process mapping aided by CPS (CP1) emphasizes the integration of technologies such as IoT, RFID, simulation, and BDA to develop and monitor 'dynamic VSM' (Lugert et al. 2018; Mayr et al. 2018; Serio et al. 2021). This CP can provide and predict output information including occupied spaces, human interfaces, the flow of materials and people and operational performance (e.g. OEE, lead time, production volume, quality, reliability and inventory). However, the evidence provided in this study highlighted the contribution of CP1 to the identification of bottlenecks and waste using data from AGVs, AIVs, RFID, and simulation. Thus, we assume that:

Assumption 5: *The analysis of value streams on the heavy vehicle shop floor is facilitated by simulation using communication technologies and AGVs-AIVs to identify bottlenecks and increase productivity through real-time data.*

Analysis of partially adherent PCs suggests that BDA is not effectively used to monitor machines and customer information. Furthermore, the utilization of collaborative robotics, AGVs and AIVs is contingent upon the specific characteristics and requirements of the factory's internal logistics. Finally, the results clearly indicate that digital practices such as 'setup reduction using machine learning', 'quality control powered by robotics', and augmented reality are still in the early stages in the Brazilian heavy vehicle manufacturing sector.

6. Conclusions

This paper provided empirical evidence regarding the LSS practices supported by I4.0 technologies in heavy vehicle production. The relevance of this study to the OPEX field is due to the possibility of expanding the use of traditional LSS tools such as *kanban*, *andon*, process mapping, control charts, etc. Among the thirteen CPs found in the literature, the results contrast six adherent CPs in both companies. The LSS practices most aided by I4.0 technologies include mistake-proofing solutions, real-time production monitoring (digital *andon*), *e-kanban* systems, statistical process monitoring, and process mapping.

The Top 3 IT requirements covered system integration, IIoT, and databases. Technologies such as RFID, PLCs, sensors, actuators, and communication protocols were reported as essential automation requirements. Finally, the competencies most evidenced by the interviewees encompass on-the-job training, analytics skills, and digital culture. Beyond the goals commonly associated with LSS practices (*e.g.*, quality, cost, and delivery), we found other results, including real-time process control, traceability, paperless management, and bottleneck optimization. Furthermore, the interviewees reported an increase in internal efficiency logistics (20 to 25%), reduction of warehouse spaces (88%), improved average storage time (from 10 to 3 days), improved efficiency in handling tasks (80%), and increased overall efficiency (15 to 20%).

Managerial implications

Although the findings of this study may encourage new LSS projects supported by digital technologies, managers and practitioners should take note of some implications. First, apart from the technical requirements discussed in both cases, the results showed that change management is essential for a successful digitization strategy. The conceptual maps and NA highlight the term "digital culture," which was cited six times. In this regard, Kane et al. (2015) warn that the relationship between I4.0 and organizational culture requires a new mindset in the leaders before technological changes are implemented. Moreover, Küpper et al., (2019) warn that change management, communication and long-term planning are the most important skills to enable the success of I4.0.

Second, contrary to traditional LSS practices that require low investments in software, hardware, and training (George, 2010; Pyzdek and Keller, 2010; Albliwi et al., 2014), the I4.0 technologies implemented in both companies have demanded large investments to implement systems and automation architectures. For instance, CoA implemented a new cab assembly line equipped with IIoT, computer vision, a vertical warehouse, an overhead transportation system, collaborative robots, and AVGs/AIVs. The investments in these technologies surpassed US$ 500 million between 2018 and 2022. On the other hand, efficiency in handling tasks has increased 80% while overall line efficiency increased between 15 to 20%. Although respondents from CoB did not report CAPEX, some investments were directed to acquire computer vision and automated measurement systems according to internal documents. This scenario is consistent with the literature since I4.0 technologies may demand more investments (Rüttimann and Stockli, 2016).

Investments in cybersecurity could be justified in terms of access control, data integrity, cyber-physical attacks, vulnerabilities associated with lack of encryption and lack of security on web platforms, and data access blocking systems and firewalls (Kagermann et al. 2013; Lee and Lee, 2015). Such concerns can mitigate or minimize the risks and uncertainties related to the CPs. Finally, considering the operational risks inherent in the heavy vehicle industry, including information and technology system malfunction, delivery chain disruptions, and machine failure (Thun and Hoenig, 2011), the lessons learned from this study could provide insights for new OPEX projects suitable for this specific branch of manufacturing.

Limitations and future research

While the study provides valuable insights from two companies in the heavy vehicle industry, it's important to note that the findings may not be applicable to the entire automotive industry. However, this paper can help practitioners and researchers by providing new digital LSS practices. On the other hand, part of the evidence collected reflects the perception of the professionals interviewed. The cut-off of 50% was arbitrarily defined to select the CPs with the highest agreement among interviewees for subsequent in-depth investigation. Considering that the LSS projects performed in both companies reflect their OPEX cultures with an emphasis on lean practices, the CPs reported here were not clearly associated with the phases of the DMAIC/DMADV models. Another limitation concerns the scope of enabling technologies investigated in depth, given the absence of evidence regarding the non-adherent CPs.

Future research could fill the following gaps: (1) setup time reduction aided by machine learning algorithms; (2) quality control supported by collaborative robotics; (3) inspection and standardization aided by augmented reality; (4) additive manufacturing to support waste reduction on the shop floor; (5) use of I4.0 technologies associated with DMAIC/DMADV phases; and (6) green/black belt training program enriched by data science and analytics techniques.

Despite these limitations, we hope that our findings may encourage further studies around the topic, radiating the application of digital LSS practices. Future works can be extended to validate the evidence provided in this paper using a large-scale questionnaire survey. In addition, complementary research approaches, like design science research and qualitative comparative analysis, could be applied in further research in order to generate more perspectives on the results.

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