Integration Opportunities between Industry 4.0 and Lean Six Sigma; A Systematic Review and Company Perspectives

Bridging the Gap for Enhanced Operational Excellence

Master's thesis in Production engineering

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Abstract

The master's thesis aims to provide a comprehensive overview of integration possibilities between Industry 4.0 and Lean Six Sigma through a systematic literature review and interviews with leading manufacturing companies in Sweden.

A sample of 99 publications was analyzed using bibliometric indicators, and an in-depth analysis of 41 highly topical articles was conducted. Semi-structured interviews were conducted with seven manufacturing companies to gather information on their current state of digitalization maturity and LSS adoption.

The findings from the literature review indicate a synergistic relationship between Industry 4.0 and LSS, leading to highly productive and agile manufacturing organizations. The study identified 11 Synergy Points, representing instances of integration between Industry 4.0 technologies and LSS concepts. Interviews with companies provided insights into LSS usage and digitalization, serving as a benchmark for the current manufacturing landscape in Sweden. The results indicate that there is still untapped potential for further development in these areas.

This thesis contributes to understanding LSS 4.0 by exploring the interactions between novel digital technologies and LSS practices. It offers valuable insights for process improvement professionals and serves as a resource for future operational excellence projects. The Synergy Points presented in this research provide inspiration and practical knowledge for industry professionals interested in adopting Industry 4.0 technologies and leveraging their synergies with LSS.

Keywords: Industry 4.0, Lean Six Sigma, Lean, Six Sigma, Systematic literature review, Digitalization.

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SIMON GOYA, Gothenburg, June LINUS BERG, Gothenburg, June

List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

AGVs	Automated Guided Vehicles
AI	Artificial Intelligence
AMRs	Autonomous Mobile Robots
AM	Additive Manufacturing
AR	Augmented Reality
BDA	Big Data & Analytics
CAD	Computer-aided Design
CPS	Cyber-physical System
DMADV	Define, Measure, Analyze, Design, and Verify
DMAIC	Define, Measure, Analyze, Improve, Control
FMEA	Failure mode and effects analysis
GLSS	Green Lean Six Sigma
I4.0	Industry 4.0
IIoT	Industrial Internet of Things
IoT	Internet of Things
JIT	Just-in-Time
KPI	Key Performance Indicator
LSS	Lean Six Sigma
OEE	Overall Equipment Effectiveness
PDCA	Plan, Do, Study & Act
RFID	Radio Frequency Identification
SLR	Systematic Literature Review
SMED	Single-Minute Exchange of Die
SP	Synergy Points
VR	Virtual Reality
VSM	Value Stream Mapping

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1

Introduction

This chapter provides the context of the thesis, focusing on the integration opportunities of Industry 4.0 (I4.0) technologies with Lean Six Sigma concepts in the manufacturing industry. The purpose and research questions are outlined, along with the limitations and scope of the study.

1.1 Background

The manufacturing industry is continuously changing as a result of the ongoing industrial digitalization of companies worldwide. In Sweden, the digital infrastructure is developing rapidly, and outdated technologies and processes quickly become obsolete. To retain their competitive advantage, leading companies must encourage innovation and actively pursue technological advancement (Shimray & Vinodh, 2023).

According to Skalli et al. (2023), concepts such as digitalization and continuous improvements should no longer be considered simply good practices; they are vital business fundamentals. With an increase in organizational complexity - as a result of ever-changing customer needs and a developing technological environment - manufacturing organizations must become more flexible and coordinated (Efimova & Briš, 2022). To stay competitive, leading companies must revise their manufacturing systems to enable increased productivity and effectiveness (Kashyap, Yadav, Vatsa, Chandaka, & Shukla, 2022).

When striving towards a more profitable, efficient, and competitive organization, companies traditionally initiate some form of Lean Six Sigma (LSS) implementation (Antony, McDermott, Powell, & Sony, 2022). Today, many large and medium-sized Swedish international enterprise work with Lean, Six Sigma, or a combination of them both, many of which have documented how LSS has improved company performance significantly. Since using LSS has been shown to notably improve business performance, companies can only remain competitive by digitalizing their LSS practices. This is especially important in the context of the fourth industrial revolution since it is theorized that digital transformation has a significant impact on organizational performance (Calabrese, Dora, Levialdi Ghiron, & Tiburzi, 2022) and that there is a positive relationship between the application of digital tools and novel technologies (Industry 4.0), and LSS initiatives (Anass, Amine, Ibtissam, Bouhaddou, & Elfezazi, 2021; Efimova & Briš, 2022; Fortuny-Santos, Lopez, Lujan-Blanco, & Chen, 2020; Skalli et al., 2023; J. E. Sordan, Oprime, Pimenta, Silva, & González, 2022; Yadav, Shankar, & Singh, 2021). I.e., the merger of the two philosophies will allow companies to take advantage of the resulting synergies acting on operational excellence, providing a competitive edge in the market. However, more empirical evidence is still needed to determine the nature of their integration (Sartal & Llach, 2021). Naciri et al. (2022) suggests that Industry 4.0 is essential in the adoption of Lean - and when the two concepts are combined, they become an exceptional tool (Skalli et al., 2023). Thus, it is proposed that the integration of LSS and Industry 4.0 will bring innovation, continuous improvements, and increased response time (Shimray & Vinodh, 2023). Consequently, the immense potential of Industry 4.0 has led to a rippling effect in the manufacturing industry, where more and more companies are strategically pursuing digital transformation (Butt, 2020).

The literature on the intersection of LSS and Industry 4.0 is scarce, lacking descriptions of practical applications and real implementations in the manufacturing industry. The overwhelming number of research papers has focused on how the integration between Lean/Six Sigma/LSS and Industry 4.0 affects organizational performance - do the concepts work in symbiosis, or are they incompatible? As mentioned earlier, several authors have proposed that the integration of Industry 4.0 and LSS do, in fact, have a net positive effect on operational effectiveness. More recent research efforts have investigated the links between the two concepts (Bertolini, Esposito, Neroni, Rizzi, & Romagnoli, 2019; Macias-Aguayo, Garcia-Castro, Barcia, McFarlane, & Abad-Moran, 2022; Walentynowicz & Pienkowski, 2020), answering the questions of *which* Industry 4.0 technologies may facilitate LSS, and why they bring value to the management philosophy. Pekarčíková, Trebuňa, and Kliment (2019) couples specific Industry 4.0 technologies (IoT, AR, BDA, etc.) with different LSS concepts (5S, Kaizen, JIT, etc.). Yet, research on the actual implementation - relating to the *how* - is somewhat limited. How can Industry 4.0 technologies be leveraged to facilitate LSS initiatives, from a technical standpoint? Narula et al. (2023); Valamede and Akkari (2020b) provides a more in-depth analysis of how total digital solutions are derived from combining different novel technologies with specific LSS concepts. J. E. Sordan et al. (2022) have created a comprehensive framework for the integration of LSS and Industry 4.0 technologies, offering detailed implementation solutions and how-to's for practitioners to follow - essentially, establishing a bridge between the two concepts.

1.2 Purpose and aim

The purpose of this master's thesis is to provide a thorough overview of existing state-of-the-art digital solutions relating to LSS, as enabled by Industry 4.0 technologies. The aim is to identify innovation opportunities within LSS and digitalization by examining cutting-edge research and exploring different industry leaders' digital transformation initiatives. Through this examination, the thesis aims to map the landscape of LSS and digitalization, identify key trends, and provide a structured approach for organizations to efficiently leverage digitalization.

1.3 Limitations

The master's thesis was subject to certain limitations:

- A 20-week time limit to finish the research, which has constricted the depth of the investigation.
- The selected keywords may have constrained the level of scope of the literature review.
- Due to the extensiveness of the topic, this thesis has focused on a specific set of 19 LSS concepts.
- The number of examined manufacturing companies was restricted to 7 Swedish companies, which may limit the generalizability of the findings.
- Neither technical implementation challenges nor soft barriers related to managerial principles are considered.

1.4 Research questions

This thesis explores how Industry 4.0 technologies can be integrated into LSS through a set of research questions:

I Which digital methods and techniques can be found in the literature on Lean Six Sigma?

The objective is to identify and present several examples of integration opportunities between Industry 4.0 technologies and LSS concepts.

II Which digital methods and techniques are used in the companies for Lean Six Sigma?

By analyzing industry leaders' As-Is state (relating to digital LSS implementation), digital solutions related to LSS can be identified and the existing landscape of leading companies in Sweden can be mapped.

III Which LSS concepts should companies and researchers prioritize in the future regarding Industry 4.0?

By comparing the findings from the literature with the current digital LSS efforts at leading companies, the most critical areas can be identified.

2

Theoretical framework

In the following chapter, a theoretical framework is presented to provide the necessary knowledge regarding the topic of this paper. The chapter is divided into six sections, which cover Industry 4.0 and related technologies, Lean manufacturing along with the Lean concepts discussed in this paper, Six Sigma, Lean Six Sigma, how Industry 4.0 can be seen as an enabler of LSS, and lastly, the sustainability aspect of Industry 4.0 and LSS.

2.1 Industry 4.0

According to Turconi, Ventola, González-Prida, Parra, and Crespo (2022) the term Industry 4.0, which refers to the fourth industrial revolution, was first introduced by Siemens in the Hannover exhibition in 2011. Although the concept of Industry 4.0 was officially announced in 2013 as a German strategic initiative to take a pioneering role in industries (L. D. Xu, Xu, & Li, 2018).

Also stated by Turconi et al. (2022), the fourth industrial revolution is considered the last evolution of the industry since its birth in the 18th century, beginning with the first industrial revolution where steam engines were one of the key elements. Then followed the second revolution also known as the technological revolution that began in 1870, which was characterized by the beginning of electrification and widespread use of machinery in manufacturing. The third industrial revolution, also referred to as the digital revolution, began in the late half of the 20th century and was the transition from mechanical and analog electronic technology to digital electronics.

Industry 4.0 can be summarized as smart manufacturing, which aims to integrate emerging technologies into all aspects of manufacturing. By applying the principles of cyber-physical systems (CPS), Internet, and smart systems with enhanced human-machine interaction, Industry 4.0 enables seamless communication throughout the value chain (Sanders, Elangeswaran, & Wulfsberg, 2016) and allows for real-time monitoring of production systems (Zhou, Liu, & Zhou, 2015).

The concept of Industry 4.0 can be divided into several different emerging technologies, which are described further in this section, the technologies are summarized in Figure 2.1.

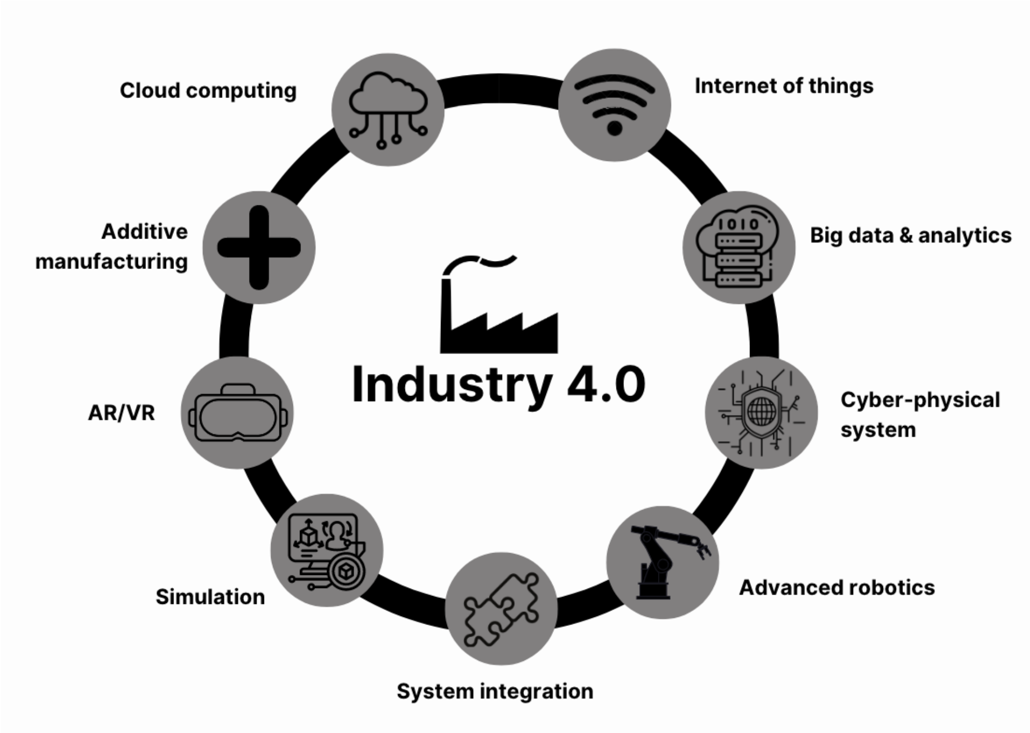

Figure 2.1: Technologies that constitute Industry 4.0, used in this paper

Simulation

The meaning of simulation in the context of Industry 4.0 refers to the simulation of industry behavior and plant operations management - data is collected from a real-world operation and is transferred into a virtual environment where the operation along with the collected data is presented (Turconi et al., 2022).

According to (Moreno et al., 2017), simulation is considered a good option for saving time and resources. It allows for management to do extensive testing, optimization, and evaluation of a new or existing operation before implementing or modifying it, which means the correct decision can be made based on reliable data (Saucedo-Martínez, Pérez-Lara, Marmolejo-Saucedo, Salais-Fierro, & Vasant, 2018; Turconi et al., 2022). Being able to test an operation before implementation is extremely advantageous as mistakes and failures can be found and corrected beforehand and therefore have no interference with the actual production, thereby the risks of new investments are reduced and management can execute the investment without hesitation.

Something that may limit the considerable benefits of simulation is the availability of reliable data. Achieving the desired results with the simulation, requires the input data to be of high quality (Turconi et al., 2022).

Internet of things (IoT)

IoT can be seen as a large category within Industry 4.0 as it covers all connected objects which transfer information or communicate over networks. Examples of such technologies are radio frequency identification (RFID) devices, sensors, global positioning systems (GPS), phones, cameras, etc. (Kumar, Rani, & Awadh, 2022; Zhou et al., 2015). In simple terms, IoT aims to connect the physical world with the digital world, which can be described with a quotation mentioned in Pallavi et al. (2022), "people and devices to be connected anytime, anywhere, with anything and with anyone".

IoT is also commonly referred to as the Industrial Internet of Things (IIoT) when in the context of Industry 4.0. IIoT can provide solutions and functions in a manufacturing setting which help to develop insight and can improve a company's ability to monitor and control their processes and assets (Lampropoulos, Siakas, & Anastasiadis, 2019).

Cloud computing

Today, a considerable amount of data is constantly flowing around and being collected, which requires space to store the data. With the rise of Industry 4.0, the amount of data for companies is also increasing significantly, and storing all this data internally would require a large amount of servers and computing power which would result in high costs for the company. By instead using the cloud, storage of data can instead be outsourced on a cloud-based service where the data is stored on servers for a fee which is based on the amount of data being stored (Lampropoulos et al., 2019; Lu & Cecil, 2015). In addition, companies in the industrial sector use several cloud-based applications for improving crucial areas of their operations such as customer relationship management and human resources (Lampropoulos et al., 2019).

One of the major benefits of using a cloud-based storage service according to Lampropoulos et al. (2019) is that the data can be accessed from any connected device in real-time, this can contribute to improved communication within a company as data is more accessible. Further benefits are reduced up-front costs along with lower entry-cost, reduced infrastructure and maintenance costs, and also the ability to scale up over time if needed (Lu & Cecil, 2015; Zhong, Xu, Klotz, & Newman, 2017).

Augmented reality (AR) & Virtual reality (VR)

AR and VR, which are similar to each other have seen an upswing in the later years since the technology has emerged at high speed. Even though AR was first introduced in 1968 and has been around for some time it is first now the technology has started to be used widely in several different fields and applications (Lavingia & Tanwar, 2020). The purpose of AR is to provide a modified physical environment for the users in real-time by presenting the physical world overlaid with electronic information such as text, graphics, and video (Díaz, Álvarez Gallego, Caro, & Portela, 2023; Lavingia & Tanwar, 2020). VR on the other hand is a completely computer-simulated virtual world that provides the user, the experience of being present in that world (Rajesh Desai, Nikhil Desai, Deepak Ajmera, & Mehta, 2014).

In the context of Industry 4.0, AR can be seen as a crucial element, especially when it comes to communication and information. The technology can contribute to several various industrial areas where there is a need for fast and detailed information such as work instructions, further on, it can help with the visual presentation of new developments as people can interact with a digital prototype before it is constructed (Nayyar, Mahapatra, Nhuong Le, & Suseendran, 2018; Zhong et al., 2017).

Additive manufacturing (AM)

AM is a process where a physical object is created based on a 3D model made in computer-aided design (CAD) software, the model is then sent to a printing machine that builds up the physical object layer by layer of material (Lemu, 2019). Additive manufacturing allows for a fast process, requiring fewer resources and steps compared to a traditional industrial process. In addition, the process also allows for free form and complex geometries which can bring great benefits to a company (Turconi et al., 2022).

These characteristics give the process great flexibility and speed, which enables changes to be carried out and implemented immediately, giving enterprises the ability to have both a fast prototype process and effective small-batch production of complex products. By streamlining the prototype process, companies can shorten the time between the prototype phase and production, further on, the process allows for higher customer integration as changes can be made and tested faster than before (Bogers, Hadar, & Bilberg, 2016; Turconi et al., 2022).

Big data & analytics (BDA)

Industrial big data refers to all the data that is generated within an industrial setting, including data collected from connected devices such as machines, mobiles, human-machine interfaces, sensors, etc. (Sharma & Pandey, 2020). This results in huge amounts of data being collected constantly, which can be used to assist in the decision-making process regarding the operational performance of a plant as it provides a clear overview of the current processes (Turconi et al., 2022). However, for the collected data to be useful, it must be properly analyzed. This is done with the help of advanced tools and technologies that can sort through large data sets and identify the most valuable pieces of information desired for the specific area (Saucedo-Martínez et al., 2018; Sharma & Pandey, 2020).

At this time, the use of BDA within companies has become a key factor for companies to stay competitive and profitable in the current fast-paced market (Turconi et al., 2022).

Artificial Intelligence (AI) is a branch of computer science and can be considered a subset of BDA. AI aims to simulate human cognition capabilities such as perception, learning, abstraction, decision, etc. (Perico & Mattioli, 2020). Further on, the overall goal of AI is to develop technologies that can augment human intelligence or assist in making undesirable jobs easier (Escobar, Macias, McGovern, Hernandez-de Menendez, & Morales-Menendez, 2022). According to (Perico & Mattioli, 2020), technology such as AI can be seen as a critical component for companies to extract valuable information from their large amount of collected data.

Cyber-physical systems (CPS)

CPS can be seen as one of the greater and more important concepts within Industry 4.0 and can even be considered as one of its main elements (Jiang, Yin, & Kaynak, 2018; Turconi et al., 2022; Zhang, Chen, Chen, & Chong, 2021). According to L. D. Xu et al. (2018), CPS can be described as engineered systems that are built on, and rely upon the seamless integration of computational algorithms and physical components to connect the virtual space with the real world. As the name suggests, the main purpose of CPS is to create a connection between the physical assets and the virtual world which can contribute with several major advantages in a manufacturing setting (Colombo, Karnouskos, Kaynak, Shi, & Yin, 2017; Monostori et al., 2016; Turconi et al., 2022).

CPS allows companies to have real-time monitoring and control of their processes. Furthermore, the collected data can be presented in the form of a digital twin which is a digital representation of a physical object or system, enabling faster and better decisions regarding the processes (Jiang et al., 2018; Jones, Snider, Nassehi, Yon, & Hicks, 2020). Further on, CPS is useful for predictive maintenance (Meesublak & Klinsukont, 2020), order and batch size planning (Huang, Chen, & Khojasteh, 2021), quality control (Colledani, Coupek, Verl, Aichele, & Yemane, 2018), and much more.

Advanced robotics

According to Kamarul Bahrin, Othman, Nor Azli, and Talib (2016), autonomous production methods powered by advanced robots are capable of performing intelligent tasks with high precision, safety, and flexibility is an essential area of Industry 4.0. Further on, the collaborative aspect is of high importance as robots and humans will be working hand in hand in the future. Cobots, automated guided vehicles (AGVs), and autonomous mobile robots (AMRs) are prime examples of robots that can collaborate with humans and enhance workflow.

A cobot is defined as a computer-controlled robot and is a collaborative robot that often is safer, smarter, and smaller compared to traditional industrial robots. Cobots also can be stopped when in contact with humans which makes them highly applicable in an Industry 4.0 setting (Goel & Gupta, 2020). AGVs are unmanned vehicles that are often used to transport goods in a factory or warehouse environment. In later years, AGVs have evolved into AMRs which have more advanced guidance systems allowing them to be more flexible and collaborative (Fragapane, de Koster, Sgarbossa, & Strandhagen, 2021; Mehami, Nawi, & Zhong, 2018). When discussing robotics in this paper, cobots, AGVs, and AMRs are mainly the technologies referred to.

System integration

The concept of system integration can be divided into two parts: vertical integration (intra-company integration) and horizontal integration (inter-company integration). Horizontal integration refers to a collaboration externally with various companies and stakeholders which allows for the creation of a seamless inter-connected system. This will enable easier exchange of data and information. Further on, vertical integration refers to the integration of systems within the company such as business systems, devices, etc., to allow for smoother collaboration and coordination between instances in the company (Suri et al., 2017).

In summary, system integration aims to interlink and connect an enterprise in its entirety along with its surroundings such as suppliers and stakeholders.

2.2 Lean manufacturing

Lean manufacturing, or simply Lean, is a widely recognized and well-established management philosophy and operational model that originated in the 1950s as part of the Toyota production system. The philosophy has a holistic approach, comprehensively encompassing several aspects of production at different levels - it provides a guiding philosophy, established principles, and a diverse array of practical tools (Cifone, Hoberg, Holweg, & Staudacher, 2021).

According to Bicheno and Holweg (2000), Lean - in its simplest terms - can be defined as “doing good for customers and stakeholders with less [sic] resources - materials, energy, pollution - to achieve ultimate sustainability”. Essentially, the model prescribes *doing more with less* (Liker, 2003; Ries, 2011; Womack & Jones, 1996), which has been a core tenet of Lean thinking for many years. Thus, Lean places a strong emphasis on the elimination of activities that do not add any value to the customer, i.e., waste.

Taiichi Ohno, the late industrial engineer who is considered the "father" of the Toyota production system, developed the concept of *the seven wastes* of Lean production. The concept aimed to identify and eliminate various forms of inefficiency in production, including overproduction, waiting, transportation, motion, inventory, defects, and over-processing. In more recent times, the concept has been revised to include an additional Lean waste - unused talent.

The description of the different types of wastes is as follows (Manos & Vincent, 2012):

- Defects
  Refers to faulty services or manufactured parts that do not conform to customer requirements.

- Overproduction
  Producing more parts than what is needed, i.e., stocking up on supplies that exceed the demand.

- Waiting
  Relates to idle machines and idle workers. Often the largest waste in lead-time calculations.

- Transport
  Handling and transporting material due to a poor factory layout or a sub-optimal transportation channel between facilities.

- Movement
  Any form of ergonomic movement of people or resources - both in the immediate and prescribed work areas.

- Inventory
  Keeping an unnecessary surplus of raw materials, components, finished products, etc. Inventory waste is directly related to both overproduction and waiting.

- Overprocessing
  When processing a part/product more than what is necessary to satisfy the customer requirements - e.g., achieving higher tolerances than requested.

- Unused Talent
  Not utilizing the employees' skills, knowledge, and expertise (Purushothaman, Seadon, & Moore, 2020).

2.2.1 The Lean toolbox

When implementing Lean, there is no one-fit-all solution - different organizations may require different approaches. According to Bicheno and Holweg (2000), the early renditions of the Lean framework were particularly tool-oriented and emphasized specific concepts such as Just-in-Time, Jidoka, Hoshin Kanri, 5S, etc. In newer renditions, however, stand-alone Lean concepts are down-played and overarching principles such as company culture, and "respect for people" are emphasized. Nevertheless, since this thesis deals with the digitalization of Lean concepts, the focus will be on said concepts.

As there are many different Lean concepts, a total of 19 concepts have been selected for this paper by analyzing the literature to determine the most frequently used Lean concepts. The concepts that are being addressed in this paper are briefly described here.

Gemba

Gemba walk is a powerful Lean concept for managers to gain a sincere overview and knowledge about their respective area that they are managing, Gemba walks are meant to engage managers and give them a detailed view of the production. The walks are mainly used to enhance the understanding of the processes for managers but are also important as it encourages managers to engage with the personnel at their workplace which can help show appreciation and boost morale among employees (Romero, Gaiardelli, Wuest, Powell, & Thürer, 2020).

Just in time (JIT)

The application of JIT to a production system represents a manufacturing approach that aims to reduce wastage related to time, labor, and storage capacity. The philosophy is based on the principle that a company should manufacture only the necessary products, at the required time, and in the appropriate quantity (Garcia-Alcaraz & Maldonado-Macias, 2015). This means that a company should only produce the number of products equal to the actual demand.

Kaizen & PDCA

Kaizen is a philosophy within Lean that refers to continuous improvement which can be described as a constant search for improvements in all aspects of an organization, further on, the concept aims to involve all employees in the improvement process ranging from the shop floor to the top management (Rewers, Trojanowska, & Chabowski, 2016a). The goal is to implement a way of working where all employees are engaged and work together in improving work areas, processes, and products in the organization, by suggesting and implementing improvements constantly, waste can be reduced and value-adding activities can increase (Helmold, 2021; Rewers et al., 2016a).

A commonly used tool within Kaizen is the PDCA cycle which stands for Plan, Do, Check, Act which is a four-step method used in the continuous improvement process. According to Helmold (2021), the PDCA process begins with the Plan step where the current situation is assessed and an improvement plan is defined. The suggested solutions are then implemented in the Do step. The results of the solutions are then evaluated in the Check step followed by the last Act step where the best solution is standardized if the results are satisfactory.

Single-Minute Exchange of Die (SMED)

According to Oliveira, Sá, and Fernandes (2017), SMED helps companies to reduce their setup and changeover times which may lead to valuable improvements in lead-time reduction, lower inventory, improved quality, etc. The method aims to reduce a machine's downtime during a changeover process, by identifying steps in the process that can be performed while the machine is still running, the actual downtime during a changeover can be reduced. According to the author, a common approach in SMED is to transform steps that can only be performed when the machine is down to steps that can be performed while the machine is running, this approach helps to reduce downtime and standardize the process.

Visual management

Visual management involves the use of visual aids to display information or communicate instructions where the main goal is to create a better understanding of processes and areas for all employees, allowing for better communication sharing and transparency in the company (Eaidgah, Maki, Kurczewski, & Abdekhodaee, 2016). Further on, visual management helps to direct information to the relevant people and can highlight problems that can contribute to problems being addressed sooner. Some examples of visual management tools within a Lean manufacturing setting are informative boards, Andon systems, and standardized work instructions.

Value-stream mapping

Value-stream mapping is a tool that allows for a detailed overview of the whole process, beginning with the acquisition of raw material to the final product (Oliveira et al., 2017). According to Tyagi, Choudhary, Cai, and Yang (2015) the VSM method is used to identify waste, non-value-added work, and inefficiencies in a process.

Kanban & Pull

As suggested by Arbulu, Ballard, and Harper (2003); Sundar, Balaji, and Kumar (2014), the Kanban system is a concept widely used in Lean manufacturing, whose aim is to control inventory levels, production flow, and production scheduling. The concept is strongly connected to pull and JIT, as the kanban system "pulls" material through the value stream according to the JIT approach. Arbulu et al. (2003) further explains Kanban as a sophisticated visual control system that centers on eliminating overproduction, enhancing flexibility to meet customer needs, and reducing waste.

The idea behind the method is to trigger material restocking only when necessary, through the use of signals, often in the form of cards containing relevant information required for a product or material (Sundar et al., 2014). Further on, there are two types of kanbans, transport kanbans, and production kanbans. Transport kanbans serve the purpose of either indicating the requirement for replenishing materials from a selected supplier or signaling the transfer of parts or subassemblies manufactured in-house to the production line while production kanbans are used to signal for initiating production or machinery changeovers (Arbulu et al., 2003).

Poka-yoke

Poka-yoke can more commonly be referred to as mistake-proofing, which means that a process or operation is secure from errors that may occur from mistakes (Rewers et al., 2016a). The main goal of the poka-yoke system is to engineer the process in a way so that making mistakes becomes impossible or easily detected and corrected instantly. By having such a system, time spent on training employees can be reduced, while still increasing the quality due to fewer defects occurring from simple mistakes (Fisher, 1999).

Andon

The Andon system is a cornerstone in the continuous flow aspect of Lean, the system allows an operator to halt production immediately if a defect is suspected, and at the same time, the system alerts management or other relevant personnel of the problem resulting in immediate response to the situation. The system is constructed so that operators push a button or pull a cord at the production line, which triggers a signal that a problem has occurred. The signal makes the responsible supervisor aware of the problem which allows them to assist in solving the problem and restart production as quickly as possible (Everett & Sohal, 1991).

Overall Equipment Effectiveness (OEE)

OEE can be defined as a performance indicator of equipment utilization and is a powerful tool within Lean to determine the effectiveness of a machine or process. OEE is calculated by multiplying three factors that are, availability, performance, and quality where a high OEE represents a high utilization rate and is therefore desirable for a company (Chiarini, 2015; Singh, Shah, Gohil, & Shah, 2013). Measuring OEE facilitates improvement work and the identification of low-performing equipment.

Key performance indicators (KPI)

Key performance indicators (KPI) are measurement tools used by companies to measure performance all over the organization and allow the company to get a clear view of all measured areas. This type of quantifiable measurement approach allows companies to gauge operational performance, and consequently, pinpoint and improve low-performing areas. An important aspect when selecting KPIs is that they must reflect the goals of the organization (Mohamad, Abdullah, Hasrulnizzam, & Mahmood, 2008).

5S

The 5S method is often seen as a basis for implementing Lean manufacturing in an organization, it is a 5-step method for achieving a standardized, clean, and structured workplace (Rewers, Trojanowska, & Chabowski, 2016b). The 5S method contains the following steps: sort, straighten, shine, standardize, and sustain F. W. Breyfogle (2007).

Daily management

According to Berlanga and Husby (2016), the Lean daily management system (LDM) can be defined as "A disciplined system for developing staff, aligning efforts and building a holistic and meaningful improvement system that will help to achieve the organization's goal".

The main goal of LDM is to support daily operations at the front line which includes escalating problems to the right level and having all employees at all levels on the same page which is done by having visual boards, present managers at the shop floor through meetings and leader rounds so that the leaders can coach and encourage employees (Berlanga & Husby, 2016).

Failure mode and effects analysis (FMEA)

FMEA is regarded as one of the most effective methodologies for systematically analyzing probable failure modes within a system under conditions of uncertainties (Kiran, 2017). By applying a qualitative step-by-step approach to analyzing failures at a component or sub-assembly level, the FMEA can identify and evaluate the effects of a specific fault or mode of failure (Long & Hillman, 2014). Generally, the methodology aims to identify failure modes by scrutinizing both existing and future operations based on the 6M's: material, man, machine, measurement, method, and environment (Pasman, 2015).

Bottleneck analysis

A Bottleneck Analysis is a Lean management concept that is comprised of any combination of tools and processes, used to identify, examine, comprehend, and/or eliminate potential constraints within a system. According to (West, Syberg, & Deuse, 2022), state-of-the-art Bottleneck Analysis consists of four building blocks: detection, diagnosis, prediction, and prescription. The latter two blocks are currently high-interest areas, as prediction and prescription capabilities could prove incredibly beneficial in manufacturing processes. Based on historical data, bottleneck prediction algorithms may assist decision-makers in identifying future potential bottlenecks (Mahmoodi, Fathi, & Ghobakhloo, 2022). Prescription capabilities will build upon predictive analytics to enable automatic bottleneck prescriptions.

5 Why´s

The 5 Why's is a root cause analysis tool that uses an iterative interrogation technique to question the underlying cause of a failure or issue, in an attempt to identify and understand the root cause. Essentially, the tool entails using the question of "why" five consecutive times, with a debriefing session in-between the questions (Serrat, 2017).

2.3 Six Sigma

Six Sigma originates from Motorola, which was a telecommunications company at the time the company launched its first Six Sigma project in the 1980s (Moosa & Sajid, 2010). A few years later, in 1988, Motorola was honored with the Malcolm Baldrige award which is a highly regarded quality award in the U.S. (Banuelas Coronado & Antony, 2002). As a result of Motorola's success and the award, interest also increased among other companies which started to introduce the Six Sigma concept in the early 1990s (Moosa & Sajid, 2010). Today, Six Sigma is a well-established concept used by a great number of companies in different sectors (Andersson, Eriksson, & Torstensson, 2006).

Six Sigma can be described as a methodology aimed at achieving continuous improvements in both customer satisfaction and profitability, which surpasses mere defect reduction and prioritizes the overall improvement of business processes (F. Breyfogle, 2003). The main focus of Six Sigma is to reduce variation in key product quality characteristics to a level where the risk of failure or defects occurring reaches a minimum, this may be accomplished by conducting improvement projects across a broad spectrum of areas and at various levels of complexity (Andersson et al., 2006; Montgomery & Woodall, 2008).

The improvement projects which drive the Six Sigma methodology are led by different improvement specialists referred to as project champions, master black belts, black belts, green belts, and white belts, where the belts refer to their expertise within the Six Sigma area. In this hierarchical order, the Six Sigma champions are responsible for setting up the organization's strategic improvement plans which are then led and performed by master black belts and black belts full-time. Black belts are also responsible for instructing and teaching green and white belts who function as part-time improvements specialists (Linderman, Schroeder, Zaheer, & Choo, 2003).

Two major improvement strategies can be found in Six Sigma, the first one is the define, measure, analyze, improve, and control (DMAIC) method which is a five-phase method used for improving already existing processes or products (Nonthaleerak & Hendry, 2008). The second method, define, measure, analyze, design, and verify (DMADV) is used to develop new processes or products (Surange, 2015). Both methods have similarities to each other and it is important that they are followed carefully and that a solution is not presented until the problem has been clearly defined (Linderman et al., 2003).

2.4 Lean Six Sigma

The term Lean Six Sigma (LSS) is used to describe the integration of the Lean and Six Sigma methodologies and can be defined as a business strategy for the enhancement of process performance which results in improved customer satisfaction as well as improved bottom-line results (Shimray & Vinodh, 2023; Snee, 2010). The combination of Lean and Six Sigma helps to address a wider set of areas more effectively compared to when using the two methodologies separately, in LSS, Lean is addressing process flow and waste issues while Six Sigma focuses on reducing variation and ensuring robust design (Yadav, Shankar, & Singh, 2020). Applying an LSS approach where the different set of tools from both Lean and Six Sigma is combined in a mutual toolbox can contribute to simplifying improvement work and achieving greater results.

According to Arnheiter and Maleyeff (2005), both Lean and Six Sigma can achieve significant positive results when used in an organization individually, however, those improvements will probably start to level out at a certain point in time since each of the methodologies put too much emphasis on their specific area. For instance, Six Sigma may be focusing more on optimizing measurable quality and delivery metrics, thus minimizing the focus on removing wasteful activities in basic operating systems. The same can be said about Lean, where too much emphasis may be put on streamlining product flow in a less scientific approach by the use of data and statistical quality control methods (Arnheiter & Maleyeff, 2005). Therefore, it becomes of high importance to use a combination of both methodologies to ensure the best results for an organization.

2.5 Industry 4.0 as an enabler of Lean Six Sigma

As has been established earlier, research suggests that Industry 4.0 and LSS are mutually synergistic and compatible. As stand-alone approaches, the two concepts are good drivers for operational improvement - but, when integrated, they become an even more powerful tool (Skalli et al., 2023). The effects of integrating Industry 4.0 and LSS surpass the sum of the potential given by each concept separately, resulting in elevated improvements in efficiency and productivity (Kassem & Portioli, 2019).

The integration of Industry 4.0 and LSS enables smarter, more efficient manufacturing process (Skalli et al., 2023). According to Naciri et al. (2022), Industry 4.0 technologies are essential in the implementation of Lean as they help overcome obstacles and limitations in the manufacturing industry. Novel technologies and digital tools facilitate the adoption of LSS concepts through increased digitization, and by filling in the needed gaps in their performance (Kassem & Portioli, 2019).

Several practical implications of integrating Industry 4.0 with LSS have been proposed. Digital technologies, such as smart sensors and smart tools, accelerate waste identification and elimination faster than traditional Lean tools (Tran, Ruppert, & Abonyi, 2021). Industry 4.0-enabled technologies allow for real-time data collection throughout the value chain, which enables rapid DMAIC roadmaps and fast optimization projects (Arcidiacono & Pieroni, 2018). With the help of Industry 4.0 technologies, organizations can optimize their manufacturing processes to cope with higher complexity (Blöchl & Schneider, 2016). According to Narula et al. (2023), most Industry 4.0 technologies are enablers of Lean tools.

Although the integration of Industry 4.0 and LSS seems to yield great benefits in the manufacturing industry as a whole, research on the topic is scarce. Sanders et al. (2016) suggests that both the spheres of Lean manufacturing (read, LSS) and Industry 4.0 are increasingly important research fields that require extensive exploration. In this paper, Industry 4.0 technologies will denote the whole spectrum of different novel technologies, methodologies, and techniques that act as enablers of LSS, as suggested by Efimova and Briš (2022). Furthermore, there are generally two themes in the literature on LSS and Industry 4.0 integration - LSS as an enabler of Industry

4.0 *(1)*; Industry 4.0 and LSS as an enabler of each other *(2)* (Macias-Aguayo et al., 2022). Although LSS might serve as a foundation for Industry 4.0 *(2)*, as it can analyze and identify prospective fields for Industry 4.0 implementation (Efimova & Briš, 2022), this paper will focus specifically on how Industry 4.0 technologies can support LSS.

2.6 Sustainability aspect of Industry 4.0 & LSS

Since sustainability is of great importance in these times in which we live, it is important that the manufacturing industry also contributes by working greener and reducing its emissions. This sustainability approach comes hand in hand with Lean Six Sigma whose main goals are to reduce waste and defects in manufacturing. Further on, Green techniques can help enhance Lean in several aspects such as cost, quality, delivery, customer satisfaction, etc. according to Bergmiller and McCright (2009).

Green Lean Six Sigma (GLSS) has been adopted by several industries in the last years as an effort to improve sustainability, GLSS is an environmental philosophy that integrates both the green aspect and Lean Six Sigma to reduce negative environmental impacts and waste generation (Belhadi et al., 2021). By further integrating Industry 4.0 into the sustainability work together with GLSS, companies can reduce their environmental impact more effectively by the usage of emerging technologies within Industry 4.0, which can lead to several benefits such as more optimized processes and efficient use of resources, to name a few (Beltrami, Orzes, Sarkis, & Sartor, 2021).

Kaswan et al. (2023) describes how some of the concepts in Industry 4.0 can help facilitate sustainability, big data can provide the ability to collect and analyze large amounts of data to obtain the best possible selection of parameters which can help reduce waste in the form of water, electricity, etc. Big Data & analytics and Cyber-physical systems further allow for the integration of intelligent systems into the manufacturing environment and the logistics system which can help facilitate a more effective way of working with product tracking, life-cycle assessment, reuse, recycling, etc., intending to close the loop in the supply chain (Strandhagen et al., 2017). Technologies such as virtual and augmented reality, autonomous robots, and sensors can support workers when it comes to repetitive and hazardous tasks which can result in stress reduction and improved work satisfaction (Kaswan et al., 2023). Additive manufacturing enables faster production while at the same time reducing used material which results in a reduced environmental impact.

3

Methodology

In this chapter, a comprehensive overview of the research methodologies used to investigate the research questions is presented and motivated. As per Research Question I, a systematic literature review was conducted to investigate emerging research on the topic of Industry 4.0 and LSS integration. Furthermore, to map the landscape of the research topic and to provide a quantitative assessment of the literature, a descriptive and bibliometric analysis was used. Finally, to supplement the findings from the literature review, and to answer Research Question *II*, several semi-structured interviews regarding Industry 4.0 and LSS integration maturity were carried out with industry leaders.

3.1 Systematic literature review

The objective of this paper is to analyze the existing literature on Industry 4.0-enabled LSS to derive the implications of novel digital solutions on LSS initiatives. Existing comprehensive studies on the integration of the two concepts are scarce and only a handful of scientific papers offer a holistic overview of the landscape and development of the Lean 4.0 paradigm - see Valamede and Akkari (2020a);Valamede and Akkari (2020b);J. Sordan, Oprime, Pimenta, Lombardi, and Chiabert (2020); J. E. Sordan et al. (2022). This research aims to fill the gap in the literature pertaining to the digital transformation of LSS leveraging Industry 4.0 technologies. A systematic literature review (SLR) was utilized to identify, collate, and methodically summarize and disseminate the available research studies within the research area.

A systematic review is a rigorous approach to gathering and sourcing literature in the most comprehensive manner possible (Gammie, Vogler, & Babar, 2017). The method constitutes explicit and reproducible methods for finding, analyzing, and synthesizing the collective corpus of scholars and practitioners in any given field (Okoli, 2015). Individually, the available literature on Lean, Six Sigma, and Industry 4.0 is considerable, making it challenging to produce high-quality summaries and reviews, let alone answer highly focused research questions. With a wide array of tools at its disposal, which facilitates the analysis of LSS and Industry 4.0, an SLR appeared to be the most appropriate research method for this paper. Furthermore, systematic reviews offer a series of techniques for minimizing bias and errors and are regarded as producing high-quality evidence (Tranfield, Denyer, & Smart, 2003), thereby enhancing authenticity and replicability.

The initial review process was adapted from (Tranfield et al., 2003), and comprised 3 phases and 9 activities:

- Planning
  - Developing the review protocol (1), Trial search (2), Eligibility criteria (3)
- Conducting
  - Identification (4), Screening (5), Selection strategy (6), Data extraction (7)
- Analyzing and synthesizing
  - Descriptive analysis (8), Bibliometric network analysis (9)

3.1.1 Planning the review

A systematic review was used for mapping the landscape of the integration between Industry 4.0 and LSS. The first step of the systematic review was to define the research questions, as prescribed by (Jahan, Naveed, Zeshan, & Tahir, 2016). Although the authors advised against formulating research questions that are too broad, the nature of this thesis entails highlighting *all* instances in the literature where Industry 4.0 technologies and LSS concepts intersect, which makes it difficult to narrow down the inquiry - i.e., having a broader scope was deemed necessary. Thus, the research question, which the systematic review was intended to answer, became:

I Which digital methods and techniques can be found in the literature on Lean Six Sigma?

More in-depth descriptions of the methodology will be discussed in the coming sections.

Developing the review protocol

Figure 3.1 presents an overview of the research protocol used in the SLR. By utilizing a predefined protocol, researcher bias is minimized, and the review's rigor and repeatability increase (Ali & Khan, 2012). It is worth mentioning, however, that the protocol used in this paper has been altered on several occasions throughout the project, which might have increased the risk of inconsistency and bias. But, as concluded by (Felizardo et al., 2017), research protocols are generally built iteratively, and "a good quality SLR could only be obtained from iterations in the process and in the protocol definition". Protocol details for each SLR activity will be addressed further in their respective sections below.

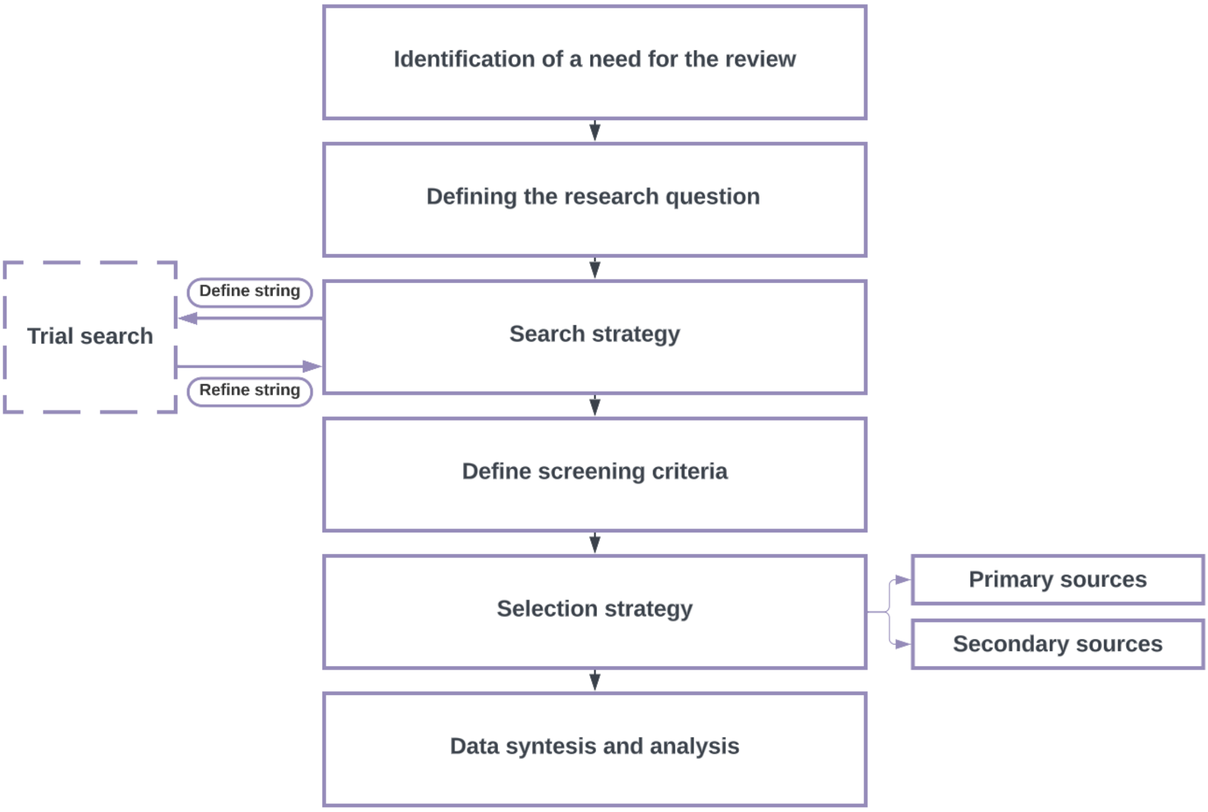

Figure 3.1: Research protocol of the systematic literature review.

Trial search

Before conducting the literature review, a pilot search was carried out to refine the search string based on results from the initial set of keywords, ensuring a more focused search strategy (Howe, Suich, Vira, & Mace, 2014). This step is important because the end results are highly dependent on the finalized keywords (Ejsmont et al., 2020). Due to the vast volume of available literature, an automatic search strategy was utilized, i.e., the search strings were entered into an electronic database. This is the most dominating method of identifying relevant papers (Chen, Babar, & Zhang, 2010).

The preliminary searches were performed in the Scopus database, and the search strings were adjusted based on the output relating to article relevancy and the number of articles. Furthermore, to establish the comprehensiveness and accuracy of the search string, the group identified a pre-specified, highly relevant set of articles, serving as a control group. If any of these articles were not found using the search string, it was revised accordingly. The results from the pilot run presented two possible alternatives for the text string that cohered to the criteria - both options produced highly relevant search results and included the pre-specified set of articles, see Table (3.1). The third revision utilizes fewer "AND" operators, resulting in a broader scope and, consequently, more articles. Generally, there is a trade-off between the extensiveness and the feasibility of a systematic review. As suggested by Fenner, Hyde, Crean, and McGreevy (2020); Gusenbauer and Haddaway (2020), to guarantee that all relevant research is included in the review, the search should be as broad and simple as possible. Nonetheless, Gusenbauer and Haddaway (2020) still argues that it is necessary to find a balance between striving for comprehensiveness and preserving the relevance of the search strategy. Since a keyword for this paper is comprehensiveness, the broader search strategy was considered more suitable.

Table 3.1: Results from the trial searches, consisting of three unique entries.

Revision	Relevancy	No. of articles	Result includes control group?
1	Medium	147	No
2	High	162	Yes
3	High	341	Yes

1	("Six Sigma" OR "Lean manufacturing" OR "Lean Six Sigma") AND (digital) AND (tool)
2	("Lean Six Sigma" OR "Six Sigma" OR "Lean manufacturing") AND Industry 4.0" OR "smart manufacturing") AND ("Digitalization" OR "digitization" OR "Tools")
3	("Industry 4.0" OR "manufacturing 4.0" OR "smart manufacturing") AND ("Lean Six Sigma" OR "Lean manufacturing" OR "kaizen" OR "DMAIC")

Inclusion/exclusion criteria

This paper used inclusion and exclusion criteria to establish the parameters for the literature review. Personal bias tends to influence the review process, potentially affecting the outcome. The use of inclusion criteria minimizes bias by neutralizing individual preferences in the study selection process (Felizardo et al., 2017), and should be stated in advance (Tawfik et al., 2019).

Since decisions regarding eligibility criteria are relatively subjective (Chen et al., 2010), the criteria were derived through discussions and gaining consensus within the group. The selection strategy comprised three steps; each with unique inclusion and exclusion criteria. The first two steps - title and keyword screening, and abstract screening - only contained exclusion criteria, as it would facilitate the screening process. The third step entails screening full texts and was based on both inclusion and exclusion criteria. The use of inclusion criteria enabled the group to classify the different papers into primary and secondary studies. The purpose for this will be explained in section 3.1.2.

The inclusion (I) and exclusion (E) criteria are presented in the following list:

Step 1 - Title and keyword screening with exclusion criteria

- **E1**: An article does not have its full text in English.
- **E2**: An article is published before the year 2016.
- **E3**: An article does not include any of the following keywords or their synonyms in the title or keywords: "Industry 4.0", "Lean Six Sigma", "LSS", or other relevant technologies or concepts related to Industry 4.0 and Lean Six Sigma methodologies.

Step 2 - Abstract screening with exclusion criteria

- **E4**: An article is not related to the application of Lean Six Sigma and Industry 4.0 technologies in the manufacturing industry.
- **E5**: An article does not have a clear focus on the integration of Industry 4.0 technologies and Lean Six Sigma.
- **E6**: An article is not relevant to the research question or objectives of the review.
- **E7**: Secondary or tertiary studies that do not focus on a specific Industry 4.0 technology or LSS concept - too broad.
- **E8**: Grey literature sources other than conference papers and proceedings.

Step 3 - Full-text screening with inclusion and exclusion criteria

- **I1**: An article provides detailed insights into the integration of Industry 4.0 technologies and Lean Six Sigma.
- **I2**: An article reports on the effectiveness or impact of Industry 4.0 technologies on Lean Six Sigma outcomes.
- **I3**: An article describes the implementation process of integrating Industry 4.0 technologies and Lean Six Sigma and provides practical guidance or recommendations.
- **I4**: An article provides a comprehensive overview of the current state of research on integrating Industry 4.0 technologies and Lean Six Sigma, including trends, gaps, and future directions for research and practice.
- **E9**: An article is not accessible due to paywall restrictions or lack of institutional access.
- **E10**: An article includes Industry 4.0, smart manufacturing, or similar terms

only in the title, keywords, abstract, and/or references.

- **E11**: An article solely presents Industry 4.0 (or related terms) as a future research direction or perspective.
- **E12**: An article use Industry 4.0 (or related terms) only as a citation or reference.

3.1.2 Conducting the review

Identification

Three databases - Scopus, Web of Science, and IEEE Xplore - were considered for the literature review. These databases were identified from prior Industry 4.0 and LSS review publications. Scopus is a multi-disciplinary global database of scientific and academic peer-reviewed publications (Perevochtchikova et al., 2019). Web of Science is the world's oldest, most widely used multi-disciplinary citation database (Birkle, Pendlebury, Schnell, & Adams, 2020). The IEEE Xplore digital library is a large database of technical publications and is governed by the 'highly regarded' Institute of Electrical and Electronics Engineers (IEEE). All three databases provide relevant conference papers and peer-reviewed publications from prestigious journals on the topic of industrial management and advanced technology. By using multiple electronic databases, the search results will not be constrained by the policies and business interests of individual publishers (Zacchia Lun, D'Innocenzo, Smarra, Malavolta, & Di Benedetto, 2019).

The same query was used in all databases, and was formulated as follows:

$$(\text{"}industry\ 4.0\text{"}\ \textbf{OR}\ \text{"}manufacturing\ 4.0\text{"}\ \textbf{OR}\ \text{"}smart\ manufacturing\text{"})\ \textbf{AND}$$
$$(\text{"}Lean\ six\ sigma\text{"}\ \textbf{OR}\ \text{"}Lean\ manufacturing\text{"}\ \textbf{OR}\ \text{"}kaizen\text{"}\ \textbf{OR}\ \text{"}DMAIC\text{"})$$

Considering the novelty and broad multi-disciplinary area of Industry 4.0, keywords such as BDA, IoT, CPS, etc., were not included in the search string, as it would significantly reduce the number of papers found. Instead, the control papers were analyzed with the purpose of extracting all relevant synonyms and abbreviations for the two topic words - Industry 4.0, and Lean Six Sigma.

The literature search procedure was performed between January 30 and February 3 and resulted in 647 papers. Scopus, Web of Science, and IEEE Xplore identified 341, 271, and 35 papers respectively.

Initial screening

Once the papers had been identified, all metadata extracted from the databases were downloaded into the Zotero software. The software allows for easy management of the collation of data to save relevant citations and weed out papers that meet the exclusion criteria.

Multiple duplicate records were detected using the Zotero software. After deleting 225 duplicates, the number of remaining articles was 422. Moreover, an additional five articles were excluded due to their non-English language. No papers were excluded on the basis of their publication date - i.e., all papers were published after 2015.

Selection Strategy

All collected studies were filtered according to the set of inclusion and exclusion criteria presented in section 3.1.1. The eligible papers were categorized as either a primary study or a secondary study, based on their adherence to the research theme. The primary studies were intended for the review and in-depth analysis to answer Research Question *I*, while both secondary and primary studies were considered for the descriptive and thematic analysis, i.e., mapping the landscape of Industry 4.0 and LSS integration. Based on the recommendations from Tranfield et al. (2003), only papers that met *all* inclusion criteria were considered primary studies. Papers that met one or several inclusion criteria were considered secondary studies. If a paper met any exclusion criteria, it was eliminated.

In steps one and two of the selection strategy (text, keyword, and abstract screening), each group member was assigned to read one-half of the papers to decide whether to exclude them or not. For the full-text screening, each member read the remaining papers independently. Then, the group looked through all the eligible and eliminated papers together to determine whether the inclusion/exclusion decision was valid or not. As recommended by (Tawfik et al., 2019), a paper was included if one or both parties agreed upon it, while a paper was excluded only if both parties agreed on it. Essentially, the screening process introduced some bias toward inclusion.

Figure 3.2 presents a PRISMA chart of the different steps in the selection process. By creating an audit trail of the decisions and procedures used throughout the review - e.g., documenting the number of included/excluded studies at different stages of the SLR process - the reporting quality and traceability are enhanced (Yang, Khoo-Lattimore, & Arcodia, 2017).

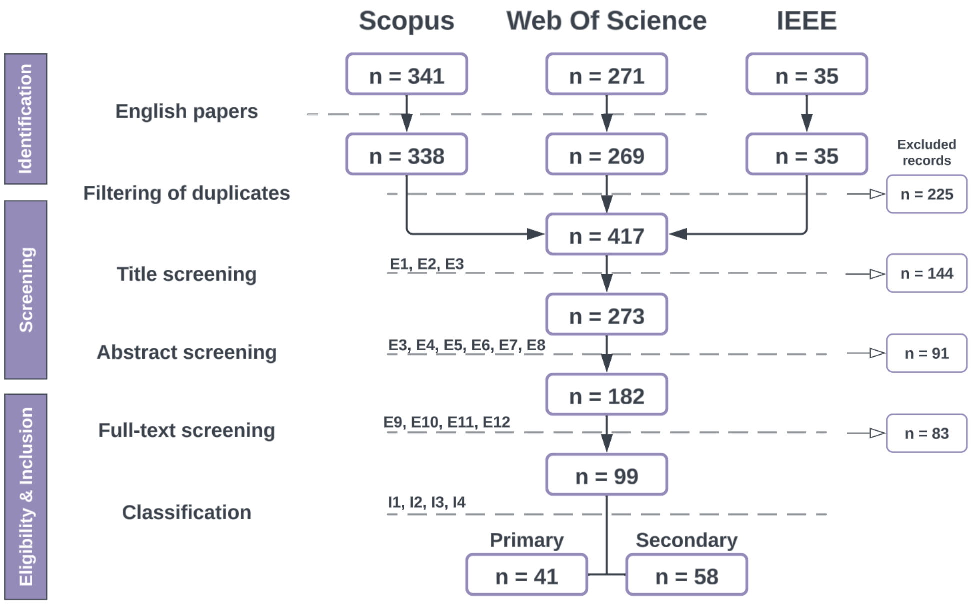

Figure 3.2: PRISMA chart of the selection process.

The title and keyword screening excluded 144 papers, leaving 273 remaining papers for the next step. The abstract screening excluded 91 papers, leaving 182 papers. Finally, full-text screening excluded 83 papers, leaving 99 papers. Of the 99 papers, 41 were considered primary studies, as they met all inclusion criteria. Consequently, 58 papers were considered secondary papers.

Data extraction

A concise data extraction form was developed to facilitate the process of collecting and synthesizing relevant data from the papers, see Table (3.2). Data extraction forms provide the foundation for appraising, coordinating, and clarifying the review's body of evidence (Büchter, Weise, & Pieper, 2020).

Table 3.2: Data extraction form used in the literature review - *adapted from Tummers et al. (2021).*

Number	Extraction Element	Contents
General Information		
1	Title name	
2	Author(s)	
3	DOI	
4	Publication year	
5	Country of origin	
6	Publication type	*Journal, Conference paper, Book, Book chapter*
7	Citations	
Description		
8	Research approach	*Theoretical study, Case study, Design research, Literature review, Modeling and Simulation, Conceptual Study*
9	Main theme of study	
10	Industry 4.0 technologies	*IoT, CPS, Additive manufacturing, etc.*
11	Lean Six Sigma concepts	*5S, VSM, JIT, Andon, etc.*
12	Perceived contact points	*"What", "Why", "How".*
13	Integration benefits	*Real-time monitoring, Predictability, Productivity, etc.*
Evaluation		
14	Personal note	

Each group member reviewed one-half of the primary studies. The data extraction was guided by the three dimensions - general information, description, and evaluation - from the extraction form. General, easily accessible data regarding publication year, country of origin, publication type, etc., were gathered directly from the databases. Google Scholar was used to record each paper's citation count. Data relating to the research questions were derived by more in-depth analysis. Finally, the relevancy and quality of the papers were determined by assessing how well the authors answered the *"What, how, and why* in regards to Industry 4.0 and LSS integration. The extracted data were recorded in Google Sheets.

3.1.3 Analysis and synthesis

The analysis was conducted with the aim to understand and classify the current research on the topic of Industry 4.0 and LSS integration and to answer the research questions. The analysis can be divided into two categories: quantitative, and qualitative variable analysis. The quantitative data analysis was comprised of a descriptive, and bibliometric network analysis. This analysis was conducted on both primary and secondary studies, to map the landscape on the topic. The qualitative variable analysis entailed assessing, comparing, and synthesizing the different primary studies, as to answer the research questions - particularly, Research question *I*.

Descriptive analysis

According to Tranfield et al. (2003), a decent systematic review should contain a descriptive analysis, as an extensive synthesis of the topic at hand makes it easier for practitioners to understand the research. Thus, A descriptive analysis was carried out on the papers that fully or partially adhered to the research theme, covering areas such as research approach, year-wise distribution, publication type, geographic distribution, etc. The results were summarized and synthesized in the form of figures, graphs, and tables. Most illustrations were created in the Tableau Desktop software, where the quantitative data was sourced from the primary Excel file. Before importing the data from Excel, it was manually formatted and sorted.

Bibliometric network analysis

In addition to the descriptive analysis, the quantitative data was consolidated through the partial assessment and interpretation of bibliometric data. Generally, when dealing with an overwhelming number of papers, a bibliometric analysis can facilitate the analysis and synthesis of a systematic review (Sharifi & Khavarian-Garmsir, 2023). The analysis offers a thorough structure of the research landscape (Han, Kang, Kim, & Kwon, 2020), and may illustrate the current state of the research topic - which may be used for future assessment of the topic's evolution over time. I.e., "Bibliometric analysis has advantages in predicting the forward trends of disciplines" (Wang & Su, 2020). In this paper, the group conducted a bibliometric network analysis to identify research trends, visualize research networks, and present co-authorships and affiliations.

The VOSViewer software was used when conducting the network analysis. VOSViewer allows for analysis such as co-citation, and bibliographic coupling, which can be used to understand the interlinkages between the bibliometric variables (Sharifi & Khavarian-Garmsir, 2023). Citation data (RIS file) was exported to VosViewer, and the records' keyword co-occurrence network was visualized using the software's text-mining functionality. The software was also used to visualize and interpret co-authorship.

3.2 Data collection - individual interviews

In this project, qualitative data collection was performed through semi-structured interviews with individuals with expertise in Lean Six Sigma, Industry 4.0, and digitalization. This interview method is appropriate when seeking to allow the respondents to raise new issues, as it allows for spontaneous questions to explore and clarify the answers (Wilson, 2014). The interviews were conducted at five large, leading manufacturing companies in different sectors, which are considered leaders in these topics. Additionally, two smaller-scale companies with between 100-1500 employees were included in the study to establish a benchmark for the general level of digitalization and the digitalization of LSS concepts in comparison to the leading companies. In total, seven companies were included in the study. The interviews were conducted to establish a foundation to answer Research Question *II* - "Which digital methods and techniques are used in the companies for Lean Six Sigma?"

Subsequently, at least one interview was conducted at each company. If the initial interview did not provide adequate information, a second interview was conducted to ensure that all relevant questions could be answered. The interviews were performed during the months of April and May. All interviews were performed digitally through Microsoft Teams, Zoom, or by phone, except for one company where an on-site interview was conducted. The duration of the interviews ranged from 40 to 120 minutes depending on the depth of the discussions.

According to Adams (2015), semi-structured interviews consist of both closed- and open-ended questions, often followed up by "why" and "how" questions, which can yield more relevant information than initially anticipated. The questions used in the company interviews were formulated around the project's second research question, with a majority of open-ended questions to avoid excluding potentially important information. Additionally, two lists were used during the interviews. One list contained the nine Industry 4.0 technologies and the interviewees were asked to rate their Industry 4.0 implementation on a scale of 0-2. The other list consisted of 19 LSS concepts and was used to determine the concepts used and digitalized at the company. In this context, the term "digitalized" denotes a level of advancement beyond basic digitization software and tools, such as Microsoft Excel. The interview questions and lists used during the interviews are presented in Appendix A.

Company overview

Table 3.3 provides relevant information regarding the interviewed companies including, the number of employees, annual sales, as well as the roles of the interviewees. The set of companies represented a wide range of segments within the manufacturing industry - aerospace, automotive, agricultural, outdoor machinery, and commercial refrigeration. The broad spectrum of industry sectors ensures a diverse representation within the study. These specific companies were selected based on their renowned position at the forefront of digitalization and advanced manufacturing. All respondents had significant knowledge about the respective organizations' Lean, Six Sigma, and/or Industry 4.0 initiatives.

Table 3.3: Company profiles

Case company	Annual Sales (mln SEK)	Employees	Industry	Interviewees	Job position
1	< 45 000	> 10 000	Aerospace	1	Director of manufacturing engineering operations
2	> 45 000	> 10 000	Automotive	3	Production System Manager, Digital Officer, Tech Scout
3	> 45 000	> 10 000	Automotive	2	Director Digitalization & IT, Lean & Production System Coach
4	> 45 000	> 10 000	Outdoor power equipment	1	Sr. Global process & Digitalization lead
5	> 45 000	> 10 000	Industrial parts manufacturing	1	Production System Champion
6	~5500	~1500	Agricultural machinery	1	Senior Lean Management Advisor
7	~200	~100	Commercial refrigeration equipment	1	Improvement Manager

4

Descriptive Analysis

This chapter provides insights into the characteristics of the papers and authors included in the review, to enhance traceability and improve the overall quality of the systematic literature review. A brief analysis of the geographical distribution, paper type, journal, research methodology, and publication timeline was carried out.

4.1 Geographic Distribution

The figures below show the geographical distribution of the authors and papers used in the systematic review. Figure 4.1 illustrates the geographic scope in a choropleth map, where all involved authors and institutions are presented. Figure 4.2 present the countries/regions of origin of only the first authors. The group found that 144 authors, representing 39 different countries, were affiliated with the papers in the review. The most prominent countries involved in the review are India, with 17 articles; Italy, with 13 articles; Brazil, with 11 articles; and the UK, with 10 articles. Other notable countries are USA, Mexico, Norway, and Spain, each representing 7 articles.

Based on the figures, it is clear that the topic of Industry 4.0 is more notable in highly industrialized and developed countries, with the exception of a few - India, Brazil, and Morocco. Although these countries are generally considered developing countries, it is worth noting that they have made rapid progress in the manufacturing industry in recent times. Nevertheless, the results from this review show that the interest in Industry 4.0 and LSS integration is context-dependent and can be attributed to the level of industrial development. Furthermore, Europe's dominance can be explained by the fact that the concept of Industry 4.0 originated in Germany - which may account for the concentration of publications and conferences in close proximity to this region. Overall, the geographical distribution of papers in the systematic review is mostly concentrated around Europe and Asia, with the majority of affiliations coming from countries in these regions.

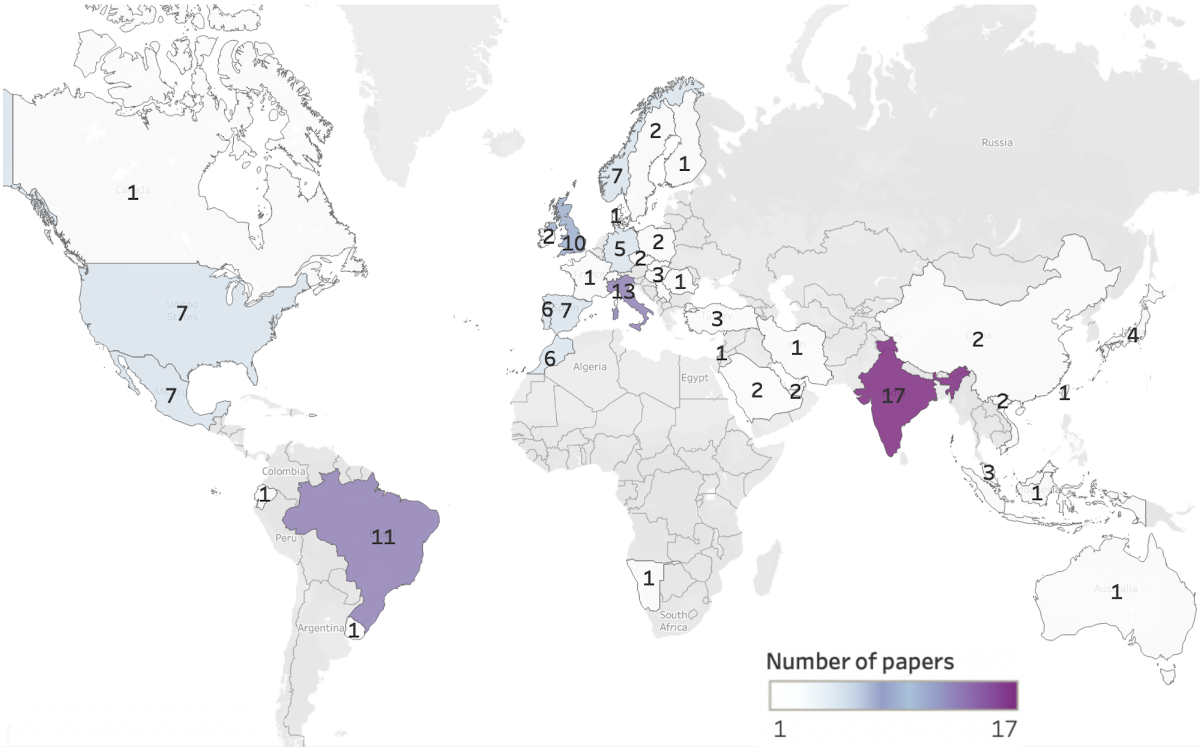

Figure 4.1: Choropleth map of the authors' countries of affiliation.

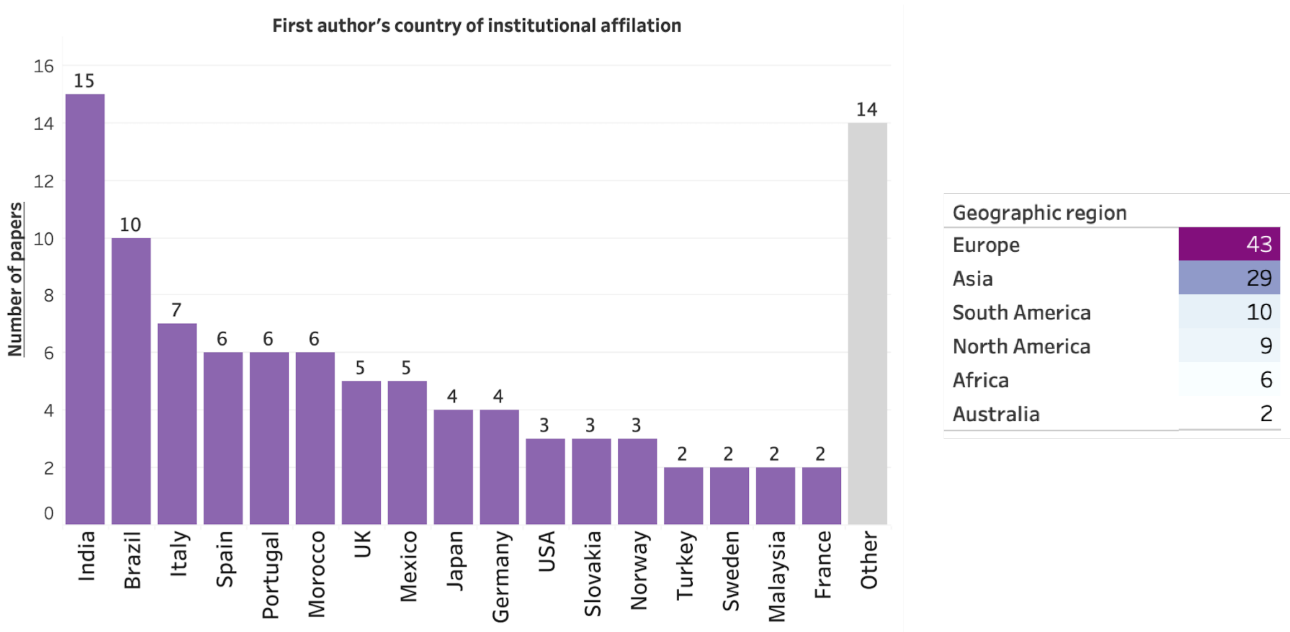

Figure 4.2: First authors' countries of affiliation.

4.1.1 Distribution per research paper type, and main journal

Table 4.3 shows the paper type distribution. Most publications were either proceedings from conferences or journal papers, with 53 and 44 papers respectively. Additionally, one book and one book chapter were used for the review. An illustration of all journals are presented in Appendix B

Publication type	
Conference paper	53
Journal paper	44
Book chapter	1
Book	1

Figure 4.3: Distribution per publication type.

The 99 publications included in the review were published in 70 different journals. Figure 4.4 shows the distribution of journals - categorized as either indexed or miscellaneous journals/conferences. The latter constitutes a collection of a larger set of journals. Only 15 of the journals have published 2 or more papers included in this review. Consequently, 55 journals only appeared once in the review. The most notable and frequently occurring journal is IFAC-PapersOnLine, with 5 publications (7%). Furthermore, The TQM Journal, Sustainability, ICIEOM, International Conference on Advances in Production Management Systems, and Applied Sciences, each presented 4 papers (5.7%). The large set of journals and conferences may indicate that Industry 4.0 and LSS integration - despite being a relatively recent addition to the industrial landscape - is developing into an increasingly established research topic. It should be noted, however, that many of these publications deal with Industry 4.0 and Lean integration, and do not explicitly discuss Lean Six Sigma.

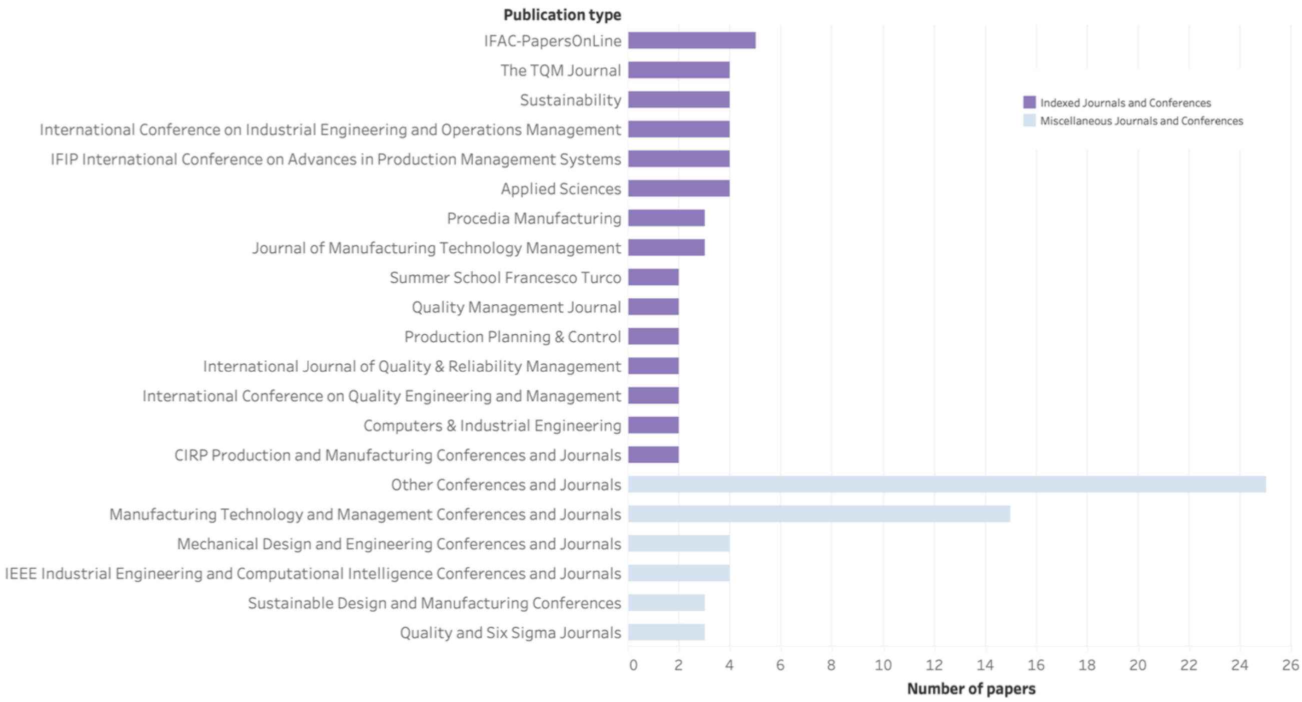

Figure 4.4: Distribution of the most frequently occurring journals

4.1.2 Distribution Per Research methodology

Figure 4.5 shows the distribution of applied research methodologies among the publications. Case studies (15) were the most common research methodology found in this review, reflecting the growing integration of novel technologies and LSS. Then there were literature reviews (8), design research (7), and theoretical studies (6). Modeling and simulation (4) were used less frequently, while the least common research approach was conceptual studies (1). The results show that the review is comprised of a healthy mix of practical and theoretical studies.

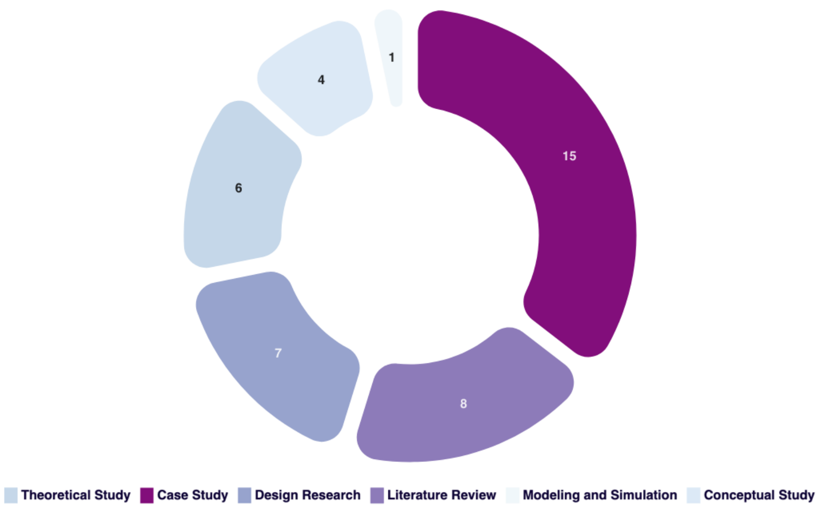

Figure 4.5: Distribution of research methodologies among the publications

4.1.3 Publication timeline

Figure 4.6 presents the annual distribution of publications between 2016 and 2023, along with the yearly citation counts for the papers included in the review. Based on the graph, the interest in the topic of Industry 4.0 and LSS integration did not gain traction until 2019. Years 2016, 2017, and 2018 presented 2, 2, and 3 papers, respectively. 2019 showed a fourfold increase in publications from the previous year, with 12 papers. This may be attributed to the growing awareness and adoption of digitalized solutions. In 2020 the number of papers almost doubled, with 23 papers. The year 2021 was the most notable year with 33 papers - a 43% increase compared to 2020. The dynamic growth in interest emphasizes the topic's importance and relevance. 2022 showed a decrease in the number of publications, but there is no sign that the interest in the topic has diminished. It should also be noted that since the literature searches were conducted at the beginning of February 2023, it may be the case that not all publications had yet been indexed in the databases. All-in-all, the data shows a clear trend in growing interest in Industry 4.0 and LSS integration. As more and more companies are investing in novel technologies, and adopting LSS principles, the trend is expected to continue.

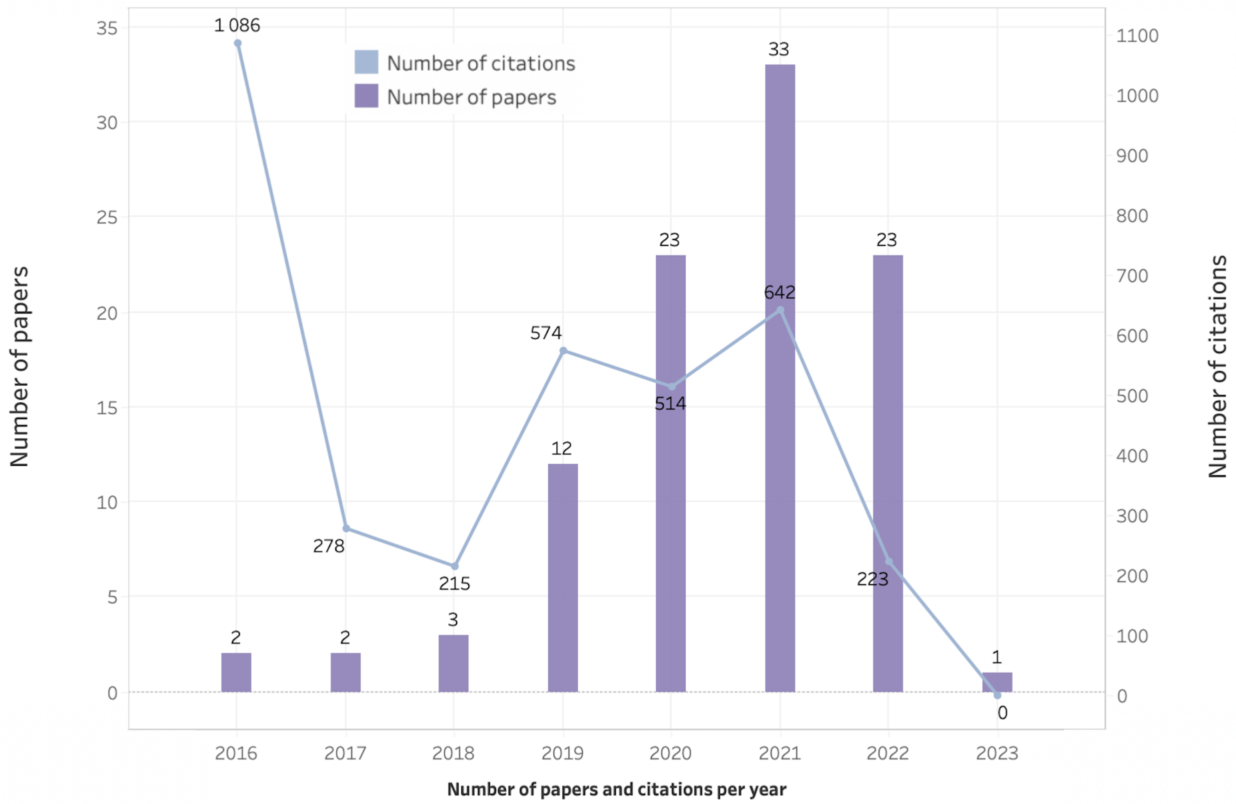

Figure 4.6: Yearly distribution of the numbers of publications and citations

In terms of the yearly citations, the trend is not as pronounced as the number of annual publications. In the review, the year with the highest citation count was 2016, with 1086 citations. Since only two publications - used in the review -

were published in 2016, it would be safe to assume that they were highly impactful and influential within the field of Industry 4.0 and LSS. The number of citations decreased from 2016 to 2018, where 2017 and 2018 showed 278, and 215 citations, respectively. 2019 saw an uptick in citation count, with 574 citations. The curve remained relatively stable through 2020 and 2021, with 514 and 642 citations. The graph shows a significant drop in citations during 2022, showing only 223 citations. This is most likely due to the recency of the publication date, as well as the increased availability of research over the past couple of years.

5

Bibliometric Analysis

This chapter introduces a bibliometric analysis that examines the research landscape by analyzing the Co-occurrence network of authors' keywords and the Co-citation network of the authors. By examining bibliometric indicators, this analysis enhances the study's quality and provides valuable insights into the interrelationships among authors, influential works, and emerging research trends.

5.1 Co-occurrence network of authors' keywords

For the analysis of the authors' keywords co-occurrences, a minimum number of 5 keyword occurrences was set as the eligibility criteria. Initially, 35 keywords were identified. However, 4 records were removed as they were deemed irrelevant - most of them were related to the applied review methodologies: *industrial research, design/methodology/approach, literature reviews, case studies, systematic literature review.* As a result, the VOSViewer software produced 31 nodes, see Figure 5.1. The size of the node denotes the frequency and weight of its occurrence in the analyzed set. Furthermore, the position of the nodes - specifically, their proximity to one another - as well as the line thickness, illustrates the link strength.

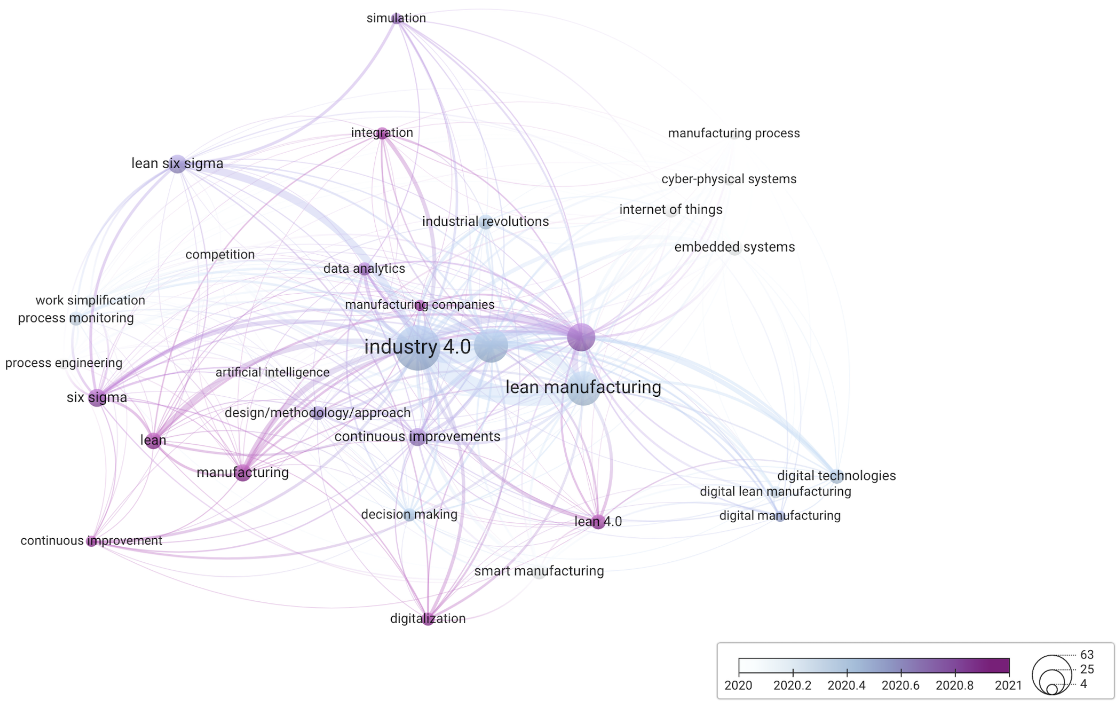

Figure 5.1: Co-word analysis network - created in VOSViewer.

Based on the data from Table 5.2, some initial observations can be made about the keywords and their relationships in the literature. The most frequently occurring keyword is *Industry 4.0*, with 83 occurrences, which links to 29 other keywords. This suggests that Industry 4.0 is the most central concept in the literature, which should not come as a surprise for this particular paper. *Lean production, Lean manufacturing* and *agile manufacturing systems* are the second, third, and fourth most frequently occurring keywords with 47, 48, and 32 respective occurrences, and with 29, 27, and 28 links.

Keyword	Occurences	Links	Total link strength
industry 4.0	83,00	29,00	81,00
lean production	47,00	29,00	47,00
lean manufacturing	48,00	27,00	48,00
agile manufacturing systems	32,00	28,00	32,00
continuous improvements	13,00	26,00	13,00
lean six sigma	14,00	22,00	14,00
six sigma	13,00	22,00	13,00
manufacturing	12,00	20,00	12,00
embedded systems	10,00	20,00	10,00
lean	11,00	16,00	11,00
smart manufacturing	10,00	18,00	9,00
process monitoring	8,00	21,00	8,00
industrial revolutions	9,00	18,00	9,00
internet of things	9,00	17,00	9,00
decision making	7,00	21,00	7,00
lean 4.0	9,00	17,00	8,00
digital technologies	9,00	15,00	9,00
data analytics	7,00	18,00	7,00
work simplification	6,00	18,00	6,00
manufacturing companies	5,00	20,00	5,00
process engineering	6,00	17,00	6,00
integration	6,00	17,00	6,00
cyber-physical systems	6,00	17,00	6,00
competition	6,00	15,00	6,00
artificial intelligence	5,00	17,00	5,00
digitalization	7,00	12,00	7,00
digital lean manufacturing	6,00	14,00	6,00
continuous improvement	5,00	14,00	5,00
digital manufacturing	5,00	13,00	5,00
manufacturing process	5,00	12,00	5,00
simulation	5,00	10,00	5,00

Figure 5.2: List of the identified keywords, as well as their respective number of occurrences, links, and link strength.

Several keywords, each providing a high number of links, are directly related to Lean: *Lean production, Lean manufacturing, Lean Six Sigma, Lean, Lean 4.0, digital Lean manufacturing*, which suggests that Lean manufacturing is a highly interconnected area of research. Digitalization is an important theme in the research on Industry 4.0 and LSS integration, as made apparent by frequently occurring keywords such as: *embedded systems, internet of things, digital technologies, digitalization, cyber-physical systems, digital Lean manufacturing, digital manufacturing*, and *artificial intelligence*. Finally, *continuous improvements, process monitoring, decision making, work simplification*, and *competition* highlights the expected benefits from a digitalized organization, and/or represent important cross-cutting themes that span multiple research domains. These five keywords essentially denote the current areas of focus, relating to the integration of Industry 4.0 and LSS.

Figure 5.3 illustrates three keyword clusters, generated by the VOSViewer software. Each cluster represents different topics and research areas relating to the topic.

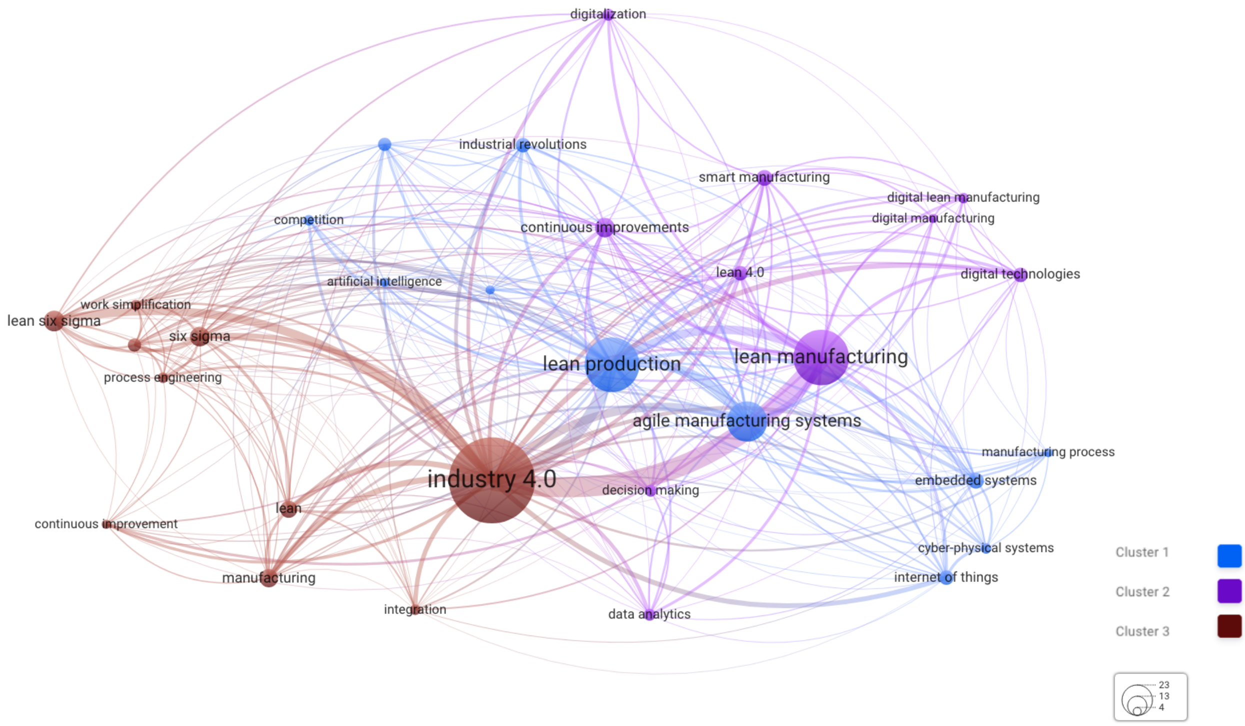

Figure 5.3: Co-word analysis network, where the nodes are classified into three different clusters - created in VOSViewer

Cluster 1 - Industry 4.0 technologies and manufacturing systems

• *agile manufacturing systems* • *artificial intelligence* • *competition* • *cyber-physical systems* • *embedded systems* • *industrial revolutions* • *internet of things* • *Lean production* • *manufacturing companies* • *manufacturing processes*

Cluster 1 mainly encompasses keywords related to Industry 4.0 technologies and their application in manufacturing systems. The list of keywords suggests that there is a strong focus on exploring the integration of novel and advanced technologies such as AI, IoT, CPS, etc, into manufacturing processes. These technologies are generally considered key enablers of Industry 4.0 and smart manufacturing and are being researched in tandem with traditional Lean production and manufacturing processes. The presence of *Competition* may indicate that organizations are looking to leverage the technologies to improve their competitive advantage.

Cluster 2 - Digital Lean manufacturing and continuous improvements

• *continuous improvements* • *data analytics* • *decision making* • *digital Lean manufacturing* • *digital manufacturing* • *digital technologies* • *digitalization* • *Lean 4.0* • *Lean manufacturing* • *smart manufacturing*

Cluster 2 revolves around the concept of digital Lean manufacturing and continuous improvement. The list of keywords shows an emphasis on digitalization - mainly, the integration of digital technologies and data analytics into the Lean manufacturing processes, which is sometimes referred to as Lean 4.0. This reflects a growing interest in leveraging the power of Industry 4.0 technologies to facilitate the efficiency of Lean manufacturing principles and concepts. *Continuous improvements*, and *decision making* suggests that researchers are exploring how advanced technologies can support and drive improvement efforts in industrial processes, ultimately resulting in *smart(er) manufacturing.*

Cluster 3 - Lean Six Sigma and Industry 4.0 integration

• *continuous improvement* • *Industry 4.0* • *integration* • *Lean* • *Lean Six Sigma* • *manufacturing* • *process engineering* • *process monitoring* • *Six Sigma* • *work simplification*

As is the topic of this thesis, cluster 3 is centered around the integration of Industry 4.0 and LSS. The cluster highlights manufacturing capabilities and LSS concepts such as *continuous improvement, process monitoring*, and *work simplification*, which indicates that researchers are looking into how Industry 4.0 technologies can complement and enhance these capabilities. Essentially, the keywords accentuate the importance of integrating novel technologies with traditional manufacturing methods to improve efficiency and quality.

Overall, the analysis of the co-occurrence network suggests that the 99 papers involved in this review focus on Industry 4.0 and LSS integration, with an emphasis on the application of novel technologies in the manufacturing industry, driving more efficient, agile, and competitive manufacturing processes. The findings from the full-text review of the primary studies will be addressed more in-depth in section 6 -*Results.*

5.2 Co-citation network of the authors

Figure 5.4 illustrates a citation network based on the selected papers. The network consists of four clusters, containing 17 different authors. The VOSViewer software has identified two separate “islands”, where one island contains clusters 1 and 3, and the other one contains clusters 2 and 4. The authors with the most links are Romero and Powell, with 8, and Thürer, Gaiardelli, and IEEE, with 6. The author with the highest number of publications is Powell, with 7, and Romero and Gaiardelli, with 6.

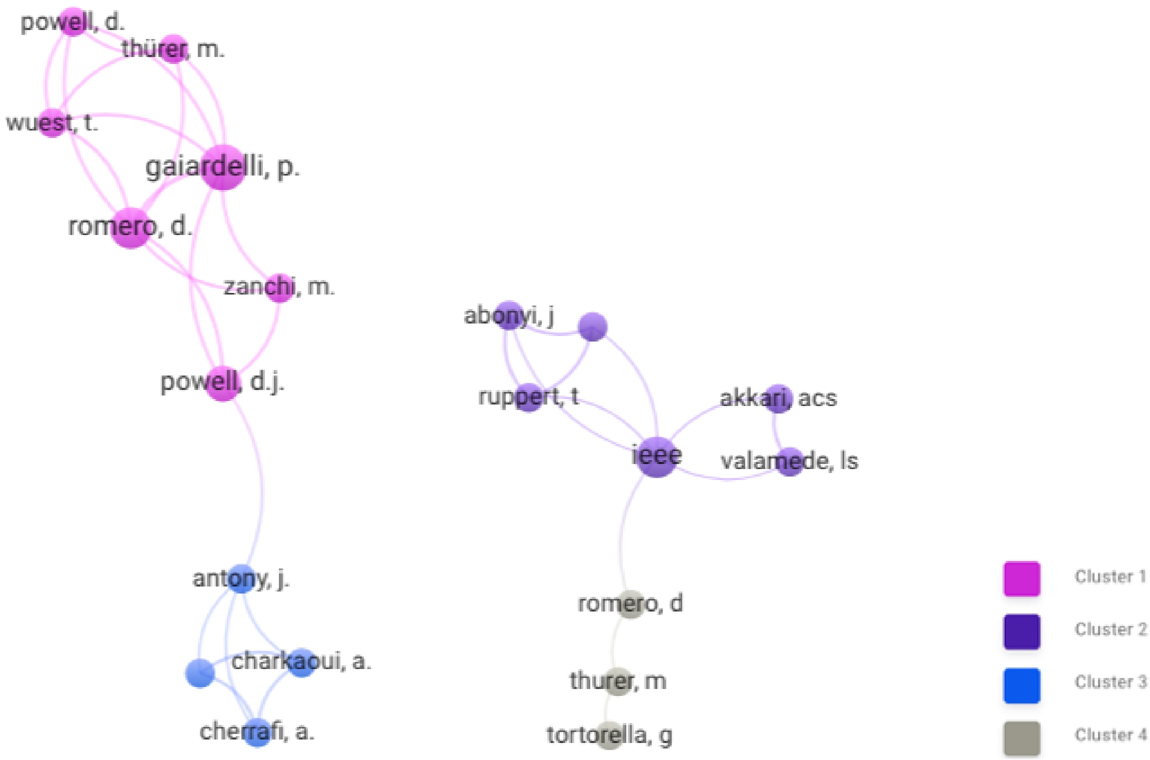

Figure 5.4: Co-occurence network - created in VOSViewer

Cluster 1 - Powell, D.; Thürer, M.; Wuest, T.; Gaiardelli, P.; Romero, D.; Zanchi, M.

Cluster 1 exhibits a research focus on digital Lean manufacturing and its intersection with Industry 4.0. The authors have collaborated on several papers, exploring many different aspects of the integration, such as intelligent Poka-yokes, cyber-physical visual management systems, and total quality management. The authors have explored the implications and benefits of implementing digital solutions relating to error-proofing, continuous improvement, cognitive automation, visualization, and quality assurance.

Cluster 3 - Antony, J.; Skalli, D.; Charkaoui, A.; Cherrafi, A.

Cluster 3 addresses the integration of Industry 4.0 with Lean Manufacturing and Lean Six Sigma. The authors have collaborated on exploring the benefits, challenges, and potential synergies between the two concepts. More explicitly, the focus has been on the integration of continuous improvement strategies, as well as integration opportunities and challenges.

Cluster 2 - Abonyi, J.; Tran, Ta; Ruppert, T; IEEE; Akkari, Acs; Valamede, Ls

The authors have collaborated on the Industry 4.0 and Lean manufacturing integration, both from a holistic perspective, as well as providing specific solutions. Abonyi, Train, and Ruppert explore how IoT technologies, such as RFID and e-labels, can enhance Lean principles, while the other authors have developed a more general framework to merge the principles of Lean with Industry 4.0 technologies - i.e., they provide a holistic integration perspective.

Cluster 4 - Romero, D; Thürer, M.; Tortorella, G

Similarly to cluster 2, the authors included in cluster 4 have explored how automation technologies can be leveraged to enhance Lean principles. Romero and Thürer have proposed a Lean automation framework that integrates Industry 4.0 technologies into the Lean production system. Tortorella further discusses the potential benefits of automation, in regards to Lean manufacturing.

6

Results

In this chapter, the key findings from the extensive literature study are presented as Synergy Points (SP), i.e., instances of integration between Industry 4.0 and LSS that demonstrate tangible examples of enhanced synergy and improved operational outcomes. The SPs mainly aim to describe the relationship between the two dimensions to answer Research Question *I* "Which digital methods and techniques can be found in the literature on Lean Six Sigma?". In addition, the results from the interviews conducted with the companies are compiled and presented to answer Research Question *II* "Which digital methods and techniques are used in the companies for Lean Six Sigma?". More detailed information on which the synergy points are based can be found in Appendix C.

6.1 Synergy points - Literature

Based on the extensive literature study, 11 synergy points have been compiled, where Industry 4.0 technologies are connected with different concepts within LSS to demonstrate how different technologies within Industry 4.0 can help enhance LSS in the manufacturing sector. The synergy points are described below.

SP1, Dynamic Value-stream mapping [D-VSM]

Several authors mention IoT as an enabling technology for the digitalization of VSM, by using sensors and RFID to capture information, companies may be able to create real-time monitoring of their processes (Peron, Alfnes, & Sgarbossa, 2021; Ramadan, Salah, Othman, & Ayubali, 2020; Romero, Zanchi, Powell, & Gaiardelli, 2022; Zarrar, Rasool, Raza, & Rasheed, 2021). According to (Romero, Zanchi, et al., 2022) one benefit of having real-time VSM is immediate feedback on decisions, which helps with the elimination of errors that are associated with inventory.

Further on, simulation is also mentioned as an enabling technology when it comes to VSM. Simulation software can be used to digitize and virtualize conventional VSMs and facilitates informed decision-making based on various scenarios created in the software (Trebuňa, Pekarcikova, & Edl, 2019). This enables businesses to test process improvements and optimizations in a simulated environment before implementing them in the real world. In a case study, the authors used the Tecnomatix Plant Simulation software to evaluate the difference between introducing a single kanban vs three kanban systems in a production process, the results from the simulation allowed the management to make informed decisions regarding the implementation.

SP2, Virtual Gemba

In an article by Romero et al. (2020), the authors suggest several technologies such as AR, VR, IoT, AI, and Big data analytics that can enhance the Gemba concept in various ways. By utilizing AR technology and equipping managers with AR glasses, relevant information from IoT-connected equipment and processes can be displayed in real-time during the walk on the shop floor, thereby enhancing the manager's awareness of the operations. Creating a virtual production setting with the help of IoT-connected devices and VR technology allows Lean managers to analyze and evaluate the production processes without causing disturbances to the production. Digital twins may also be used in the environment to offer an even more detailed view of the processes.

By utilizing IoT devices and Big data, Gemba walks can be planned and guided based on data-driven trend predictions. Additionally, the Andon system can be integrated to further highlight problem areas in need of managerial attention. By combining AI technology with the Gemba walks, managers can receive detailed information about potential problem areas. The AI utilizes the network of sensors together with analytical tools to analyze and explain potential deviations or problems allowing the managers to make sense of the problems and take appropriate actions (Romero et al., 2020).

SP3, Electronic SMED [e-SMED]

SMED can be enhanced by several I4.0 technologies, where IoT plays a key role in its success. The authors in Peron et al. (2021) refers to a system called Plug'n'Play for reducing setup times which is a system of connected IoT devices integrated with machine learning that can identify the correct times for machine changeovers. This system can be achieved by combining cloud, IoT, and big data & analytics. To-Be operations are stored in RFID tags connected to the part which directly transfers the information to the machine upon arrival, resulting in quicker changeover of machine parameters. The same kind of approach is mentioned by other authors as well; Perico and Mattioli (2020) mentions machine learning in combination with sensors as a way to enhance SMED where information regarding the part to be processed can be communicated easily. Further on, Zarrar et al. (2021) mentions RFID tags as a way to store information about a part beforehand, thus enabling an easier changeover process. Using sensors as a tool to acquire statuses such as setup times of equipment is also mentioned by Pecas, Faustino, Lopes, and Amaral (2022).

Augmented reality is pointed out as a technology that can promote SMED by providing digital work instructions for operators, which allows them to visualize and understand the changeover process (Peron et al., 2021). Additive manufacturing is mentioned as an enabling technology for SMED as setup times can be decreased drastically in such a process due to it requiring no tooling, even for more complex parts (Peron et al., 2021).

SP4, Smart Poka-yoke

Several authors mention AR as an enabling technology for Poka-yoke. AR has a strong quality significance and can help to prevent errors from occurring in manufacturing and assembly processes, it further allows for quick identification and correction of mistakes (Romero, Zanchi, et al., 2022; Walentynowicz & Pienkowski, 2020). In addition, AR can help to eliminate an operator's unnecessary motion by indicating the most efficient route to transport material (Valamede & Akkari, 2022). AR-based guide system can assist operators in the assembly sequence to ensure that the correct task is performed according to the standard procedure, thus preventing errors, or eliminating them as soon as they occur (Romero, Gaiardelli, Powell, & Zanchi, 2022).

Combining the cloud with IoT can contribute to the Poka-yoke method. Intelligent machines and robots can send information regarding errors to production and maintenance teams instantly, resulting in easier error identification and the ability to prevent new failures (Valamede & Akkari, 2022).

The authors in Romero, Gaiardelli, et al. (2022) emphasize a variety of technologies that can improve Poka-yoke, including AI, IoT, and Big data & analytics. Sensors can be used to detect errors or defects which are then further analyzed by using Big data & analytics. Additionally, RFID or Vision systems equipped with AI cameras can be utilized to monitor parts and products, enabling real-time identification. In a case study by Martinelli, Lippi, and Gamberini (2022), the concept of a vision camera integrated with AI was used in an assembly operation to detect if a seal was placed correctly or not as a measure to mistake-proof the process, by implementing this solution, productivity increased by 34%.

AI technology can further aid in the mistake-proofing process in other departments than manufacturing such as purchasing, logistics, planning, etc. (Walentynowicz & Pienkowski, 2020). Romero, Zanchi, et al. (2022) emphasizes the use of RFID for enhancing the identification of spaces by providing clear indications, enabling fast picking and storage tasks. Pick-to-light and put-to-light are two examples of digital Poka-yoke solutions for reducing human errors in storage operations. The authors in Dănuţ-Sorin, Opran, and Lamanna (2021) have utilized the CPS technology in their Poka-yoke processes, where sensors are used to collect data regarding material quality, mechanical status, measuring, etc. The data is integrated into a CPS which can manage the interaction between the components and processes, provide instructions, and correct or alert issues.

SP5, Andon 4.0

The authors in Naciri et al. (2022) describe an Andon system that uses IoT and cloud technology to enhance the abilities of the system. Sensors are used to provide real-time information between operators and machines and if an error would occur a notification is sent instantly to the relevant person responsible for that type of error. All Andons that occur are then stored in an archive on the cloud to provide instructions for future anomalies.

A similar system is described by Ito, Rahman, Mohamad, Rahman, and Salleh (2020), where data collected through sensors provide real-time data to alert personnel once an error occurs - a notification can be sent through email to the relevant person to provide immediate support. Notification by email to alert the relevant person regarding an error is also mentioned by Romero, Zanchi, et al. (2022). The authors in Walentynowicz and Pienkowski (2020) emphasize vertical integration as a beneficial addition when it comes to digitalizing the Andon system due to easier visualization of results and quicker problem-solving.

SP6, DMAIC 4.0

Both Rifqi, Zamma, and Ben Souda (2021) and Dogan and Gürcan (2018) emphasize Big data & analytics as an enabling technology for the five phases of the DMAIC cycle. The authors mention that the technology can assist decision-makers in their work to identify problems and make qualified decisions based on collected data during the DMAIC process.

In a case study by Acosta-Vargas, Chicaiza-Salgado, Acosta-Vargas, Salvador-Ullauri, and Gonzalez (2021), simulation was used during the improvement step in the DMAIC cycle where collected data from the previous steps - define, measure, and analyze - was inserted in the simulation tool to perform predictions on possible changes in the production process to reduce manufacturing times and eliminate waste.

SP7, Enhanced Visual Management

The authors in Pecas et al. (2022) suggest that Visual Management in collaboration with the I4.0 technologies, IoT, and system integration can facilitate the use of visual management by having relevant key performance indicators (KPIs) displayed and continuously updated through collected data from sensors and other IoT technologies as well as integrated business systems such as ERP and MES. Further on, visual management combined with I4.0 technologies can help with the visualization of the Andon system where information can be proactively delivered and displayed to facilitate fast awareness and response to production errors (Romero, Zanchi, et al., 2022).

SP8, Real-time OEE

In a case study made by Abd Rahman, Mohamad, and Abdul Rahman (2020), simulation and IoT was used to determine OEE and identify bottlenecks. Collected data from sensors were used as input for a simulation model which was used to estimate system capabilities for the optimal setting of decision variables. This allowed managers to acquire reliable information regarding the current OEE levels which facilitates making informed decisions concerning production. In another case study by Bakhsh and Raj (2019), a real-time management software was implemented, which provides the status of the machines such as blocked, running, waiting, etc., through collected data from sensors. Further on, the system has a built-in alert system that notifies personnel in case of a problem, which resulted in an increase in the OEE at the company.

AI technology can further assist in improving OEE by analyzing data from sensors and monitors and by allowing it to make decisions regarding maintenance, the lifespan of parts, etc. - measures can be taken before an actual problem occurs, thus, resulting in an improved OEE (Mendoza Valencia, Hurtado Moreno, & Nieto Sánchez, 2019).

SP9, Kaizen 4.0

Based on the literature study, it is clear that IoT and Big data & analytics are the most mentioned technologies when it comes to enhancing the kaizen concept. Walentynowicz and Pienkowski (2020) mentions that IoT can support the improvement process by providing management and operators with reliable real-time data. Kolberg, Knobloch, and Zühlke (2017) mentions that CPS can aid in the identification of potential improvements through statistical methods of reported data.

The authors in Hambach, Kümmel, and Metternich (2017) emphasize the importance of digitalizing the continuous improvement process, underscoring various advantages such as enhanced transparency between departments and a more streamlined improvement process where Big data & analytics could be a key technology to create such a process. In Umeda et al. (2019), an innovative approach to continuous improvement is proposed - the authors present a digital triplet that consists of three worlds, the physical world, the cyber-world, and the intelligent activity world, where digital twins create the connection between the physical and the cyber-world. The intelligent activity world is proposed by the authors as a place where engineers can implement changes and improvements.

In a study made by Martinho et al. (2022), an automatic detailed diagnosis tool is proposed. The tool is based on IoT technology and can assist in the diagnosis and problem-solving phase of the continuous improvement process. The tool is made up of a variety of sensors that collect information and sends it to the cloud for storage. The data is then retrieved by an application that constructs a detailed report regarding operator-machine interaction. Big data & analytics and IoT are mentioned by Romero, Zanchi, et al. (2022) as enabling technologies for the PDCA cycle. Reliable data collected from IoT devices and analyzed by Big data & analytics can help in making the right decision in the continuous process. A digital twin is mentioned as a supporting tool for production management for each of the phases in the PDCA cycle on the shop floor (Shibuya, 2020).

SP10, Electronic Kanban [e-kanban]

One way of facilitating Kanban is by using smart bins equipped with RFID or e-labels to enhance visual feedback. Sensors can be used to automate inventory management by automatically sending notifications for the restocking of parts (Romero, Zanchi, et al., 2022). Smart bins are further discussed by Peron et al. (2021), who describes sensors as a way to receive the exact status and location of production batches as well as recognize empty bins and automatically call for restocking. The authors further emphasize the use of sensors combined with cloud and Big data & analytics as well, which can provide real-time monitoring of a production flow and integrate systems in the plant and allow the system to make decisions regarding batch sizes, work plans, market demands, etc. Ortega, Amrani, and Vallespir (2022) suggests using sensors as a way to constantly monitor work in progress and to increase the transparency of material consumption. System integration and real-time data exchange supported by Big data & analytics are mentioned by Valamede and Akkari (2022), as they allow for a system where inventory levels can be monitored more efficiently, which facilitates the Kanban system.

Both Ortega et al. (2022) and Peron et al. (2021) discuss simulation as a tool to achieve the ideal Kanban parameters such as lot size, delivery frequency, supply route, etc. This approach allows parameters to be tested before implementation in the production which can help achieve lead-time and cost reductions. Naciri et al. (2022) further discuss RFID to assist in a digitalized Kanban system. RFIDs attached to batches or products help to keep track of the process and send signals to the MES system when a batch/product reaches its designated destination, which then generates a Kanban order. The concept helps to avoid overproduction, overstocking and to locate missing parts.

Automated guided vehicles (AGV) are pointed out as a facilitator for kanban. By having AGVs working together with humans in production it can assist in transporting material according to production flow needs and thereby reducing unnecessary motions for humans (Valamede & Akkari, 2022). This approach is beneficial for inventory minimization, and the immediate replenishment of material contributes to the Kanban system.

SP11, Just-in-time 4.0 (JIT 4.0)

Additive manufacturing (AM) is mentioned by Valamede and Akkari (2022) as an enabling technology for Just-in-time. By using AM, products can be easily customized according to specific customer needs while at the same time minimizing the possibility of defects. AM also has the ability to produce an exact volume of products requested by the customer, which promotes both inventory reduction and the concept of Just-in-time. Furthermore, AM technologies such as 3D printing contribute to reducing waste by adding material in the process rather than removing it. In a case study by Y. Xu and Chen (2016), IoT technology was used to enhance the JIT concept - RFID tags were used for real-time monitoring of machines, tools, materials, and operators to achieve a detailed overview of the production, allowing the management to make the correct informed decisions according to the JIT logic.

Walentynowicz and Pienkowski (2020) emphasizes Big data & analytics and Cloud as a way to facilitate JIT by enabling easy information-sharing and real-time monitoring, which allows for the correct information to reach relevant personnel, enabling them to make informed decisions. AGVs that autonomously can transport material can further enhance JIT logic.

6.1.1 Integration benefits

The synergy points above describe the relationship between Industry 4.0 technologies and LSS concepts (*what*), and *how* they can be integrated. Table 6.1 presents the potential benefits of such integration, answering the question of *why*. The table shows the 12 most frequently mentioned types of results found in the literature. Real-time data capabilities and waste reduction were both expressed in 21 articles, while productivity, quality, and flexibility were mentioned in 19 articles. Efficiency was mentioned in 18 articles, and decision-making and cost in 17 articles. Additionally, benefits relating to setup-, lead-, or cycle time reduction were expressed in 15 articles, visualization and planning in 12 articles, and downtime reduction in 11 articles. Less frequently mentioned benefits, which are not included in the table, were operational performance, learning, process improvement, improved accuracy, increased automation, customer satisfaction, competitiveness, safety, streamlining, and increased utilization.

Table 6.1: Integration benefits as described in the literature review - primary studies

	Results											
References	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12
Bazaz et al. (2019)	X	X	X			X	X	X				X
Pecas et al. (2022)	X		X	X				X		X		
Shibuya (2020)			X								X	
Umeda et al. (2021)			X									
Romero et al. (2022)		X	X	X		X	X	X		X	X	X
Umeda et al. (2019)			X									
Tran et al. (2021a)	X	X						X	X			
Ortega et al. (2022)				X	X			X	X			
Ito et al. (2020)	X						X				X	
Tran et al. (2021b)	X	X		X	X	X			X			
Romero et al. (2020)	X				X		X					
Dogan and Gürcan (2018)				X			X	X				
Romero et al. (2019a)		X	X	X	X			X				
Hambach et al. (2017)						X				X	X	
Abd Rahman et al. (2020)							X					
Buer et al. (2018)				X	X			X				
Bakhsh and Raj (2019)	X							X		X		
Peron et al. (2021)	X		X		X	X	X		X			
Valamede and Akkari (2022)	X	X	X	X	X	X	X	X	X			X
Martinho et al. (2022)	X	X							X	X		
Romero et al. (2022)	X	X		X			X		X			
Martinelli et al. (2022)		X	X	X		X		X	X			
Mendoza Valencia et al. (2019)			X	X	X		X	X				
Ramadan et al. (2020)	X	X				X			X		X	
Perico and Mattioli (2020)			X	X	X	X	X		X		X	
Trebuňa et al. (2019)		X		X	X	X		X	X		X	X
Aksar et al. (2022)		X					X	X	X	X		
McKie et al. (2021)										X		
Mahmoodi et al. (2022)	X		X		X		X	X				X
Romero et al. (2019b)		X		X		X					X	
Zarrar et al. (2021)	X	X	X	X	X	X	X	X	X		X	X
Jayaram (2016)	X	X		X		X		X		X		
Krishnaraj et al. (2021)			X			X						X
Walentynowicz and Pienkowski (2020)	X	X		X	X		X			X	X	X
Ghobakhloo and Fathi (2019)	X	X	X	X	X	X			X	X	X	X
Quenehen et al. (2019)					X							
Dănuţ-Sorin et al. (2021)	X	X	X		X						X	
Naciri et al. (2022)	X	X	X			X	X					X
Rifqi et al. (2021)		X			X	X	X					
Kolberg et al. (2017)	X				X					X		X
Acosta Vargas et al. (2020)	X	X	X	X	X	X			X	X		
total	21	21	19	19	19	18	17	17	15	12	12	11

(R1) Real-time data; (R2) Waste reduction; (R3) Productivity; (R4) Quality; (R5) Flexibility;
(R6) Efficiency; (R7) Decision-making; (R8) Cost; (R9) Setup-/lead-/cycle time reduction;
(R10) Visualization; (R11) Planning; (R12) Downtime-reduction

6.2 Industry 4.0 maturity level within the Swedish manufacturing sector

Interviews were conducted with five leading Swedish manufacturing companies in various industries where the interviewees were asked about their degree of maturity within Industry 4.0. Further on, two smaller companies were interviewed to establish a benchmark compared to the leading industries.

Table 6.2 below is a compilation of the maturity level of the different Industry 4.0 technologies at the various companies, which gives a clear overview of how far along the interviewed companies are in the implementation of Industry 4.0. The scoring in the table is between 0-2, where 0 indicates that the technology is not implemented within the company, 1 indicates that the technology is implemented and used in some areas or applications within the company, and 2 indicates that the technology is widely used at the company. Further on, a total score is given in the table to create an instant overview of how far the companies have come in their digitalization, this also gives an understanding of the difference between the smaller companies and the leading companies.

Table 6.2: level of Industry 4.0 maturity at the case companies.

	Case Companies							
Industry 4.0 Technologies	**1**	**2**	**3**	**4**	**5**		**6**	**7**
BDA	2	2	1	1	1		0	0
Cloud Computing	0	1	2	2	1		2	0
IoT	2	2	1	1	2		0	0
Additive Manufacturing	2	1	1	1	2		0	0
Simulation	2	2	1	1	2		1	0
CPS	2	0	1	1	1		0	0
VR/AR	1	1	0	1	1		1	0
Advanced Robotics	1	2	2	1	2		0	0
System Integration	2	1	2	1	1		0	0
Total	14	12	11	10	13		4	0

6.3 Industry 4.0 and LSS integration within the Swedish manufacturing sector

In table 6.3 the responses from the interviews regarding the usage and digitalization of LSS tools at the company are presented, where the symbol "-" indicates that the company does not work with the specific LSS concept, "x" indicates that the concept is used but not yet digitalized, and "D" indicates that the concept is actively used and digitalized in some way at the company. The table presents an overview of the usage and digitalization of the LSS tools at the interviewed companies, serving as a benchmark to understand the current state of LSS digitalization in the Swedish manufacturing industry. To facilitate comparison among the different case companies, each digitalized tool ("D") is attributed 1 point. The total points for the companies are presented at the bottom of the table.

Table 6.3: Usage and digitalization of LSS concepts

	Case companies							
LSS Concepts	**1**	**2**	**3**	**4**	**5**		**6**	**7**
JIT	-	D	D	D	D		D	-
Kaizen	x	D	D	x	D		D	x
Daily Management	x	-	D	x	D		D	x
SMED	D	x	-	x	D		x	D
5S	x	D	x	x	x		x	-
VSM	D	D	x	D	D		-	-
Bottleneck Analysis	D	D	D	D	D		-	-
Kanban	D	D	D	D	-		x	D
OEE	D	D	-	D	D		D	-
Poka-yoke	D	D	D	x	D		x	-
DMAIC	-	x	-	-	x		-	-
Gemba	-	x	x	x	x		x	-
Andon	D	D	D	D	D		-	-
Visual Management	D	D	D	D	-		D	-
Pull	-	D	-	x	-		x	-
PDCA	D	D	x	x	D		D	-
KPI	D	D	x	D	D		D	D
5 Whys	D	-	x	x	x		-	-
FMEA	D	D	x	D	x		D	x
Total:	12	14	8	9	11		8	3

6.3.1 Compilation of interactions between LSS and Industry 4.0

In this section, the interactions between Industry 4.0 and LSS that were found at the five larger, leading manufacturing companies are presented. All concepts are not described below due to either insufficient information or the fact that no company had digitalized the concept.

Poka-yoke

Some of the interviewed companies have implemented digital solutions to aid in mistake-proofing. One company has implemented a system in which the operators must scan the material barcodes, which provides the operator with component-specific information relating to what material processing tools should be used for the specific operation. Another company utilizes vision cameras to ensure proper fixture/component alignment. In addition, the company also uses ultrasound to calibrate the positions and alignments. A pick-by-light system - ensuring that an operator picks the correct components at the given operation - is used by one of the companies. Furthermore, in critical processes, the company's operators use assembly tools that records and uploads torque and angle data to internal software, which automatically stops a process if, e.g., the tightening of a bolt is not adequate.

Andon

The Andon concept is supported digitally in several ways at the interviewed companies. At some of the companies, physical buttons are used for alerting the Andon system, and once the system has been set off a message is sent to the responsible personnel - e.g., a team leader or maintenance personnel. Another company has a similar approach, but instead of physical buttons, operators submit the issue to the enterprise resource system SAP, which then notifies relevant staff.

Just-in-time

Four out of the five companies use integrated ERP solutions to enable JIT capabilities, allowing them to manage and monitor JIT calls, and request replenishment. In addition to this, at one of the companies, the logistics department is responsible for electronically triggering a JIT call. Two companies utilize AGVs to automate their JIT principles, facilitating the transportation of resources. Another company utilizes an electronic kanban solution to facilitate two-way communication with its suppliers, enabling it to adhere to its JIT principles.

Value-stream mapping

Four out of five companies had some sort of digital solution when value stream mapping - most of which still use a mix of digital and analog solutions to VSM. Pen and paper - and whiteboards - are still commonly used (and sometimes preferred) when mapping the material- and information flows at the companies. Two of the companies first map the value stream with pen and paper, and then use visualization software to present and conceptualize the VSM. Only one of the companies uses simulation software, such as Siemens Plant Simulation, and SimVSM to model the value stream, allowing for dynamic visualization and calculation of throughput times and flow rates. Another company has the necessary technological prerequisites to digitalize their VSM, albeit, no practical implementation has been conducted as of yet.

Visual management

Visual management is widely used at the interviewed companies and is digitalized in similar ways through different digital visual aids. Several companies use digital screens together with different software to visualize information regarding takt time, the status of machines and progress, Andons, OEE, etc. One company mentioned that digital instructions for the visualization of tasks are widely used at the company.

Daily management

A mix of whiteboards and digital displays are used at one company to visualize relevant operational measurements that are to be shared during daily management meetings. One of the companies replaced some of their whiteboards with digital screens (small-scale). Another company makes regular use of the *Planner*-function in Microsoft Teams to facilitate planning and streamlining the daily activities and meetings.

Bottleneck analysis

Several companies have connected machines that allow for real-time monitoring of their status. The information is used to locate bottlenecks in the system in various ways. One company uses measured cycle times to locate potential bottlenecks while another company uses mainly OEE and other data to locate bottlenecks. Lastly, one company uses proprietary software to analyze their daily flow in real-time, while also using additional collected data from the software to locate larger bottlenecks.

Overall Equipment Effectiveness

One company uses its proprietary software to calculate and visualize the machines' OEE. The software monitors production lines in real time and displays the actual performance of each line. Another company uses data extracted from its MES system to display OEE while one company utilizes digital software to gather the relevant data but manually calculates or visualizes the OEE.

Kanban

The Kanban system at one company enables automatic replenishment of tools and materials by keeping real-time inventory levels through the scanning of barcodes - which are connected to the ERP - throughout the process. The other companies use inventory data from the ERP system (or equivalent system) to automatically trigger replenishment.

Failure mode and effects analysis

One of the companies uses proprietary software to format and route process flow and process capability data from machines - data which are then used in the FMEA. One company uses mainly Excel when performing an FMEA, but may also sometimes utilize the Avix software. Another company uses undisclosed finite-element analysis software in its FMEA process.

Kaizen

To facilitate Kaizen, the interviewed companies worked with different digital solutions such as applications for submitting Kaizens that are directly connected to the collaborative platform SharePoint, or digital templates along with an AI-powered digital coach.

5S

5S was one of the least digitalized tools and only one of the companies used a digital aid to facilitate the tool in the form of an application for conducting 5S audits.

Single-minute exchange of die

Two of the interviewed companies utilized digital aids to facilitate SMED, with one company specifically mentioning Avix as a commonly used tool. Additionally, another company employed proprietary software for the analysis and improvement of setups

PDCA

One company uses proprietary software to enhance the work with PDCA in which the progress of PDCA projects can be both tracked and categorized. Another company has digital aids in the form of a digital coach and digital templates to facilitate the company's work with PDCA.

5 Whys

Only one company listed 5 whys as digitally enhanced while the other companies that used this tool performed it in an analog way. The company uses the business system SAP to conduct its 5 Whys analysis.

Table 6.4 presents a summary of how many of the interviewed companies have digitalized a specific concept. "*" represents that one concept has been digitalized at one company in the table.

Table 6.4: Degree of Industry 4.0 and LSS integration among the Swedish companies

LSS Concepts	Degree of digital adoption
JIT	****
Kaizen	***
Daily Management	**
SMED	**
5S	*
VSM	****
Bottleneck Analysis	*****
Kanban	****
OEE	****
Poka-yoke	****
DMAIC	-
Gemba	-
Andon	****
Visual Management	*****
Pull	*
PDCA	***
KPI	****
5 Whys	*
FMEA	***

6.4 Future areas of improvement within LSS

During the interviews, the interviewees were asked about what areas or concepts within LSS they think should be prioritized in the future when it comes to digitalization and Industry 4.0. This gave valuable insights into what the industry in Sweden demands regarding the digitalization of LSS.

Visual management emerged as a significant area requiring further development, as mentioned by three interviewees. The existing solutions on the market do not adequately meet the specific requirements of these companies. One interviewee pointed out customization as an important aspect of visual management - a company should be able to make changes without the help of the supplier. Another interviewee addressed the importance of easily accessible information such as work instructions.

One company emphasized the importance of VSM and the need for easier access to relevant data that is required to construct a VSM to get a better overview of their workflows. Furthermore, one interviewee addressed the challenge of lead times between when a problem is discovered and a solution is implemented, which aligns with the LSS concept of Kaizen.

7

Discussion & analysis

In the following chapter, the results obtained in the previous chapter are discussed and analyzed. The main focus of this section revolves around the three research questions while including the implications and limitations of the thesis as well as an agenda for further research.

7.1 Industry 4.0 enhances LSS practices

The results from the literature review confirm that the integration of Industry 4.0 and LSS may yield a highly synergistic relationship, giving rise to highly productive and agile manufacturing organizations. By combining LSS's focus on continuous improvement and waste reduction with Industry 4.0-enabled capabilities such as data-driven decision-making and real-time monitoring, companies can achieve greater levels of quality, efficiency, and customer satisfaction. The list of Synergy Points, presented in Section 6.1, summarizes the key findings from the literature review and highlights 11 instances where the two concepts may synergize, enabling organizations to optimize their operations and enhance their competitive position. Below, the different integration points have been classified into three categories - Supply chain and inventory management, Production efficiency, and Quality improvement - based on their respective capabilities and benefits.

Supply chain and inventory management

In terms of Supply chain management, Synergy Points *SP1 - D-VSM, SP10 - e-Kanban, and SP11 - JIT 4.0* illustrates the potential of various Industry 4.0 technologies and devices, such as smart bins, simulation software, AGV's and additive manufacturing, in visualizing and improving inventory management, as well as promoting just-in-time production. While simulation software as a tool for mapping an organization's value stream is not a new concept - a practical application of simulated VSM was proposed by McDonald, Aken, and Rentes (2002) over two decades ago - novel IoT and CPS technologies such as indoor positioning systems enable real-time data acquisition, which greatly facilitates decision-making by providing immediate feedback. Smart bins, powered by RFID or e-labels, may ease inventory management by providing real-time monitoring of stock levels and positioning, as well as automatic restocking of orders. Coupled with AGVs and AMRs, the inventory management process can be partially or fully automated. Consequently, these technologies enhance JIT principles by increasing traceability and real-time information sharing. Additionally, as 3D-printing technologies are rapidly improving (see Castelvecchi (2015); Roach et al. (2019); Saucedo-Martínez et al. (2018), the manufacturing industry might witness an uptick in products manufactured by additive manufacturing, thus, further promoting JIT by enabling continuous flow production.

Production efficiency

Production efficiency is a crucial aspect of any manufacturing process, and its optimization is essential for companies to remain competitive in the market. Synergy Points *SP2 - Virtual Gemba, SP3 - e-SMED, SP7 - Enhanced Visual Management, and SP6 - Real-time OEE*, offers novel monitoring, decision-making, and overall production optimization capabilities, which may help streamline existing production processes. As suggested by Letmathe and Rößler (2022), digital work instructions improve employee performance in assembly tasks by facilitating learning and reducing human errors. In terms of e-SMED, AR technologies can be adapted to seamlessly provide the operators with digital setup instructions. While the technology is in its very early stage of adoption (Bottani & Vignali, 2019), AR is a perfect example of a non-invasive, sensory enhancement technology, mainly used to amplify human cognitive abilities, which may prove beneficial in both assembly and changeover tasks. Changeover times can be further minimized by attributing changeover data to key components using RFID tags, which will allow the operator to gain access to the relevant parameters more quickly. IoT technologies can help optimize production efficiency by enabling enhanced Visual Management. Smart sensors, integrated with the ERP system, can provide real-time, detailed KPIs, which will facilitate strategic and operational decision-making. Real-time OEE capabilities will also help facilitate informed process-related decision-making by enabling companies to monitor their equipment's performance and identify bottlenecks, allowing them to make immediate adjustments to improve their production efficiency. With the help of Virtualized Gemba walks, the management will be constantly up-to-date regarding changes in production, and AI technologies can provide them with in-depth analysis and explanations of the shop-floor state. Regarding machine performance, connected smart sensors will provide machine status data at all times, which can be used to automatically trigger maintenance orders. AI technology can analyze the data from said sensors to gain valuable information about machine performance, which essentially enables preventive, condition-based maintenance.

Quality improvement

Synergy Points *SP4 - Smart Poka-yoke, SP5 - Andon 4.0, SP6 - DMAIC 4.0, and SP9 - Kaizen 4.0* address the new era of continuous process improvement, centered around improving quality and reducing defects. The increasing adoption of Industry 4.0 technologies has drastically bolstered the mistake-proofing potential within the manufacturing sector. Smart Poka-yoke systems are comprised of a variety of solutions to introduce "redundancies" in every step of the production process. Instead of using traditional fixtures to ensure alignment, vision cameras - coupled with AI technology - guarantees proper calibration and positioning, and that the correct parts and tools are used at any given time. Smart bins and RFID tags permit pick-by-light, AR and AI calculate and indicate the most efficient transport route, and smart sensors help detect and communicate machine errors. The opportunities of a digitalized Poka-yoke system are boundless. Similarly, Andon 4.0 ensures that any error of defects are communicated to the relevant personnel and logs the errors to help deal with future occurrences. By using AI, state-of-the-art Andon systems can detect process and parameter anomalies both before, and during processing, which automatically prevents a process from starting, or stops a running process. DMAIC 4.0 and Kaizen 4.0 further integrate data analytics into the traditional continuous improvement efforts, allowing for a more thorough analysis of the production processes and facilitating the identification of problem root causes. By leveraging these Synergy Points, organizations may able to achieve unprecedented levels of quality and efficiency in their operations.

7.2 Current state of LSS and Industry 4.0 implementation in Sweden

By analyzing the data collected from the interviews, a clear overview of how leading manufacturing companies in Sweden utilize and digitalize Lean Six Sigma (LSS) concepts was established, as presented in Table 6.3. The findings indicate that there is widespread usage and digitalization of LSS concepts among all interviewed companies. However, it is clear that the solutions presented in section 6.3.1 could benefit from further support through the integration of Industry 4.0 technologies. Many of the solutions are less advanced compared to solutions found in the literature. In addition, none of the companies have fully digitalized *all* the examined LSS concepts included in this study. Several factors may contribute to this, such as the notion that not all concepts within LSS currently benefit from digitalization or that it does not align with the companies' manufacturing strategies. Furthermore, several companies expressed caution when it comes to digitalization, avoiding unnecessary implementation with little to no tangible benefits to their operations.

During the literature search, it was observed that Six Sigma, by definition, is not as widely used compared to Lean. A large majority of the reviewed articles focused solely on Lean while only a few included Six Sigma. This trend could be seen during the interviews as well, where most companies stated that they do not strictly adhere to the Six Sigma methodology. Instead, certain aspects of the methodology are integrated into their production system, which is mainly based on the Lean philosophy. Consequently, the results of the project have been more focused on Lean rather than LSS and Six Sigma, as originally intended.

As can be seen from the results, there is a significant difference between larger manufacturing companies and the smaller companies included in the study in terms of both their LSS implementation and digitalization of these concepts as well as their digitalization level in general. As seen in Table 6.2, the larger companies scored between 10-14 in their implementation of Industry 4.0 technologies while the smaller companies scored between 0-4. This clear contrast in digitalization maturity may be attributed to organizational differences relating to resource allocation capabilities, business strategy, and/or the number (and level) of experienced personnel. This claim is further supported by Cotrino, Sebastián, and González-Gaya (2020). However, the data in Table 6.3 shows that company 3 and company 6 have the same total score in terms of the number of digitalized LSS concepts, which may create some confusion. But, as seen in Table 6.2, company 3 scored 11 in their Industry 4.0 implementation while Company 6 scored 4, which suggests that the implemented solutions at Company 6 could be seen as less extensive compared to Company 3. This is made apparent by the nature of the digitalized solutions at the two companies, as they differ in complexity. Company 3 has digitalized more complex concepts related to process improvement such as Andon, Poka-yoke, VSM, etc, involving advanced techniques for process optimization and problem-solving. Company 6 has focused more on concepts that offer capabilities in structure, organization, and visualization.

Based on the discrepancy in digitalization maturity, concerning the number of digitalized concepts and their complexity, smaller organizations may fall behind in their LSS digitalization efforts. However, this also provides an opportunity for smaller companies to learn from larger organizations and implement successful and proven methods, expediting their own LSS digitalization efforts.

7.3 Future areas of improvement within LSS in terms of digitalization

The interviews with leading manufacturing companies have identified the most critical areas requiring further digitalization within Lean Six Sigma. The areas pointed out by most companies were Visual management, value-stream mapping, and continuous improvement (Kaizen). In Table 6.4, it can be observed that these concepts have already been partially digitalized by most companies, which indicates that existing solutions in use do not fully meet the companies requirements. Comparing the companies' digital solutions with the findings in the literature reveals significant potential for improvement in the industry.

Value-stream mapping is used by all five companies, with digitalization implemented to some extent in four of them. However, further improvement is necessary. A noteworthy solution from the literature study found in SP1 - D-VSM, is real-time VSM that uses IoT devices such as sensors and RFID for real-time monitoring of the companies' processes, enabling immediate feedback on decisions. One of the reasons why companies have not yet implemented this solution may be because of the large investment and infrastructure required for it to work, as it would involve connecting and integrating a large portion of machines and equipment into the systems.

Another solution for enhancing VSM that was mentioned in the literature was simulation software. This was only used by one of the interviewed companies, while the other companies used less advanced digital solutions to facilitate VSM. Simulation could be an appropriate next step for companies to implement as it can be seen as a cost-effective alternative compared to real-time VSM and is a proven concept since one of the companies is using it today.

Visual management was highlighted by three interviewees as an area in need of further development due to the existing market solutions failing to meet their specific needs. One interviewee mentioned that there are too many constraints in the current solutions and that it is difficult to implement changes in the system without the help of the supplier, which led to the company developing its own software for visual management. The interviewed companies use similar solutions to those mentioned in the literature when it comes to visual management, indicating that both industry and research need to develop in this area. This area was considered highly important by the leading industries, as it was mentioned by three out of five companies as an area needing improvement.

In terms of visual management, IoT, Big data & analytics, and system integration can be considered crucial Industry 4.0 technologies. IoT is needed to collect large sets of data, while BDA can be used to analyze the data to retrieve relevant information. System integration is necessary to share and display information quickly.

One company mentioned kaizen as an area in need of further development, specifically focusing on shorter lead times in the process from when an event occurs to a solution has been implemented. The digital solutions used by companies today are mainly phone and desktop applications for audits and submitting of kaizens, as well as digital templates. The solutions mentioned in the literature are not necessarily suitable for solving the specific problem of long lead times. However, IoT and Big data & analytics are mentioned as the two Industry 4.0 technologies that can contribute the most to improving the kaizen process and can therefore be of interest in solving the problem with long lead times.

7.3.1 Conceptual Framework Foundation

Based on the results and discussions, the foundation for a conceptual framework was developed - see Figure 7.1. The purpose of the framework is to visualize the concept of Industry 4.0 and LSS integration, including the relevant drivers, support functions, benefits, technologies, future research areas, etc. In its current state, the framework presents a superficial overview of the elements constituting the digital transformation of LSS. Future research is required to elaborate on the individual constituents - especially, elements relating to technical challenges and prerequisites, and managerial and organizational barriers.

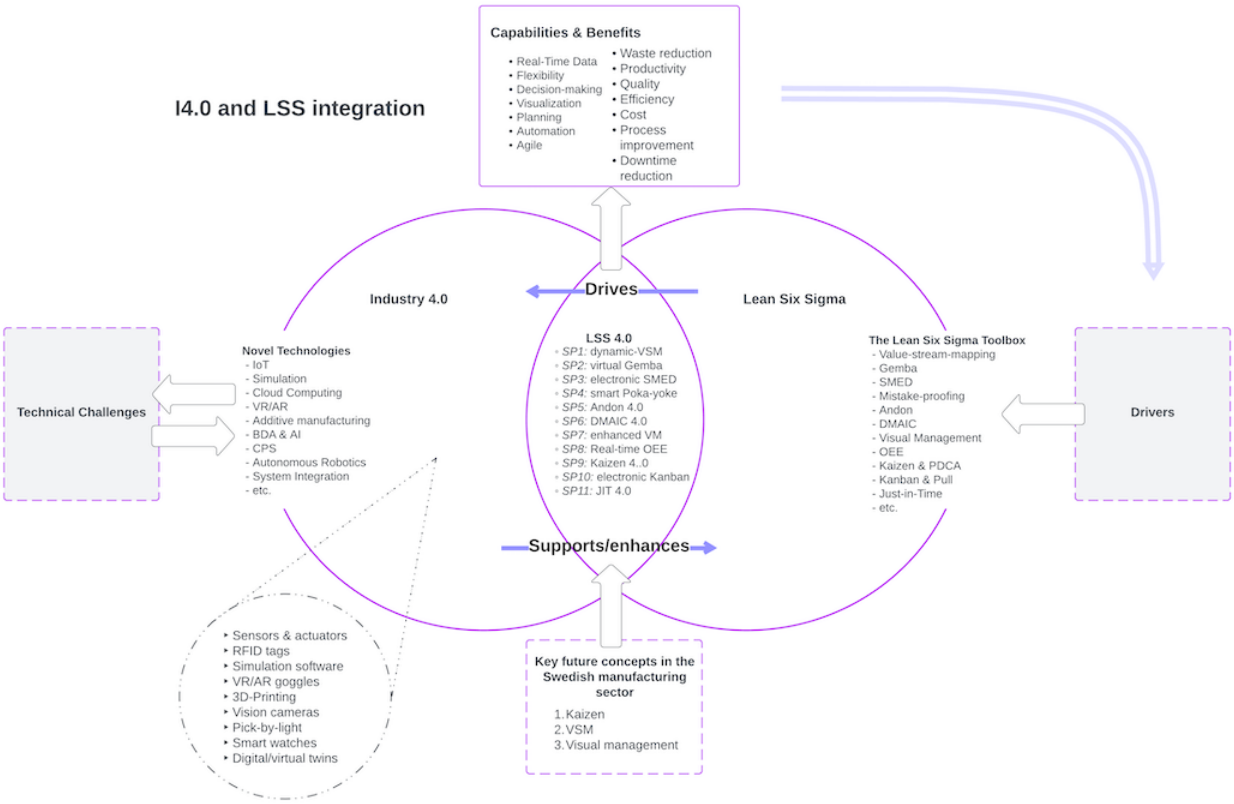

Figure 7.1: Foundation for a conceptual framework

7.4 Practical implications and research limitations

This report intends to provide process improvement professionals with valuable insights into existing digital transformation initiatives, assisting in future operational excellence projects. The list of Synergy Points serves as a valuable reference, highlighting real-world examples of how digital solutions have been successfully integrated into the LSS framework. Manufacturing professionals may examine these integration instances to gain inspiration and practical knowledge on which Industry 4.0 technologies have been adopted, how they can be integrated into LSS (from a technical standpoint), and the potential synergies between the two dimensions. Moreover, the list of benefits presented in 6.1.1 may hold some managerial decision-making implications. The benefits shed light on process capabilities and opportunities that future digitalization investments can bring to organizations.

Throughout the project, various factors were identified that potentially impacted the outcome. Due to the time limitation of the project, only five companies were examined when studying the level of digitalization maturity at the leading manufacturing companies. To get a broader knowledge of the current state of the Swedish manufacturing industry, more companies could have been included in the study. Further on, to minimize bias from the participating companies it would have been beneficial to include more participants from the same company in the interview section.

Considering the length of the project, the topic can be considered too broad as it has been difficult to analyze the topic on a deeper level, which has led to the findings being somewhat superficial. To obtain a deeper knowledge and more detailed result regarding the digitalization of specific LSS concepts, narrowing down the scope to 4-5 concepts would have been preferable instead of 19. Many of the LSS concepts analyzed in the report are extensive enough to warrant the report's sole focus.

The literature search using a specific search string yielded 41 primary sources, all of which discussed practical and theoretical integration solutions. While this number was sufficient to generate a list of Synergy Points covering various LSS concepts and Industry 4.0 technologies, further refinement of the search string could have identified additional relevant publications. Including separate search strings for each Industry 4.0 technology may have yielded more Synergy Points, however, the extensiveness of the report would have been significantly affected. Alternatively, a snowballing approach could be used to control the scope of the literature search, which involves identifying relevant papers by exploring the reference lists of already sorted and eligible papers.

7.5 Agenda for further research

Due to the novelty of the research topic, only a limited number of papers explore the integration of Industry 4.0 into the LSS approach - most papers solely address the Lean philosophy. Thus, further conceptual and practical research is needed to identify drivers, motivations, and barriers related to the impact of novel technologies on LSS. This research could be used to expand on the foundation presented in 7.1, to develop an LSS 4.0 framework. Furthermore, real-world applications of the Synergy Points reference list, presented in this paper, are needed to validate its feasibility.

Typically, the vast majority of research papers addressing the rationales and procedures of LSS and Industry 4.0 integration explore individual LSS (read, Lean) concepts and technologies, and lack a holistic, all-encompassing perspective of the interplay between the dimensions. There is a desperate need for research focusing on end-to-end solutions, where Industry 4.0 technologies are used to facilitate the core principles and philosophies of Lean and Six Sigma, rather than specific concepts and tools. For instance, instead of studying the digital transformation of specific concepts like JIT 4.0, and e-Kanban separately, researchers could explore how novel technologies can be leveraged to facilitate the Pull principle. Additionally, the preferred implementation sequence of LSS 4.0, whether concurrent or sequential, needs to be addressed.

Swedish manufacturing leaders specifically request digital solutions in Visual Management, VSM, and Kaizen, due to the scarcity of existing overall solutions. In the list of Synergy Point, the solutions addressed in SP7 - *Enhanced Visual Management* - is similar to the ones found at the case companies. Yet, the companies are not fully satisfied, suggesting that further research regarding the required specifications is needed.

8

Conclusion

This paper aimed to identify and present integration opportunities between Industry 4.0 technologies and LSS concepts by analyzing existing research in the literature, and real-world applications in the Swedish manufacturing industry. The findings have led to the development of a list of Synergy Points, which represent instances of integration between the two dimensions. Additionally, a foundation for a future LSS 4.0 integration framework was established. Both the Synergy Points list and the framework can provide valuable references for industry professionals undertaking future operational excellence projects, offering insights into successful integration initiatives, including the *'what,' 'how,'* and *'why'* aspects.

Further details regarding the three research questions will be discussed in the following sections.

Research Question I - *"Which digital methods and techniques can be found in the literature on Lean Six Sigma?"*

A systematic review was carried out to examine which digital solutions could be found in the literature. The review identified 41 primary sources published between 2016 and 2023, relating to the research topic. Based on the findings, a total of 11 Synergy Points in three different manufacturing capability areas were identified.

In **Supply chain management**, SP1 - D-VSM, SP10 - e-Kanban, and SP11 - JIT 4.0 illustrates how Industry 4.0 technologies and devices, including smart bins, simulation software, AGVs, and additive manufacturing, have the potential to enhance inventory management visualization and improve just-in-time production.

In terms of **production efficiency**, SP2 - Virtual Gemba, SP3 - e-SMED, SP7 - Enhanced Visual Management, and SP6 - Real-time OEE provides innovative monitoring, decision-making and production optimization capabilities by leveraging AR, IoT (RFID, Sensors), AI technologies. These Synergy Points may help streamline current production processes and enhance overall operational efficiency.

Finally, **Quality improvement** capabilities can be enhanced with SP4 - Smart Poka-yoke, SP5 - Andon 4.0, SP6 - DMAIC 4.0, and SP9 - Kaizen 4.0, by introducing redundancies with the help of AI, IoT (Vision cameras, RFID, sensors), and AR technologies. These technologies will be vital in continuous improvement efforts centered around reducing defects and handling errors.

Further research about the integration of Industry 4.0 technologies into the LSS framework is required to fully understand the interplay between the different LSS 4.0 concepts, as well as to leverage the Six Sigma aspect of the framework.

Research Question II - *"Which digital methods and techniques are used in the companies for Lean Six Sigma?"*

The results presented in Table 6.3 and section 6.3.1 intend to answer Research Question *II* by presenting the usage and digitalization of the LSS concept at five leading companies in Sweden. This helps estimate the current state of LSS and Industry 4.0 implementation in Sweden.

The group's assumption based on the mentioned results is that there is still a lot of potential left when it comes to digitalizing LSS at Swedish companies. However, as discussed, external factors such as the insufficient development of digital solutions tailored to specific company needs and cautiousness regarding digitalization implementation can impact the pace of LSS digitalization.

Additionally, two smaller companies were included in the study to establish a benchmark between large and small manufacturing companies in terms of LSS digitalization. The results showed that there was a great difference between these, both in terms of digitalization and the general use of LSS. This gap causes smaller companies to fall behind in the implementation, while also presenting an opportunity for them to analyze and adopt already implemented and tested solutions suitable for their operations.

Research Question III - *"Which LSS concepts should companies and researchers prioritize in the future regarding Industry 4.0?"*

Based on the results and discussion of this thesis, it is evident that the short-term focus should prioritize three key areas; Visual management, Value-stream mapping, and Kaizen, as identified by the leading manufacturing companies.

Among these areas, visual management can be seen as the most critical area requiring further research and improvement, as it was consistently mentioned by a majority of the interviewed companies as an area in need of enhancement. The research points to this being an area that is relatively unexplored as the solutions that were mentioned in the literature were similar to those that companies use today.

Furthermore, additional exploration of the Six Sigma aspects of the integration is needed.

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A

Interview Questions and Extraction Form

- **What is your role at the company? What are your areas of responsibility? How long have you been working with Lean/Six Sigma/LSS or digitalization?**

- **To what extent do you work with Lean/Six Sigma at the company?**

- **What digital tools do you use to facilitate work with Lean and Six Sigma? (See extraction form)**

- **Have you thought of anything within Lean Six Sigma that could be made easier through digitalization?**

- **In your opinion, what should be the next area of focus within LSS when it comes to digitalization?**

Case Company:

Position:	**Yes/No**			
	Concept is widely used	Concept is digitalized	How?	Comments:
JIT - Just-in-Time				
Kaizen				
SMED - Single Minute Exchange of Die				
Daily Management				
5S				
VSM - Value Stream Mapping				
Bottleneck analysis				
Kanban				
OEE				
Poka-Yoke				
DMAIC				
Gemba				
Andon				
Visual management				
Pull (Continuous flow)				
PDCA – PDSA				
KPI - Key Performance Indicators				
5 Whys – Root Cause Analysis				
FMEA				

Industry 4.0	0-2
BDA	
Cloud Computing	
IoT	
AM	
Simulation	
CPS	
VR/AR	
Advanced Robotics	
System integration	

B

Journals and conferences

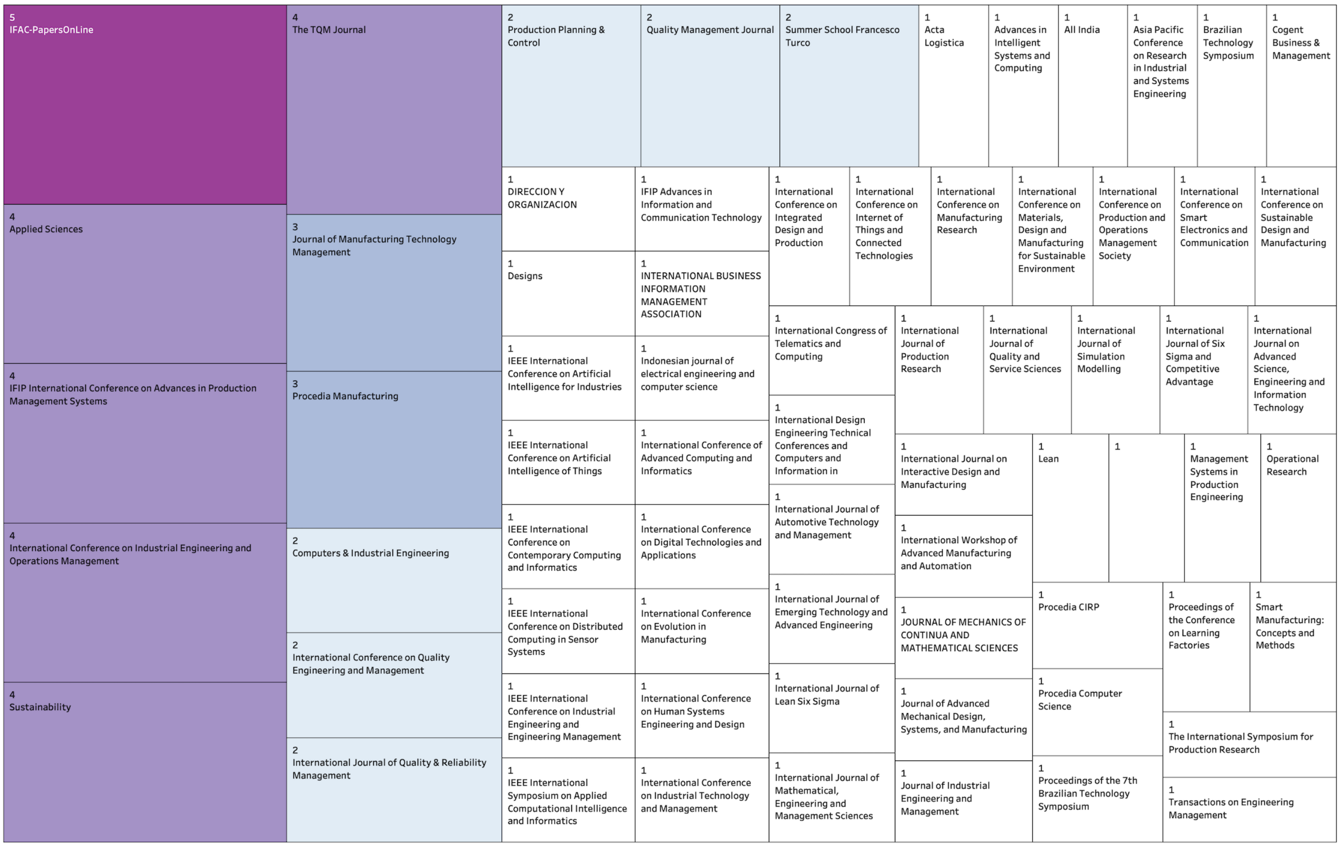

Figure B.1: Compilation of journals and conferences from the literature review

C

Data extraction form

Authors (Year)	Contact points perceived	I4.0 technologies	LSS practices/concepts	Research approach	Country
Bazaz, Lohtander, and Varis (2019)	a) Digital Twin can be used to specify the type and amount of materials, and the processes and methods required to produce the desired product, which can reduce inventory and prevent overproduction	Digital twin, real-time data	reduce inventory, reduce overproduction	Theoretical Study	Ireland
	b) Digital twins can be used to plan a precise schedule for the lifecycle of a prodcut and thereby reduce downtime		reduce downtime		
Pecas, Faustino, Lopes, and Amaral (2022)	**[e-VMB]** The author's suggest creating a KPI repository, where each KPI is nurtured with automatic data acquisition systems, and supported in IoT. A novel e-VMB methodology takes advantage of the present communication and information technologies to present the information in a dynamic way, permanently updated. Furthermore, If the VMB is integrated with the technologies of digitalization and data acquisition, communication and information of the I4.0 (IoT), the potential is much higher.	ERP/MES- systems	Visual Management Board (VM/VMB)	Case Study	Portugal
	[e-SMED] With the help of industry 4.0 technologies, traditional SMED methodologies can be enhanced - allowing operators to systematically minize variability. Sensors can be used to acquire equipment statuses (including setup times), which will contribute with valuable information to the SMED repository. The sensors, together with an IoT platfrom, will aid in data processing and information retrieval. The data should be linked to the ERP system.	Sensors, IoT (data processing)	Single-minute exchange of die		
Shibuya (2020)	A digital twin can be used to support production mangement opeartions at the shop floor at each phase of the PDCA	Digital twin	PDCA	Case Study	Japan
Umeda et al. (2021)	Digital twins can be used in the concept of digital triplet where the digital twin plays a key role. The purpose of a digital triplet is to enable an "intelligent activity world whre engineers can excecute engineering activities	Digital twin	continuous improvement	Design Research	Japan
Romero, Zanchi, Powell, and Gaiardelli (2022)			**Visual Control (Mieruka) - 7I's**	Literature Review	Mexico, Italy, Norway
	[Digital Poka-Yoke] RFID or other automatic identification tools may be able to digitally enhance the *identification of spaces* by providing clear indications, enabling fast picking and storage tasks. Pick-to-light and put-to-light are two examples of digital Poka-Yoke (*a solution aimed at reducing or eliminating human error)* in finding & storage operations	Automatic Identification (RFID,e-labels), projection mapping	- Identify (Poka-Yoke)		
	[e-Kanban] Smart bins - constructed using RFID or e-labels - can enhance visual feedback, and manual counting of inventory levels can be replaced with automatic counting by implementing sensors. This could result in automatic e-notifications for restocking tasks, which will facilitate inventory management.	RFID (e-labels), sensors	- Identify (Kanban)		
	[VSM 4.0] With the help of smart sensors, modern value stream maps will be IIoT-enabled, providing accurate real-time information about the machines' and the operators' workstation performance.	IIoT, smart sensors, real-time data	- Identify (VSM)		
	[Digital Andon] "Through digital Andon devices, information can be proactively delivered and visualized by the appropriate workers using targeted e-notification systems" - fast response to production abnormalities	IIoT	- Inform (VM)		
	"information can be proactively delivered and visualized by the right workers using targeted e-notification systems to quickly react to any production abnormalities"	e-notification, smartphones, tablets, etc.	- Inform (Andon)		
	[Digital Poka-Yoke] "AR is a key enabling technology for improving the transfer of information from the digital to the physical world in a non-intrusive way for the operator." The technology is an enabler of *Digital Assistance Systems for reducing human errors, as well as the dependence on printed work instructions, computer screens, and operator memory.*	AR	- Instruct/illustrate (Poka-Yoke)		
	[Digital Poka-Yoke] Integrated simulation technologies can help test and schedule countermeasures before implementation of visual planning tools - Kanban, A3 sheets, etc.	Simulation, IIoT	- Instill/inspire (Poka-Yoke, standardization)		
	[Digital Poka-Yoke] AR-enhanced Visual Procedures allows for higher productivity rates, and error-proof processes.	AR, Digital Assistance Systems	- Improve (Poka-Yoke)		
	[Digital Heijunka] "IIoT-based Heijunka boards are able to automatically scan the pace of production, thanks to smart sensors, and support a "truly holistic" production (re-)scheduling in real-time and just-in-sequence logic - avoiding waste risk creation due to the lack of a systemic scheduling approach"	Smart sensors, IIoT	- Indicate (Heijunka)		

	[PDCA 4.0] "Digitally-enhanced PDCA cycle can automate and/or augment its data acquisition, data integration, data processing, and data visualization activities with the use of IIoT, data analytics, and real-time visualization technologies for avoiding continuous improvement decisions/actions based on obsolete data."	IIoT, Data integration, Data processing, Data visualization (BDA), real-time	- Indicate (PDCA - continuous improvements)		
Umeda et al. (2019)	A digital triplet which consists of digital twins, phyical world and the intelligent activity world where the last allows engineers to pursue improvements in the phsyical world through the help of digital twins/CPS. This enables engineers to implement contionous imrpovement etc. in the era of industry 4.0 and CPS.	Digital twin	continuous improvement/kaizen	Design Research	Japan
Tran, Ruppert, Eigner, and Abonyi (2021)	Digital twins in cobination with real-time location systems (RTLS) gives the ability to have a real-time overview/simulation of your physical system such as a production line.	Digital twin & IPS	Reduce leadtime, reudce waiting time, reduce loss time, "säkert mer också men som inte nämns i artikeln"	Case study	Vietnam & Hungary
Ortega, Amrani, and Vallespir (2022)	a) **[Kanban 4.0]** "One of the multiple ways of industry 4.0 to complement Lean is with the usage of automatic guided vehicles (AGVs). Accordingly, with receiving instructions, AGV calculate the optimal path to complete the task giving their autonomy and mobility"	AGV	Kanban	Conceptual Study	France
	"The application of wireless sensors attached to the materials on the production floor, permits companies to constantly monitor the work in process and increase the transparency of the consumption of materials. The comparison with the actual demand enabled the reduction of the inventory translated into cost reduction (Mayr, 2018). The introduction of industrial sensors for the real-time monitoring of production volumes enabled the company studied in (Ghobakhloo, 2020) to decrease unfinished work in the process as well as problems for reprioritizing tasks to adapt to the demand. It enhanced the work flow by enabling workin-process (WIP) restrictions, tracing lead times and examination of workflow."	Wireless sensors			
	c) Simulation can help to test the behavior of Lean concepts and principles before implementing them (different solutions). "The expected demand for each Kanban station needs to be entered in the simulation system for it to exit the most efficient supply route and number of operators required not to overpass the maximum lead time. The cost, lead time of the company can be positively impacted when the Kanban calculation and parametrization are simulated and provided by optimized systems (Santos et al., 2020)."	Simulation			
Ito, Rahman, Mohamad, Rahman, and Salleh (2020)	**[Digital Andon]** Deploy an Andon signaling board, where the signal notifies others when a problem occurs within the production or quality control streams. The Andon system uses data collected through sensors, providing real-time data. An iPaaS software "can be employed to automate processes like approval process and email triggering via mobile notification to provide immediate support when there is an occurrence, in order to prevent line stop."	Sensors, IoT, Real-time	Andon	Design Research	Malaysia
Tran, Ruppert, and Abonyi (2021)	a) Real-time monitoring of the position of semi-finished products and resources, calculation of the lead and cycle times	IPS, camera, bar-code, RFID	Reduce lead-time	Litterature rewiew	Hungary & Vietnam
	b) With the help of technologies such as RFID, IPS, cameras etc. the lean concept 7 waste can be managed through real-time spaghetti diagrams, tracking items in inventory, tracking semi-finished goods in order to manage waiting times and discover overproduction. Reduced defect can also be achivied through IPS-based poke-yoke solutions and better monitored reworkflows.	RFID, IPS, camera, sensorns, bar-code	7 waste		
	c) Improved control of the inventory level and e-kanban solutions reduce internal inventories	RFID, IPS	Reduce inventory		
	d) Discover queeing areas near workstations	RFID, IPS	Contionous flow		
	e) Improved activity time analyses thanks to sensor fusion	Camera, RFID, IPS	Line balanceing		

	f) IPS based dynamic work instructions improve operator work (Smart operator)	Camera, RFID, IPS	Standarized work		
Romero, Gaiardelli, Wuest, Powell, and Thürer (2020)	Novel digital technologies allows for a number of new forms of Gemba walks: a) Augmented Gemba walk - utilizing Augmented reality (AR) smart glasses to enhanze the managers' situational awareness by augmenting their field of view, providing them with relevant data and information from IIoT-enabled machines/operators/processes. b) Virtual Gemba walks - Remote interaction with IIoT-enabled smart, social machines and operators through digital twins, in a Virtual Reality (VR) production setting. This allows lean managers to simulate and analyse work processes and view them from different perspectives without any disruption of a production resource. *c)* Automated guided Gemba walks - The Gemba walks are planned and guided based on data-driven trend predictions provided by IIoT-enabled smart, social machines and operators. Andon systems could be used to hihglight particular problems areas in need of managerial attention. d) Human Cyber-Physical Gemba walks - Creating a "joint cognitive system" between lean managers and AI-enabled systems. The AI uses their networks of sensors within the facilities as well as analytical tools, to analyse and explain potential deviations or abnormalities, allowing the managers to make sense of the problems at hand.	IoT, Handheld smart devices, sensors, VR, AR, BDA, AI	Gemba	Theoretical	Serbia, Hungary, Mexico
Dogan and Gürcan (2018)	"Big data" such as data mining, Big data analytics and process mining can help utilize the DMAIC cycle in LSS. By using these technologies in the different phases of DMAIC/DMADV it helps to make effective decisons regarding quality problems.	Big data analytics	DMAIC, DMADV	Litterature review	Italy, Turkey
Romero, Gaiardelli, Powell, Wuest, and Thurer (2019)	Communicate machine readings to the cloud via single board computers (e.g., Arduino). Gather readings from sensors (vibration, acoustic sensors) and analyze the data using prediction algorithms (e.g., tool wear predictions). The data can be used to allow for automatic tool adjustments and replacements. AR can be used to provide the maintenance operators with valuable information - do we have adequate capacity? Availability of tool-repair equipment? A simple text-based system (sms to the operator's mobile phone) would suffice.	Sensors, single board computers, ML, AR	Jidoka	Theoretical	Mexico, Italy, Norway, USA
Hambach, Kümmel, and Metternich (2017)	Digitalizing the continuous improvement process promotes several benefits such as transparency between departments and more efficient improvement processes. According to the authors, digital tools such as data collection, data storage and access, and data analysis may help to create a more digitalized continuous improvement process.	Big data	Continuous improvement/kaizen	Theoretical	Germany
Abd Rahman, Mohamad, and Abdul Rahman (2020)	The authors developed a simulation of a production line where the machines were not performing ideally - frequent machine breakdown and lost speed. The simulation (DES) made use of machine data (speeds, run-times, etc.) acquired from sensors. The data from the sensors were compiled into the database (MySQL) and then aligned based on the simulation input, such as cycle time, quantity, number of operators, etc. The DES model was then used to estimate system capabilities for the optimal setting of decision variables. By using sensors and simulation models, the managers acquired information about the current OEE levels and bottlenecks, which will allow them to make informed decisions regarding their production processes,	Sensors, Simulation	OEE	Case	Malaysia
Buer, Fragapane, and Strandhagen (2018)	4 levels of kanban is discussed in this article. Level 1 - Traditional kanban, Level 2 - e-Kanban, Level 3 - Autonomous kanban, Level 4 - Self-optimizing kanban Level 2 - e-kanban - The kanban signal is transmitted electronically, however the transmitting of kanbans is still manual. Level 3 - Autonomous kanban - An industrial example of this is the iBin system which automatically records the material level and sends it to the inventory control system. Based on this, orders are sent automatically to suppliers when needed. Level 4 - Self-optimizing kanban - Such system is an development of the autonomous kanban system which is able to automatiaclly run the kanban loop but aslso uses the collected data to analyze and prioritize improvements. A self-optimizing Kanban system autonomously adjusts the bin size as well as the number of cards in circulation according to predefined performance objectives, such as cost, throughput time, or similar	nämns inte ordagrant vilka teknologier	Kanban	Conceptual Study	Norway

Bakhsh and Raj (2019)	The authors implemented a real-time data mangement software - Think7 - at a consumer goods component manufacturer, in an attempt to increase their OEE. The installation of Think7 required PLC upgrades of the current machines, a very fast internet connection, and a computer. The software provides the status for all machines - blocked, running, waiting, breakdown, etc, and has a built-in alert system which notifies the relevant engineer or operator when an issue arises. In the case study. the company's report verification time, real time data acces, report processing time, data processing costs, and data storage costs significantly decreased, while the writing accuracy increased. The IoT system allowed the company to take necessary measure, and thus, improve their OEE.	IoT	OEE	Case	Saudi Arabia, India
Peron, Alfnes, and Sgarbossa (2021)			**Just-in-Time**	Multi-Case	Norway
	By using AGVs, single units can be transported through a flexible material flow in an efficient way - no need for material handling devices such as belts or roll conveyors. The automated vehicles will lead to reduced congestions, as they can reroute their paths accordingly. Supplying material to the workstations will become mistake proof, since human interaction (forklift operators) will be minimized or eliminated. Advanced algorithms and intergrative technologies will enable intelligent routing systems which can analyze traffic information in real-time, reducing waiting times (Güner, A.R., Murat, A., Chinnam, R. B, 2012) and ensures a proper flow without interruptions, bottlenecks, or delays.	Advanced vehicles - AGV, advanced algorithms	Continuous flow		
	[Dynamic VSM] - Dynamic value stream mapping, or real-time VSM, allows for immediate feedback on decisions and elimination of errors associated with inventory. Sensors and RFID (or other indoor positions systems) will allow real-time data about the materials and equipment, and big data analytics will help analyze the data, eliminating inventory errors, and maintainign a low level of stock. The combination of DVSM and cloud computing will provide real-time KPIs - enabling more informed decision-making processes Phuong, N.A., Guidat, T(Phuong, N.A., Guidat, T, 2018).	Sensors, BDA	Continuous flow, VSM		
	Combining sensors, BDA, and cloud computing with a simulation tool allows for simulation-based real-time solutions - ensuring continuous flows by detecting bottlenecks (Rosin, F., Forget, P., Lamouri, S., Pellerin, R., 2020)	Simulation	Continuous flow		
	Real-time, Flexibility, Setup time reduciton, Decision-making, Safety, Productivity, Efficiency, Visualization, Planning, Waste reduction, Lead time reduction,	Additive manufacturing	Continuous flow & Pull		
	[e-Kanban] Sensors can be used to provide the exact status and location of production batches, recognize missing and empty bins automatically, and even trigger replenisments (IoT) (Rosin, F., Forget, P., Lamouri, S., Pellerin, R., 2020). An example of this is the iBin systems - a small module with a camera, which is installed in the the small parts bins.	Sensors, IoT	Pull (Kanban)		
	[e-Kanban] Sensors, coupled with cloud computing and big data analytics, can be used to constantly monitor the production flow and holistically integrate all sectors of the intelligent plant - allowing the system to become self-organized through decentralized decisions. the e-kanban can automatically adapt to changes in batch size, market demands, work plans, etc., (Mayr, A., Weigelt, M., Kühl, A., Grimm, S., Erll, A., Potzel, M., et al, 2018)	BDA, Cloud computing, sensors, IoT	Pull (Kanban)		
	Digital support systems, enabled by digital twins or simulation tools, can be used to test different parameters of kanban, allowing the identification of ideal kanban parameters - e.g., lot size, stock, delivery frequency, etc. (Kolberg, D., Zühlke, D, 2018)	Simulation, digital twins	Pull (Kanban)		
	[e-SMED] Connected systems equipped with self-optimizing and machine learning behaviours allows for the identification of the correct procedures for any given changeover process (Brettel, M., Friederichsen, N., Keller, M., Rosenberg, M, 2014). This is done by implementing an IoT system, where machines, sensors, BDA, and cloud computing are all interconnected. For example, parts/components can be equipped with RFID tags, which communicates with the machines upon arrival, and provides the operator with the appropriate changeover instructions - resulting iun reduced setup times .	IoT, Plug&Play	SMED		

	Complicated elements of manual changeover can be simplified using digital work instructions. Using AR, each step of the changeover process can be visualized, boosting operator productivity and safety (Brunet-Thornton, R., Martinez, F, 2018).	AR	SMED		
	Additive manufacturing has a high impact on setup times, since it requires no tooling, even for complex parts	Additive manufacturing	SMED		
Valamede and Akkari (2022)	"AGVs can adapt to dynamic environmental conditions in manufacturing processes through decentralized decision-making. Acting jointly with workers on production lines, these smart devices contribute to the reduction of unnecessary human motions by transporting materials according to production flow needs. This immediate replenishment also results in inventory minimization and reduction of space occupied by raw materials, contributing to demand-driven production Kanban systems" (Mayr, A., et al, 2018)	AGV	7 wastes (Kanban)	Literature review	Brazil
	"Holistic cross-sector integration and real-time data exchange by Big Data reduce the time from occurrence until the notification of an equipment failure. This corroborates a self-organized system where the inventory level can be kept to a minimum, which facilitates the introduction of Kanban systems." "iBin (smart bins) can automatically send orders to suppliers according to demand as well as to reduce regulatory inventory" (Kolberg, D., Zühlke, D, 2015)	BDA, sensors,	7 wastes (Kanban, reduced inventory levels)		
	"AM allows the manufacture of products customized according to the specific needs of each consumer, minimizing the possibility of defective or non-compliant parts occurrence. This innovation can produce the exact volume of products demanded by the client, which contributes to inventory items reduction and attends the JIT logic. Finally, product creation by adding material through a machine (such as a 3D printer) prevents the non-value-added processing steps as well as unproductive periods" (Sanders, A., Elangeswaran, C., Wulfsberg, J, 2016).	Additive manufacturing	7 wastes (JIT - inventory reduction, pull)		
	"The Cloud is able to receive notifications from intelligent robots and machines about failures, which contributes to errors identification and to prevent new failures, aiding in the logic of Poka-Yoke devices (Mayr, A., et al, 2018). Once the error is found, this technology alerts production and maintenance teams, resulting in less downtime greater control over the quality of processes. In addition, providing automatic material management in flow processes, The Cloud can act with Internet Protocol cameras, which can provide the visual indication (Andon) as well as the audio according to each process status, allowing the employee to promote preventive and corrective actions (Roy, V., Alam, I., Alam, S, 2017)."	Cloud, IoT	7 wastes (Poka-Yoke)		
	"AR helps to eliminate the unnecessary employee motions, indicating which route is more efficient to transport materials according to JIT logic. This technology can enable Poka-Yokes digital systems and provides greater efficiency in completing manual tasks, reducing the occurrence of defects or rework"	AR	7 wastes (Poka-Yoke. transportation)		
Martinho et al. (2022)	In this study an automatic detailed diagnosis (ADD) tool is proposed which is based on IoT platforms and devices. The ADD tool is constructed to help in the diagnosis and problem-solving phase of the lean concept continous improvement. The ADD concept is composed of a variety of sensors to collect information which is sent to a cloud-based platform where collected data is stored. That information is retrieved by an application that builds a detailed report on operator–machine interaction.	Sensors, IoT, cloud	Continouos improvement	Case study	Portugal
Romero, Gaiardelli, Powell, and Zanchi (2022)	Make use of sensors to detect errors or defect - analyze the error using big data analytics - find the root cause using real-data based simulations (e.g., digital twins) - avoid error or defect recurrency by (re)designing or implementing tools using advanced modelling and simulation tools. Smart sensors and auto-ID technologies (RFID) can be used to enable real-time identification of parts and products. Visions systems (and AI-cameras) can be used for the same reason - keep track of parts/products/machines/processes. AR-based guide systems can be used to ensure correct assembly sequences.	Smart sensors, BDA, digital twins, simulation, AR	Poka-Yoke	Design Research	Mexico, Italy, Norway

Martinelli, Lippi, and Gamberini (2022)	The authors studied an assembly line where the operators had problems of the incorrect assembly of oil seals in the final assembled product. By installing a vision system (camera), and training a convolutional neural network, the system could detect whether or not the seal was places correctly - disabling the hydraulic press if placed incorrectly. The re-engineering of the assembly line increased the line productivity from 46% to 80%.	ML (CNN), Vision-Camera	Poka-Yoke	Case study	Italy
Mendoza Valencia, Hurtado Moreno, and Nieto Sánchez (2019)	AI technology can increase OEE by analyzing data from sensors and monitors allowing it to make decions regarding maintenance, change of parts, lifespan of parts etc. The AI makes the decision before the actual problem occurs which results in a higher OEE.	AI	OEE, tror de tillhör TPM??, The OEE is the key metric of TPM	Case study	Mexico
Ramadan, Salah, Othman, and Ayubali (2020)	**[Digital-VSM]** - enable the VSM with real-time data capturing capabilities using RFID, different types of sensors, and machine data. RFID readers and sensors can be used to track smart products with required timestamps, such as processing/breakdown/maintenance [start/end].	Sensors, RFID	VSM	Design Research	Palestine, Saudi Arabia, India
Perico and Mattioli (2020)	Sensors and the identification and communication technologies in the production system, to create smart objects that interact with smart machine, which embedded cognitive computing ability to sense and react according to different production tasks. For example, such equipment is able to communicate with the item to be processed, select the needed tools, and work out a production schedule that complies with quality standards and technical specifications and thereby assist in the SMED process.	Machine learning/AI	SMED	Theoretical Study	USA
	a) AI based TPM assumes that if equipment fails, it is due to some physical phenomena that can be identified thanks to machine-learning through abnormal behavior detection. Then failures could be brought under control and possibly even eliminated by using knowledge reasoning. b) Moreover, an efficient TPM has to combine concepts of preventive, predictive and prescriptive maintenance. Application of various machine learning algorithms to design predictive maintenance policy and capabilities improve main- tenance planning to avoid failures and save the resultant costs	Machine learning/AI	TPM		
Trebuňa, Pekarcikova, and Edl (2019)	The authors suggests using simulation software to digitize and virtualize conventional VSM processes (as opposed to pencil and paper). Make a current state map model - analyze waste in the current state map using a simulation program - eliminate waste through optimization - simulate different variants of future state map to optimize results. With the help of a Tecnomatix Plant Simulation, the authors could evaluate the difference between implementing one single kanban systems vs three kanban systems, in a production process. - allowing the management to make informed decision - which could ultimately result in lower lead times.	Simulation	VSM	Case study	Slovakia, Czech Republic
Aksar, Elgun, Beldek, Konyalıoğlu, and Camgöz-Akdağ (2022)	Same as above -> use simulation tools (Arena Software) to develop future state maps.	Simulation	VSM	Case study	Turkey
McKie, Jones, Miles, and Jones (2021)	**Sharepoint**: Facilitates communication by centralizing information and knowledge: how to guides, training material, LAM sheets, lean adherence data, **kaizen** adherence, etc. - all stored in the same place	Sharepoint/system integration?	Communication/vertical integration?	Case study	UK
Mahmoodi, Fathi, and Ghobakhloo (2022)	IoT technologies such as sensors, RFID and Wi-fi which presents real-time data together with a deep neural network is able to predict bottlenecks in real-time.	IoT	Bottleneck analysis	Litterature review	Sweden
	A cloud-based service is beneficial in real-time bottleneck analysis to handle and process all required data. Further on, a cloud-based service helps to share information between all participating parties.	Cloud	Bottleneck analysis		
	AR technology can be used to implenement an augmented go-and-see approach. "GO & See" is one of the bottleneck detection techniques developed under lean manufacturing. With the help of AR, one can walk through the production line and draw applicable conclusions about the production flow	AR	Bottleneck analysis		
	Machine learning algorithms used in Bottleneck analysis can be employed for two purposes: extracting features of bottleneck machines using machine log data and classifying machines into bottlenecks and non-bottlenecks	ML	Bottleneck analysis		

Romero, Gaiardelli, Powell, Wuest, and Thürer (2019)	With the help of I4.0 technologies, such as ML and BDA, novel QM 4.0 practices can offer early alarms and fault diagnosis of deficient manufacturing processes, and optimization parameters for optimized process settings (Li, X., et al., 2017). Mixed reality technologies can improve current concepts of virtual meetings, enhancing the digital presence of remote workers (Perera, C., Liu, C.H., Jayawardena, S, 2015).	ML, BDA, mixed reality	TQM (six sigma?)	Theoretical Study	Mexico, Italy, Norway, USA, China
Zarrar, Rasool, Raza, and Rasheed (2021)	Dynamic Value Stream Mapping Solution (DVSMS) utilizes intelligent characteristics such as real-timemonitoring IoT solution for assessing the current state map of the production plant regarding lean targets set by the company. DVSMS improves accuracy by automatically carrying out numerous observations using low cost and low energy sensor-based efficiency monitoring system	IoT	VSM	Literature review	Turkey
	Currently, In the flexible manufacturing system, RFID tags are also used to reduce setup time by automatically adjusting the industry 4.0 smart machine according to the customer requirements in the numerous small batches. In each RFID tag, the information for the sequence of tasks and processes that need to be performed are stored beforehand. The manufacturing equipment automatically detects these commands using RFID receivers and orders the change of SMED and the parameters required by the customer.	RFID (IoT)	SMED		
	N. Belu, L. M. Ionescu, A. G. Mazăre, and N. Rachieru developed an algorithm that carries out real-time processing using machine learning (Deep Learning Networks). Self-harvesting sensors are used for realtime data acquisition, whereas ad hoc and radio networks for the data transfer and communication for generating virtual production e-Kanban tickets as soon as the demand is generated to improve production efficiency. Furthermore, RFID based wireless operations are performed to monitor the pull production, which incorporates the number and location of material batches. It also monitors the changes in the schedule, so overall automated production flow is controlled with automatic material replenishment monitoring, which overcomes the limitations in the conventional pull productions through active schedule tracking and monitoring	IoT, Machine learning, RFID	e-Kanban, Pull production		
	Y. Xu and M. Chen applied IoT based JIT manufacturing framework capable of reacting to the dynamic scheduling according to the current manufacturing progress and customers' orders on vehicle harness manufacturing. In this case RFID tags were used to obtain real-time monitoring of tools and material which resulted in a detailed overview of the production. This enables the right decision to be made to obtain a JIT production	RFID	Just in time (JIT)		
Jayaram (2016)	Product/vehicle/logisitcs sensors/trackers (RFID) can be used to keep track of inventory levels, transport of wares (prevent loss of goods), and identify/monitor unique goods (counterfeit prevention)	RFID (IoT)	7 wastes - inventory - counterfeits - transport (Supply chain)	Design Research	India
Krishnaraj, Gomathi Prabha, and Yuvaraja (2021)	In this case study, the authors coupled a machine with a flow sensor and a raspberry pi. The single-board computer and the flow sensor provided and analysed data related to the lubricants flow rate, which helped identify flow issues. It could even determine what caused the issue, and predict the time of failure of the lubricant. After the implementation, machine downtime reduced, and the OEE increased significantly (51% to 76%).	IoT - smart senors (single-board computers + flow sensors)	Maintenance - DMAIC (Measure	Conceptual study + Case Study	India
	Cloud computing and BDA facilitates JIT priniciples by providing access to information and enabling real-time data monitoring, allowing employees to "get the right information at the right time and the right place".	Cloud Computing, BDA	Just in time (JIT)		
	Cloud computing and BDA supports real-time calculations when monitoring manufacturing operations, enabling real-time problem solving resolutions and information flow waste reductions.		WIP, OEE		
	Enables improved communication and information flow within an organization and is beneficial in escalation processes when using Andon.	Vertical integration	Andon		
	Horizontal integration can faciliate JIT deliveries and shipments by reinforcing real-time status updates and improve communication	Horizontal integration	Just in time (JIT)		
	AR has a strong quality significance. The technology may help prevent non-conformities in different manufacturing and assembly processes, and allows for "quick identification and correction of mistakes".	Augmented Reality	Poka-Yoke		

Walentynowicz and Pienkowski (2020)	IoT technologies may support improvement efforts by providing the management and operators with real-time and big volume data.	IoT	Kaizen	Review + interview	Poland
	Shadow boards and other visual supports can be produced using 3D printing technologies - tailors 5S tools for a specific area of application.	Additive manufacturing	5S		
	Additive manufacturing technologies such as 3D printing helps minimize or eliminate batch production, enabling greater flexibility within the production.		Continuous flow		
	Autonomous robots such as AGVs may help minimize wastes in logisitics and production processes, by using unmanned milk-runner cycles to optimize material flow. JIT deliveries can be improved by implementing AGVs which autonomously travels on designated routes at defined hours.	AGV	JIT, 7 wastes (transport)		
	CPS and ML/AI enables intelligent automation and allows for increasingly automated processes which can detect process malfunctions and product defects.	M2M communication (CPS?), ML	Jidoka		
	AI can aid in mistake-proofing processes, such as purchasing, planning, logistics, etc.	AI	Poka-Yoke		
Ghobakhloo and Fathi (2019)	**[e-Kanban]** The case company integrated its Kanban into its ERP system which increased the visualization of work and workflow, and optimized the company's manufacturing processes for specific orders. Human errors such as lost kanban cards, calculation inaccuracies, entry errors, etc., were eliminated. The adoption of industrial sensors increased the company's workflow by allowing it to track lead times, set WIP limits, and analyse the workflow. I.e., the sensors enabled real-time monitoring of their processes - which was useful during order reprioritization and task switching.	Sensors, ERP,	Just in time (JIT), Poka-yoke	Case study	Sweden
	By implementing a real-time SPC software (WinSPC), the company operators and shop-floor personell could provide the management with real-time SPC data points. Using the software, several different valuable charts (pareto, x-bar and s, x-bar and r, etc.) could be automatically created. Additionally, the software was able to instantly evaluate the control charts (based on real-time data) and provide QM with real time stop/go instructions. Coupled with the ERP, the softwares built-in FMEA tool enabled efficient failure analyses, resulting in reduced number of defects.	IT, ERP	SPC, 7 wastes (defects)		
	By adopted a computerized maintenance management system (CMMS), the machines' MTTR reduced, while their MTBF increases significantly. The CMMS provided data about breakdown patterns, and had a built-in breakdown/idle alert system. The system automatically calculated the OEE. The application of industrial sensors - enabling real-time machine data monitoring - allowed the company to focus more on predictive maintenance.	CMMS (IoT) , ERP, sensors	OEE, maintenance, 7 wastes (defects)		
	The use of cloud computing allowed the digital solutions and softwares to be accessed remotely, which helped the company to remove information silos, and enabled it to expand geographically.	Cloud computing	Communication?		
Quenehen, Pocachard, and Klement (2019)	"By introducing Cobots in collaboration with humans. Cobot integration can have some positive impacts on operation performance, even with limited development time. In some industrial applications, this may support a Takt time change without having to add under-utilised human resources, or limit the usage of overtime (Gil-Vilda et al., 2017). To that extent, the collaborative robot may support flexibility of the Lean Manufacturing environment. This experiment also highlights Lean Manufacturing techniques – standardised work analysis, continuous improvement (Kaizen),"	Advanced robotics	Kaizen, stanardized work, takt time	Case study	France
Dănuţ-Sorin, Opran, and Lamanna (2021)	The authors has developed a model which provides necessary steps to integrate and automate Poka-Yoke in a production system. By using sensors - already integrated or externally installed - parameters relating to raw material quality (humidity, physicochemical characteristics), preparation, measuring, and mechanical status (temperature, ventilation) can be measured to monitor and evaluate product quality. The measured data is integrated into an asset administration shell, which enables and facilitates the Cyber-physical system. The Poka-yoke model is then able to manage the interaction between the components and processes, communicate instructions, and correct or alert issues.	CPS (Asset administration shell - AAS), sensors	Poka-Yoke	Design Research	Romania, Italy

Naciri et al. (2022)	**[Andon 4.0]** Integrated machine sensors provide real-time continuous information flows between operators and machines. Following the detection of a process anomaly, the relevant engineer/operator/manager is automatically sent a notification to his/her smart watch via an andon central server (which connects various departments). This improves the traceability of anomalies, and minimizes the time and effort spent on both identifying and resolving the issue. An archive of the andons are stored on the cloud. The archive provides machine adjustment instruction for future anomalies.	IoT - sensors, smart watch, cloud	Andon	Modeling and Simulation	Morroco
	[e-Kanban] Once a batch of parts or semi-finished products has been processed/manufactured in any given production unit, and placed in its dedicated location, an indoor tracking readers detects the batch's RFID signal, and sends a signal to the MES. The MES then generates a kanban order for the same production unit. The e-kanban concept eliminates overproduction and overstocking. The RFID also helps locate missing parts.	IoT - RFID	Kanban, 7 wastes (overproduction, inventory)		
Rifqi, Zamma, and Ben Souda (2021)	"LSS 4.0 dramatically optimizes processes through the structured Define, Measure, Analyze, Improve and Control (DMAIC) approach, but the huge amount of data collected requires the use of different mining techniques, such as Big Data Analytics (BDA), data mining, and process mining. By using mining techniques, decision makers save time by identifying, with a very high degree of accuracy, what is difficult to see at first glance because decisions are based on data [23]."	Big data and analytics	DMAIC	Literature review	Morroco
	Table 1 Lean six sigma framework with Big Data analytics [8] Phases of LSS Define: • Text mining • Video mining • Process discovery Measure: • Conformance checking • Confidence interval • Process sigma Analyze: • Decision trees • Association rules • Clustering • Classification • Machine learning Improve: • Artificial intelligence • Machine learning • Predictive analytics • Flow diagrams Control: • Graphing • Visualization • Causality BDA techniques and technologies for all dimensions				
Kolberg, Knobloch, and Zühlke (2017)	Kanban systems can be automatized and mistake-proofed by digitalizing the production control to avoid lost Kanban. The CPS consists of sensors and actuators, PLCs, and HUman-machine-interfaces.	CPS, sensors, smart devices	Kanban	Conceptual Study	Germany
	By coupling CPS-encapsulated work station with smart devices, the andon system can directly communicate breakdowns to the relevant personell, reducing maintenance times.		Andon		
	Automate the identification of potential improvements by using statistical methods of reported data, with the help of the CPS architecture.		Continuous Improvements		
Acosta Vargas, Chicaiza-Salgado, Acosta-Vargas, Salvador-Ullauri, and Gonzalez (2020)	We suggest the use of production line simulation software such as FlexSim that allows the simulation of manufacturing processes and the identification of phases in which processes can be optimized and waste reduced. Simulation tools are innovative tools with predictive technology used to know in advance the behavior of a system under different configurations or operational policies.	Simulation	Waste, ((optimization = contionous improvement??))	Case study	Spain, Ecuador
	In the case study by ((Towards Industry Improvement in Manufacturing with DMAIC)) simulation was used in the improvement step in the DMAIC process. Collected data from previous steps were used in the simulation to do predictions on possible changes in the production process in order to eliminate waste and reduce manufacturing times.		DMAIC - improve step		

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