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Synergies and trade-offs between Lean 4.0 and Production Strategy: an exploratory study on Italian manufacturers

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0. EXECUTIVE SUMMARY

Lean Manufacturing is a management philosophy founded by Taiichi Ohno in '50s and, nowadays, is generally considered one of the most widely used program to improve manufacturing operations. All the long of Lean Manufacturing implementation, authors have studied the correlation of this approach and automation. In the last decade, with the rise of Industry 4.0, the benefits of Lean Manufacturing's classic techniques could be enhanced catching the big opportunities offered by this revolution, raising Lean Manufacturing to an upper level: Lean 4.0.

The purpose of this study is to investigate possible synergies or trade-offs between Lean 4.0 and Production Strategy in increasing company's Operational Performances (i.e. RQ4). By inquiring this relationship, a set of other research questions needs to be investigated: the link between Lean Manufacturing and Industry 4.0 (i.e. RQ1), the applicability of each one of these approaches in different production environments (i.e. repetitive and non-repetitive production; RQ2) and the effect of contextual factors on Lean 4.0 implementation (i.e. RQ3).

The study is articulated in two main phases, characterized by two different research methodologies: survey and semi-structured interviews. While the dataset of the former (i.e. sample of 105 Italian manufacturing companies) was analysed to inquire RQ1, through factor analysis and scatter plot, RQ2 and RQ3, through chi-squared test, and RQ4, through analysis of variance; the dataset of the latter (i.e. sample of 19 interviewees) was analysed to further investigate RQ4, through Bayesian Network.

Main results suggest that, when processes are not robustly designed and continuous improvement practices are not established (i.e. low adoption of Lean Manufacturing), companies may not be focused on adopting Industry 4.0 technologies. In addition, Lean Manufacturing, despite high demand variability may influence its introduction in a non-repetitive plant, can be successfully applied also in mass customization environments. Moreover, the pervasiveness of the interrelation between Lean Manufacturing and Industry 4.0 may overcome the effects of some contextual factors enabling manufacturers to benefit from the conjoint implementation of these approaches disregarding the context. Finally, a positive synergy between Lean 4.0 and Production Strategy is proved unveiling that a company with a repetitive Production Strategy and a high level of Lean 4.0 implementation is more likely to obtain better Operational Performances.

1. INTRODUCTION

Lean Manufacturing is a management philosophy, founded in '50s by Ohno at Toyota, that focuses on value adding activities by eliminating any form of waste during the production process in a continuous improvement perspective (Ohno, 1988).

Thanks to new digital technologies and smart systems, the Fourth Industrial Revolution has brought virtual connections and improvements in the manufacturing processes, especially in the Lean Manufacturing ones. However, Industry 4.0 is not the simple interconnection of processes, but it is a wider informatization strategy which aims at creating a Smart Factory, that can transform companies' business model and supply chain (Deloitte Report "Italia 4.0: siamo pronti?", 2018).

According to 2016 The Boston Consulting Group Focus "The Factory of the Future", if either Lean Manufacturing practices or Industry 4.0 tools are applied alone, conversion costs can be reduced by 15%. However, if these two approaches are applied together conversion costs can be decreased by 40%, quality costs by 20% and work-in-process inventory costs by 30%. In other words, the correlation of Lean Manufacturing and Industry 4.0, namely Lean 4.0, allows to achieve higher benefits beyond the typical limits of the two approaches implemented alone. The correct implementation of Lean 4.0 has payback time, in terms of production results, less than three years. However, to reach benefits in this short time period, processes have to be efficient, before the introduction of Industry 4.0 tools. Otherwise, the risk is to automate non-value-adding or non-standardized activities (The Boston Consulting Group Focus "The Factory of the Future", 2016). According to the 2017 Report "With Lean Thinking and Industry 4.0 to Operational Excellence" of Berlin School of Economics and Laws, the classic seven wastes of Lean Manufacturing can be eliminated with a digital transformation. According to the framework presented in *figure 1*, companies' operational potential can increase more than proportionally by applying the right Industry 4.0 technology to the right Lean Manufacturing process. However, in order to obtain higher flexibility and efficiency through digitalization, Lean Culture and Lean Thinking have to be already rooted and developed. Lean Manufacturing practices are so the enablers that allow a correct and efficient implementation of Industry 4.0, by preventing the automation of wastes. On the other side, novel technologies can allow Lean Manufacturing processes to reach operational excellence ("When Lean Meets Industry 4.0", The Boston Consulting Group Focus, December 2017).

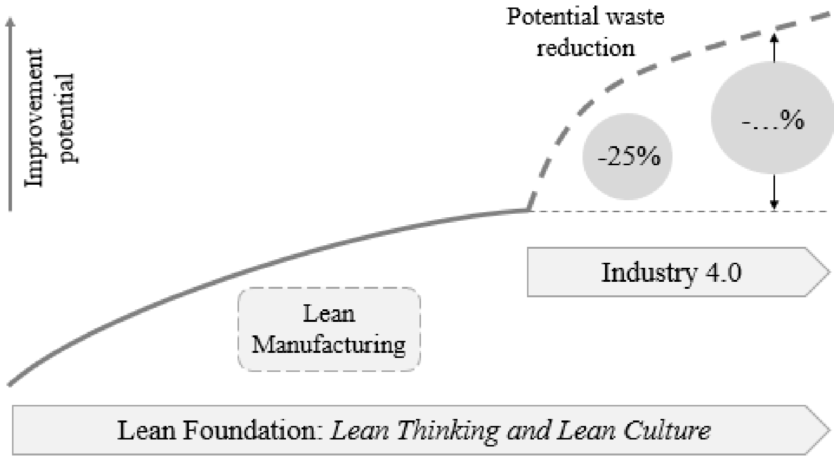


Figure 1: Lean 4.0 potential improvement

However, according to Ernst & Young Focus “Sfida Italia 4.0”, one of the most important assets of Lean 4.0 is constituted by people: thanks to kaizen, in fact, people are trained to be always open to new technologies and innovation. Company’s culture readiness is a critical success factor that enables companies to apply Industry 4.0 tools to consolidated Lean Manufacturing processes and to produce customized products at mass production costs.

According to Mayr et al. (2018), current literature is aware about the potential benefits of Lean 4.0, but studies are guided by three main different perspectives:

- **Lean Manufacturing as enabler towards Industry 4.0:** This assumption states that wastes and inefficient processes should not be automated (Mayr et al.,2018). Indeed, Lean Manufacturing should guide Industry 4.0 tools introduction in order to enhance efficiency (Huber 2016, Künzel 2016, Ketteler and König 2017, Staufen 2016, Köther and Meier 2017, Wang et al. 2016, Metternich et al. 2017, Quasdorff and Bracht 2016, Bick 2014, Zühlke 2010).
- **Industry 4.0 advances Lean Manufacturing:** Industry 4.0 may allow to develop new opportunities and overcome limitations of Lean Manufacturing, which processes can be stabilized and refined (Wagner et al. 2017, Pokorni et al. 2017). Through Industry 4.0, higher levels of flexibility can be reached in order to cope with the rising market complexity and its fluctuating demand (Wagner et al. 2017, Pokorni 2017, Rüttimann and Stöckli 2016, Kolberg and Zühlke 2015, Spath et al. 2013).

- **Correlation between Lean Manufacturing and Industry 4.0:** Most authors approve the general compatibility of Lean Manufacturing and Industry 4.0 (Mayr et al.,2018). Indeed, these two approaches can coexist and complementarily support each other (B. Mrugalska and M. K. Wyrwicka, 2017). The reduction of complexity, the simplification of processes and the essential role of employees are targets common to both Lean Manufacturing and Industry 4.0 (Sanders et al. 2016, Vogel-Heuser et al. 2017, Mrugalska and Wyrwicka 2017).

To reach Lean 4.0, Industry 4.0 and Lean Manufacturing have to be combined in order to create a Smart Factory, efficient and flexible. However, sometimes not only Industry 4.0 tools are not sufficiently implemented, but also Lean Manufacturing practices are not well developed. As reported by 2017 McKinsey Report "L'Industria 4.0 e le nuove frontiere del Lean", although Lean Manufacturing practices seem to be successfully implemented inside small-medium enterprises' processes, most of them are struggling in reaching the expected outcomes. According to *figure 2*, this misalignment between expectations and results is often created by an incorrect launch of Lean Manufacturing programs caused by an incomplete maturity assessment. Without a visual analysis, it is not possible to evaluate correctly actual processes, competences and mindset. Companies that start from Lean Manufacturing practices and not from their needs, may adopt tools that do not give appropriate results in their specific environment. The correct assessment of processes and needs allows to identify non-value adding activities and suggests appropriate and concrete actions (McKinsey Report "L'Industria 4.0 e le nuove frontiere del Lean", 2017).

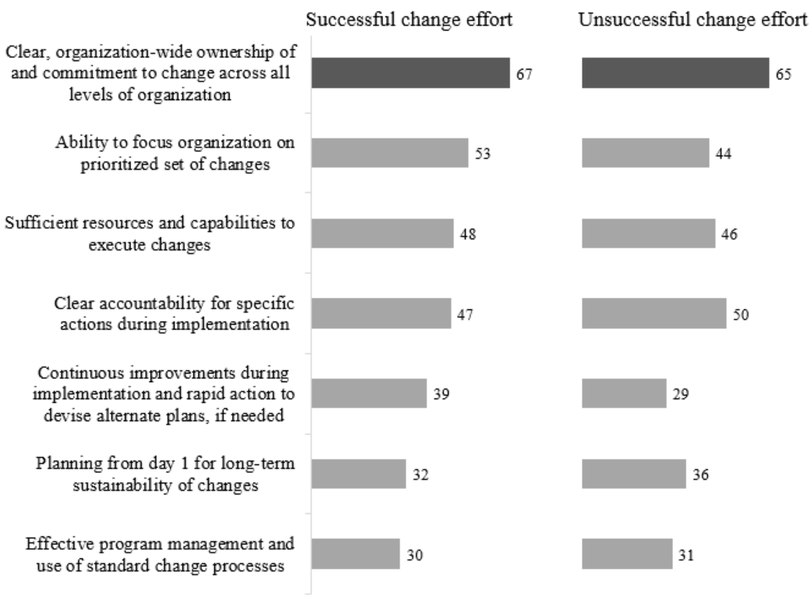


Figure 2: Reasons beyond successful and unsuccessful Lean Manufacturing adoption

On the other hand, the digitalization in Italy seems to be underdeveloped: although in Europe 30% of companies have implemented at least one tool of Industry 4.0, in Italy only 15% of the companies have introduced it. This data shows that in Italy, due to an industrial environment characterized by small-medium enterprises (SMEs), the Fourth Industrial Revolution has not disrupted the market with new digital technologies yet. The Italian panorama, in fact, according to the 2018 Small Business Act Fact Sheet presented by the European Commission, is characterized for the 99.9% by SMEs which generate value added for the 67.1 % against a European average of 56.8 %. However, as stated by the 2018 Deloitte Report “Italia 4.0: siamo pronti?”, in 2017 Italian Government decided to introduce the plan “Piano Nazionale Impresa 4.0” in order to encourage the adoption of new digital technologies and new industrial machineries with fiscal incentives and 18 billion euros invested for the years 2017-2020. Main government’s investments were done in the fields of optical fibre, open-source standards for machine-to-machine (M2M) communication and digital networks. Thanks to “Piano Nazionale Impresa 4.0”, Italy is facing a continuous improvement and, according to estimations of Osservatori Digital Innovation of Politecnico di Milano, the Italian market of cloud computing technologies was grown by 18% in 2017, reaching almost a value of 2 billion of euros, and the market of IoT technologies was grown by 32% in 2017, reaching a value higher than 3.5 billion of euros compared to 2016. However, even though Italian Government introduced “Piano Nazionale Impresa 4.0” and increased investments, a huge discrepancy with the world is still present in Italy in the education of workforce. “Ministero dell’Economia e delle Finanze” states that Italy represents values significantly lower than the European average according to the diffusion of digital competence in the workforce (29% vs. 37%) (*Figure 3*).

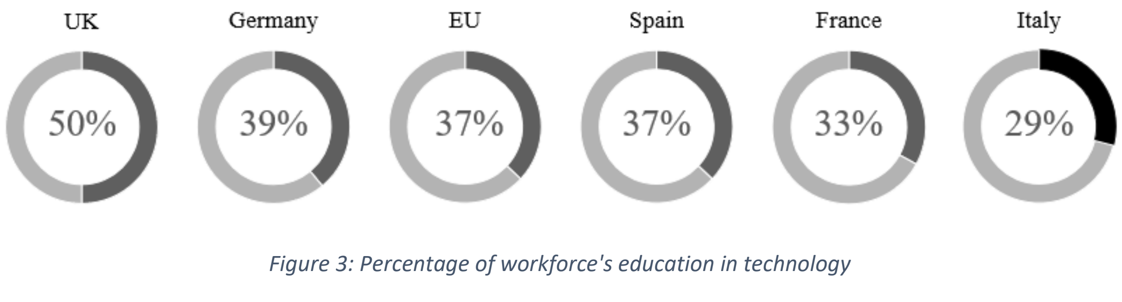


Figure 3: Percentage of workforce's education in technology

Summarizing, the 2018 Deloitte Report (*figure 4*) shows the degree of use and diffusion of Industry 4.0 technologies in Italian enterprises according to a scale that covers values from “not in use” till “fully implemented”.

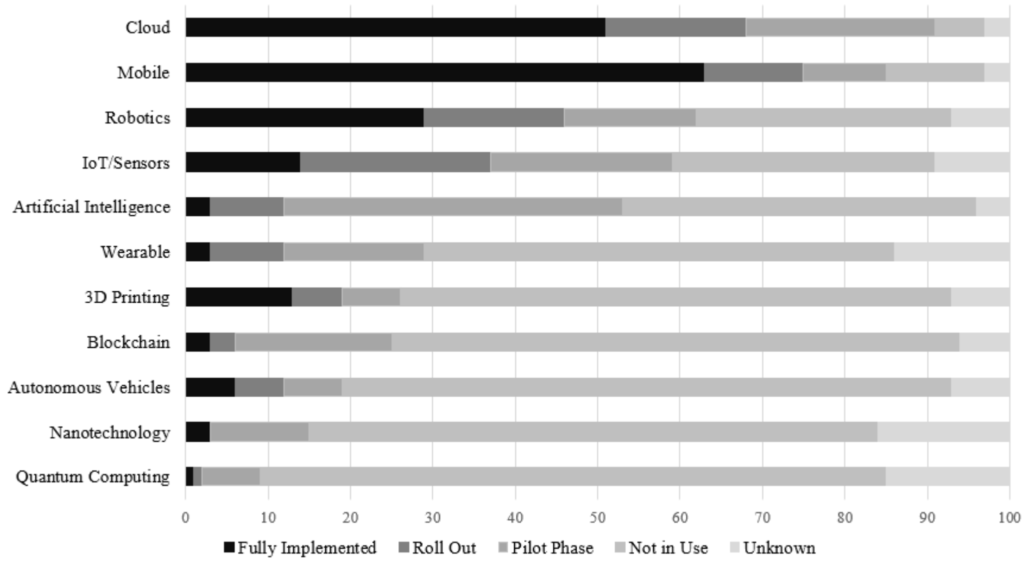


Figure 4: Implementation of Industry 4.0 technologies in Italy

According to 2017 Digital Innovation Hub Focus "Lean Management e Industria 4.0", the main obstacles that companies may face in the process of digital transformation are:

- Personnel resistance to change
- Absence of experience in guiding digitalization
- Insufficient organization structure
- Limited budget
- Absence of general digitalization strategy
- Difficult coordination among digital team and operations team

According to 2017 The Boston Consulting Group Focus "When Lean Meets Industry 4.0", in contrast with this list of barriers, huge benefits can be reached by companies that successfully implement Industry 4.0 tools in combination with Lean Manufacturing practices:

- **Flexibility:** thanks to flexible operations, manufacturers can make multiple products in a single production line, by decreasing changeovers and set-up time. These wastes can be reduced by applying Lean practices such as single-minute exchange of dies (SMED) and by implementing new sensors, software and RFID tags that can automatize the product identification and allow the production line to set tools to the right parameters automatically.
- **Productivity:** usually high inventory levels and low productivity are caused by failures and breakdowns. With predictive and preventive maintenance, combined with Industry 4.0 tools such as advanced analytics algorithms and machine

learning techniques, overall equipment effectiveness (OEE) can be exploited and failure times can be reduced. Moreover, thanks to these initiatives, also continuous improvement programs can be boosted.

- **Speed:** in a market that requires highly customized products (i.e. batch size reduction and product variants increase), the ability to react quickly and produce rapidly is becoming a critical success factor. Sometimes Lean practices such as shop floor management and daily routines are not enough to plan and control production in real time. With control tower (a digital tool that collects data and controls material movements) and horizontally integrated value chain, manufacturers can generate daily an ideal production plan on the basis of inventories, capacity utilization and orders. By managing shop floor in real time, also continuous improvement programs can be enhanced. Moreover, with cameras installed in the customer warehouse, a supplier can replenish materials in stock out: this way also just-in-time restocking is improved.
- **Quality:** The increasing importance of production quality allows suppliers to decrease costs of reworking and meet efficiently customer requests. With Lean Manufacturing, practices such as poka yoke, jidoka and self-inspection, the number of defects and the likelihood of errors is reduced, but not completely eliminated. To reach a target of zero defects, Industry 4.0 is necessary: through data-driven analytics, correlation models, camera-based visual inspection and real-time monitoring, defects can be identified, and the root causes of errors can be tracked.
- **Safety:** To work properly and act at the maximum of their capabilities, operators have to feel safe. Some companies use Lean Manufacturing approaches to track incidents and to tell operators where they may walk, other companies implement Industry 4.0 tools such as wireless sensors, used for fire and gas detection, and virtual reality to train workers in a virtual simulation of the real environment.

Nowadays, these determinants are becoming even more important as critical success factors (CSF) for companies that want to cope with the increasing demand of customization: new techniques of digital manufacturing allow the decrease of batch size, bringing companies to pass from a repetitive to a non-repetitive production. This way, companies may be able to process small orders, decrease the level of inventories and, consequently, reduce costs. (Synchrono's 2016 Focus "Demand Driven Manufacturing in the Engineer-to-Order Space").

All over the world, Lean Manufacturing implementation is no longer limited to mass production, but it is started to be used by low-volume-high-variety companies, such as Make-to-Order (i.e. MTO) and Engineer-to-Order (i.e. ETO) productions (Portioli-Staudacher &Tantardini, 2012). Indeed, Lean Manufacturing, combined with a correct and suitable pull approach, may exploit due date performance and reduce cycle time in non-repetitive environments (E.R. Melchert et al., 2006). Lean Manufacturing principles, such as multi-skilled workers, set-up reduction, simple and small machines, help companies to achieve flexible manufacturing and cope with market variability (E.R. Melchert et al., 2006).

According to Synchrono's 2016 Focus "Demand Driven Manufacturing in the Engineer-to-Order Space", another approach which could allow modern ETO production to provide to final users customized products in a faster and cheaper way are the Demand-Driven Manufacturing (i.e. DDM) and automated processes. DDM is a modern manufacturing approach based on actual demand, rather than demand forecasts, that use pull and just-in-time techniques to synchronize customer orders, production scheduling and supply chain. In combination with process automation, DDM may provide an engineering costs reduction, a quicker turnaround and a significant increase in ETO throughput. Extending these approaches, benefits can arrive beyond firm borders by allowing alignment with customer needs. Extending the discussion, also Make-to-Order, Assemble-to-Order (i.e. ATO) and Make-to-Stock (i.e. MTS) productions can enhance profitability through synchronization, thanks to DDM methodologies.

Bain & Company, in its 2019 report "Digital Lean: a guide to manufacturing excellence", explains that advanced analytic, by deeply integrating digital platforms and production execution systems, facilitates MTO manufacturing processes and nearly all other components of the production life cycle. This is only an example of the wider range of Industry 4.0 applications in the production environment, that may give to companies the opportunity to develop their customization potential by leveraging automation, interconnectivity, machine learning and real-time techniques. However, passing from a mass production to a not-repetitive production may increase the complexity of the production and of the warehouse. Without managing this situation with advanced tools, companies may face difficulties that can lead to a missed achievement of CSF target and to a service level reduction. For this reason, common ERPs and Excel files can be insufficient to handle with such complexity: modern Advanced Planning Systems (APS) can be necessary to make production planning more efficient and reactive to external inputs. In this context of uncertainty, best-fit techniques and machine learning algorithms may allow to better forecast future situations, simulation techniques may be necessary to elaborate data gathered in real time and other Industry 4.0 tools can be used to improve non-repetitive tasks efficiency (Cybertec Focus “La pianificazione della produzione 4.0. Gestire la mass customization”, 2018)

Summarizing, with new technologies and management techniques, it is possible to combine Lean Manufacturing and Industry 4.0 (i.e. Lean 4.0) in an effective and efficient way.

2. LITERATURE REVIEW

The objective of this chapter is to present a literature review analysis that can help to find and understand a possible link between Industry 4.0, Lean Manufacturing and the company's Production Strategy. In paragraph 2.1 and 2.2, possible relations between company's Production Strategy and the separate implementation of Lean Manufacturing and Industry 4.0 are inspected. Since Lean Manufacturing is one of the most widely used programs to improve manufacturing operations in last three decades and since, in recent years, Industry 4.0 has emerged as one of the most discussed concepts, paragraph 2.3 is dedicated to exhibit how current literature presents the possible combination between this two trends (i.e. Lean 4.0). Finally, in paragraph 2.4 the link between company's Production Strategy and Lean 4.0 is inquired.

The researches carried out a systematic literature review using Scopus as main database. Although narrative review technique is still the most used approach to develop scholarly literature reviews, its main drawback is its subjectivity (e.g. Rousseau, 2012; Rousseau, Manning, & Denyer, 2008). Indeed, with this approach, authors offer their personal critical overviews of the literature in the form of written narrative assessments (G. P. Hodgkinson and J. K. Ford, 2014). For this reason, in order to avoid a subjective analysis, a systematic review technique is adopted. Indeed, the systematic review solves this drawback by collecting the whole evidence, inherent to a given research question, and evaluating it in terms of scientific excellence (G. P. Hodgkinson and J. K. Ford, 2014). Summarizing, a systematic review is a comprehensive and reproducible method for identifying, evaluating and synthesising works produced by researchers, scholars and practitioners (Okoli and Schabram, 2010).

2.1 LEAN AND PRODUCTION STRATEGY

a) <u>Screening Process</u>

Lean Manufacturing, nowadays, is considered as a fundamental approach that any firm has to follow in order to improve its production operations (Womack and Jones, 1996). In order to inspect how current literature presents the possible interrelation between Lean Manufacturing and company's Production Strategy, papers related to the aforementioned themes were searched on Scopus database using the keywords presented in *figure 5*.

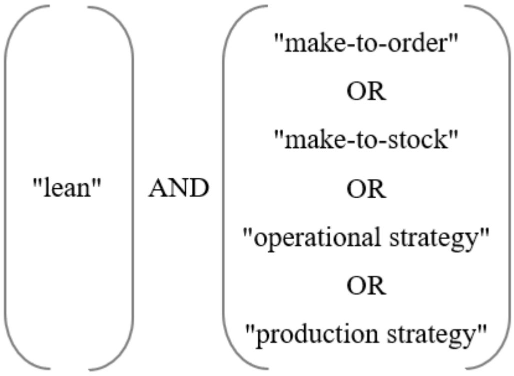


Figure 5: Research keywords of Lean and Production Strategy

The formula used in the research has the following syntax:

TITLE-ABS-KEY (“lean” AND “production strategy”)

The research conducted, using each one of the aforementioned keywords’ combination, generated a result of 181 inherent papers. Due to the different combinations used (i.e. “lean” AND “production strategy OR “lean” AND “make-to-order”), the same paper could be present as result of more than one research. For this reason, from the total number of papers founded, the duplicated articles were eliminated. Moreover, to narrow the research on our area of interest, three filters were applied:

- Only journal articles
- Only English language
- Only Business and Engineering area of interest

Only 73 articles respected the filters applied and, consequently, to analyse them, a first screening was conducted by reading their abstract. Only 24 papers were considered relevant in relation to Lean Manufacturing and Production Strategy themes.

Furthermore, a second screening aims at guaranteeing the reliability of the references researched. In order to evaluate the different publications, we decided to select and analyse only the articles published on Q1 journals (i.e. quartile 1) according to the rank drawn up by Scimago. The Scimago Journal & Country Rank is a public available portal that includes journals and country scientific indicators developed from the information contained in the Scopus database (i.e. Elsevier B.V). These indicators can be used to assess and analyse scientific domains evaluating the average number of weighted citations received during a selected year per document published in that journal during the previous three years. According to this value, journals was clustered into four quartiles where Q1 represents the journals with the highest rank. This second screening highlighted only 14 relevant papers.

Finally, entirely reading each one of these papers, only the 7 articles presented in table 1 were considered relevant in order to understand the guidelines of this research.

Abstract Title	Journal	Journal Rank	Authors	Year
2MTO, a new mapping tool to achieve lean benefits in high-variety low-volume job shops	Production Planning and Control	Q1	Bertolini, Romagnoli, Zammori	2017
Lean control for make-to-order companies: Integrating customer enquiry management and order release	Productions and operations management	Q1	Thurer, Stevenson, Silva, Land, Fredendall, Melnyk	2013
Workload control and order release: A lean solution for make-to-order companies	Productions and operations management	Q1	Thurer, Stevenson, Silva, Land, Fredendall	2012
The impact of manufacturing and supply chain improvement initiatives: A survey comparing make-to-order and make-to-stock firms	Omega	Q1	Olhager, Prajogo	2011
Integrating lean and other strategies for mass customization manufacturing: A case study	Journal of Intelligent Manufacturing	Q1	Stump, Badurdeen	2009
Fixed-cycle smoothed production improves lean performance for make-to-stock manufacturing	INFORMS	Q1	Bernegger, Webster	2014

Table 1: Relevant papers concerning Lean and Production Strategy

All these 7 papers are focused on Production Strategy (e.g. Make-to-Stock, Assemble-to-Order, Make-to-Order and Engineer-to-Order) and are faithful to the definition of Lean Manufacturing given by American Production and Inventory Control Society (APICS) Dictionary:

"*Lean Manufacturing refers to an approach to management that focuses on reducing or eliminating waste in all facets of the manufacturing system*"

b) <u>General Overview</u>

Manufacturing firms, in order to gain competitive advantage and to improve the efficiency and the effectiveness of their performances, apply different production systems, enhancing internal operations but also external supply chain. Lean Manufacturing, which is one of these methodologies, is typically considered as a fundamental program for any firm that wants to improve its manufacturing operations, by removing waste and creating a smooth production flow (Womack and Jones, 1996). Such practices are generally considered to be beneficial for any type of manufacturing firm, while some researchers suggest that some improvement initiatives are more applicable in certain manufacturing environments with respect to others (Olhager and Prajogo, 2011). Indeed, literature reports a significantly higher number of implementations of Lean Manufacturing control principles in high volume Make-to-Stock environments than in Make-to-Order ones (White and Prybutok, 2001). In other words, the context in which seems to be easier to apply Lean tools are high-volume-low-variety (HVLV) environments (Pine 1993, White and Prybutok, 2001), where products are standard with low level of complexity and the demand is huge and stable. Interestingly, despite traditionally Lean Manufacturing tools have been developed and applied to mass production (Pool et al., 2011), empirical evidences support that they can be successfully applied in low-volume-high-variety companies as well (Birkie and Trucco, 2016, Abdulmalek and Rajgopal, 2007). In other words, despite the limited presence in literature of papers that addresses lean transformation in a low-volume-high-variety (LVHV), Lean transformation at each of the product assembly lines is an effective way of significantly improving performances for highly customized manufacturing environments (Raghavan et al. 2014, Portioli-Staudacher and Tandardini 2011).

However, due to the low-volume, high-variety, high-variability and high customization of the business, MTO, ATO, ETO companies face different problems with respect to the MTS ones. Hines et al. 2004 and Stevenson et al. 2005, in fact, support that many of Lean's Production Planning and Control (PPC) techniques cannot be directly applied to shops that produce a high variety of products, such as small and medium-sized Make-to-

Order (MTO) companies. Indeed, Make-to-Order, as Assemble-to-Order and Engineer-to-Order companies (i.e. low-volume high-variety production), are described by different and mainly unique projects characterized by non-repetitive production steps, while Make-to-Stock mass and series production (i.e. high-volume low-variety production), are characterized by repetitive production steps (Matt and Rauch et al.. 2014).

The main tools applied in a non-repetitive company are hybrid Production Planning and Control (PPC) systems (Bertolini, Romagnoli, and Zammori 2017; Hopp and Spearman 2004), such as Constant Work in Process (CONWIP) and Workload Control (WLC). These very promising systems enable non-repetitive companies to achieve Lean benefits (Thurer et al. 2012). However, WLC is almost never considered in Lean literature because it is not included in the standard Lean toolbox, that considers only Kanban and CONWIP as possible ways to streamline the manufacturing process (Bertolini et al. 2017). Nevertheless, WLC systems provides low-volume-high-variety (i.e. LVHV) companies with many of the benefits of Lean's PPC techniques by levelling demand and production over time when work is not standardized and when it is not possible to synchronize flows on the shop floor (Stevenson et al. 2005). Hybrid PPC is good, but most of its techniques are not included into standard lean toolbox. For these reasons, Bertolini et al. 2017 propose a new method following a flow chart called 2MTO, that can be applied both to Lean-friendly (adopting well-known techniques), and non-friendly environments (mapping the system at multiple levels of details). The main drawback of this method is the requirement of many historical data and, possibly, of an ERP system (Bertolini et al. 2017).

c) <u>Non-Repetitive Production</u>

Literature sustains that Lean Manufacturing is better suitable in a high-volume-low-variety environment (White and Prybutok, 2001, Pine 1993, Raghavan et al. 2014). Considering, instead, a low-volume-high-variety context, authors disagree on which could be possible applications of Lean Manufacturing, and even on the effects of those practices on results (Olhager and Prajogo, 2011, Abdulmalek and Rajgopal, 2007). The main problems that a company could undergo in applying Lean Manufacturing principles in an LVHV organization are well summarize by Jina et al. 1997:

- The very high variety and customized product with respect to a low volume (e.g. less of 20.000 units for HVLV, more than 100.000 for LVHV).
- The level of vertical integration ranging from very high value, in order to keep greater control of both uniqueness and variety, to low value. Many LVHV organizations, such as aerospace firms, who cannot keep inhouse control of the technological complexity and cannot afford the high investment required, usually outsource their products (Jina et al. 1997).
- A manufacturing facility that has to satisfy the need of disparate customers' segments may suffer of a not well-established planning system (Jina et al. 1997).

In addition, as investigated by Womack et al. 1990, the four types of turbulence, presented in the following list, have a far greater impact in the low-volume-high-variety enterprise than in high-volume-low-variety one.

- **Schedule:** Changes in the schedule in a period closer to the delivery due date.
- **Product mix:** Marked differences of product mix between one period and the next.
- **Volume:** Marked differences in volume between one period and the next.
- **Design:** The degree and frequency of product change within the period of customer lead time expectations.

Due to the higher number of difficulties that a LVHV company could face, Lean Manufacturing could be adapted to such an environment (Jina et al.1997, Bertolini et al. 2017, Hopp and Spearman 2004).

An example of hybrid system, often implemented in LVHV companies, is the WLC, which is a hybrid PPC system designed for non-repetitive companies which enable to simultaneously control inventory, capacity, lead times and to integrate production and sales into a hierarchical system of workloads which buffer against variance (Kingsman 2000, Kingsman et al. 1989). More precisely, the aim of WLC is to maintain work-in-process (i.e. WIP) at a predefined level, optimizing the trade-off between high-throughput rates and short and stable Lead Times (i.e. LT), ensuring a lower number of tardy jobs and, so, allowing a variance reduction helping companies to become Lean (Bertolini et al. 2017). Thus, WLC can be an important step toward implementation of Lean Manufacturing into LVHV companies, first, by providing benefits equivalent to those achieved through lean PPC techniques in repetitive manufacturing companies; and second, by reducing the inventory, capacity, and lead-time buffers necessary in environments characterized by high variability (Thurer et al.2013). Moreover, thanks to WLC, Lean benefits could be also achieved in small and medium sized non-repetitive companies allowing them to reduce and predict the lead times, to effectively control the capacity, to supervise WIP and inventory in a simple way (Thurer et.al 2012). In order to control WIP, a study conducted by Slomp in 2009 tested the applicability of Lean Manufacturing in a LVHV environment and measured the enhancement in terms of on time delivery showing an improvement from 55% to 80% (Slomp, 2019).

Many other examples of successful Lean implementation in LVHV exist, such as the study of Raghavan et al. 2014, which tested the applicability of Lean Manufacturing principles in electronics assembly environment, showing a 40% decrease in cycle time and a reduction of the number of defects by 10-30 per cent (Raghavan et al. 2014).

Another point of interest emerged from the literature review, is how different companies combine their internal practices with external strategies according to their production strategy. In particular, the internal Lean practices and supplier rationalization are fundamental for repetitive plants, while the external logistics integration with suppliers is more important for non-repetitive plants (Olhager and Prajogo, 2011). Thus, there is a clear distinction as to what creates the business advantage for the different types of production strategy.

d) Repetitive Production

As stated in previous sections, literature supports that high-volume-low-variety and mass productive organizations are facilitated to apply Lean Manufacturing principles with respect to non-repetitive companies (White and Prybutok, 2001, Pine 1993, Raghavan et al. 2014).

Product's standardization, a stable manufacturing planning system, low product variety and complexity and high production volume are some of the characteristics which enable companies to better implement Lean tools. Literature suggest that the main common techniques of Lean Manufacturing, such as just-in-time (JIT), total preventive maintenance (TPM), total quality management (TQM) and human resource management (HRM), are well suitable in a repetitive firm (Abdulmalek and Rajgopal, 2007).

The only gap emerged in current literature regards the inventory management which represent, according to the Lean philosophy, one of the main wastes. Three main models emerged as most used attaching this problematic:

- Ehrhardt (1997) models a just-in-time make-to-stock inventory system by considering the fixed replenishment quantity required in a specified production interval that minimizes the inventory cost in relation to the length of the interval.
- Webster and Weng (2001) model the inventory and production rate according to a fixed-cycle smoothed production policy for demand that is both stochastic and dynamic.
- Matzka et al. (2012) attempt to model a Heijunka-Kanban system as a queuing network that replenishes finished goods inventory buffers.

No other models for manage inventory in repetitive systems are evident in current literature.

e) <u>Conclusion</u>

In conclusion literature on one hand presents different kinds of application of Lean practices in any firm or environment, on the other hand suggests the it is not possible the same application of each practice in each company.

The main problems that a non-repetitive firm could face, with respect to a repetitive one, are the high variability in demand, that implies a difficult demand levelling, and the complexity in building a perfect Kanban system (Kolberg and Zühlke, 2015). In high-volume-low-variety environments, instead, the standardization and the stable demand simplify the application of line balancing and Kanban (Abdulmalek and Rajgopal, 2007).

However, the cultural approach to Lean Philosophy can be pervasive to each firm independently by the production strategy it follows (Portioli-Staudacher and Tandardini, 2011). As an example it is possible to mention practices such as Asaichi, which is an inter-functional morning meeting on daily base, or visual control and management tools, which allow the different company's departments to be involved along the entire process and to be aware about the status of all the activities, identifying earlier the problems, finding faster the solutions, and managing priorities efficiently and effectively (Pero et al., 2018). Another example regards the approach to follow in facing new problems. Independently from the context, in fact, companies need to map the current situation in order to take any consideration or build the action plan. However, the main tool, the Value Stream Mapping, mostly focuses on a single product family ignoring the distinctive features of high volume-low variety job-shop (Bertolini et al., 2017).

2.2 INDUSTRY 4.0 AND PRODUCTION STRATEGY

a) <u>Screening Process</u>

Industry 4.0, in recent years, has emerged as one of the most discussed concepts and the huge number of new manufacturing technologies are becoming more and more important. In order to inspect how current literature presents the possible interrelation between Industry 4.0 and company's Production Strategy, a research related to the aforementioned themes is conducted on Scopus database using the keywords presented in *figure 6*.

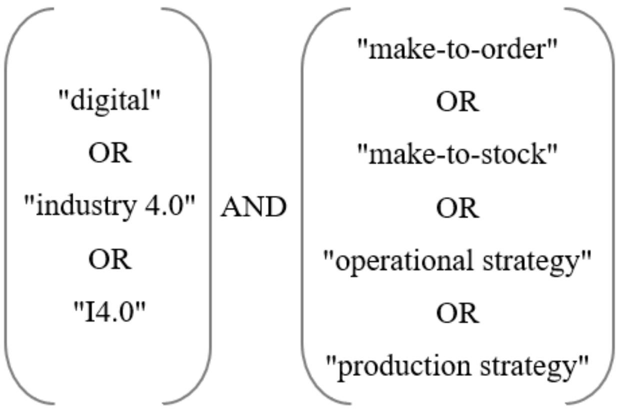


Figure 6: Research keywords of Industry 4.0 and Production Strategy

An example of the syntax used to conduct the study is:

TITLE-ABS-KEY ("industry 4.0" AND "production strategy")

The research conducted using each one of the aforementioned keywords' combination, generated a result of 160 inherent papers. Due to the different combinations used (i.e. "digital" AND "production strategy" OR "digital" AND "make-to-stock"), the same paper could be present as result of different researches. For this reason, from the total number of articles founded, the duplicated papers were eliminated.

Consequently, to narrow the research on our area of interest, three filters were applied:

- Only journal articles
- Only English language
- Only Business and Engineering area of interest

Only 36 papers respected the filters applied. To analyse the articles selected, a first screening was conducted by reading the abstract of each one of them. Only 11 papers were considered relevant in relation to Industry 4.0 and Production Strategy themes.

The second screening applied aims at guaranteeing the reliability of the references researched. In order to evaluate the different publication, only article published on Q1 journals (i.e. quartile 1), according to the rank proposed by Scimago, were selected. This second screening highlighted only 7 relevant papers.

Totally reading each one of these articles, finally, only the 4 papers presented in table 2 were considered relevant to understand the guideline of this research.

Abstract Title	**Journal**	**Journal Rank**	**Authors**	**Year**
Unpacking IT use and integration for mass customisation: A service-dominant logic view	International Journal of Production Research	Q1	Jitpaiboon, Dobrzykowski, Ragu-Nathan, Vonderembse	2013
From legacy-based factories to smart factories level 2 according to the industry 4.0	International Journal of Computer Integrated Manufacturing	Q1	Orellana, Torres	2019
A Cloud-Based System for Improving Retention Marketing Loyalty Programs in Industry 4.0: A Study on Big Data Storage Implications	ISEE Access	Q1	Galletta, Carnevale, Celesti, Fazio, Villari	2017
Towards facades as Make-To-Order products - The role of knowledge-based-engineering to support design	Journal of Facade Design and Engineering	Q1	Montali, Overend, Pelken, Sauchelli	2017

Table 2: Relevant papers concerning Industry 4.0 and Production Strategy

All these 7 papers are focused on Production Strategy (e.g. Make-to-Stock, Assemble-to-Order, Make-to-Order and Engineer-to-Order) and are faithful to the definition of Industry 4.0 presented by Klaus Schwab (2018) in "The Fourth Industrial Revolution":

“*range of new technologies that are fusing the physical, digital and biological worlds, impacting all disciplines, economies and industries, and even challenging ideas about what it means to be human*”

Moreover, each paper was published later than 2011, year in which the concept of Industry 4.0 first appeared at the Hanover Fair.

b) General Overview

Increasing item variety, life cycles reduction and mass customization are becoming competitive weapons in today’s manufacturing world (Radder and Louw 1999). Therefore, despite Make-to-Order companies are becoming extremely important, high customization increases the complexity of production processes (Kundu, Portioli-Staudacher et al. 2018). The main problems that a low-volume-high-variety company could face are raw material losses, a large number of non-conform products, defective products and, therefore, a collection of guarantees for delayed deliveries, non-productive times (Orellana and Torres et al. 2019). To attach these criticalities, Industry 4.0 may play a strategical role. The new technologies, in fact, allow real-time monitoring of systems supporting decision-making process thanks to systems that exploit data obtained from the execution of procedures and feedbacks from production (Shrouf, Ordieres, and Miragliotta 2014).

Indeed, it is proved that the 82% of the organizations that have implemented Industry 4.0 declaired to have experienced an increment of the efficiency in the fabrication’s process (Orellana and Torres, 2019). However, the implementation of Industry 4.0 still involves few companies due to the huge investments required. Nevertheless, thanks to tools like IoT which enable companies to gather more data, and exploit available information, companies could reach the benefits of smart factories without prohibitive costs (Orellana and Torres 2019).

Nowadays, emerging technologies such as Internet of Things (IoT), Advanced Analytics, Autonomous Vehicles, Virtual and Augmented Reality, Robotics, and Digital Manufacturing are revolutionizing Industry 4.0 enabling a faster smart factory deployment globally. According to a recent Forbes’s market analysis, it is estimated that smart factories will deliver 500 billion dollars in value by 2022. In this context, the growing global economy and demand for customized products are bringing the manufacturing industry from a market of sellers to a market of buyers (Galletta et al. 2017). Smart manufacturing, in fact, is changing the whole production cycle of industries specialized in different kinds of products. On one hand, the advent of social media is making customers' experience more and more inclusive, whereas on the other hand Cyber-Physical System (CPS) technologies help industries to change, in real time, the cycle of production according to customers' needs and preferences (Galletta et al. 2017).

The awareness that customer's unique requirements are fundamental for mass customization, has led firms to view customers as strategic partners in the value creation process (Piller et al. 2004). Companies, in fact, use information technology (IT) to connect with customers, enabling them to recognize individual preferences, tailor products accordingly, produce in a timely manner, and sell at a reasonable price (Sophie Lee et al. 2000). IT could be used also for internal operations, such as for planning infrastructural and operational actions. This way, firm's integration with its customers and suppliers could be enhanced (Jitpaiboon et al. 2013).

Another example of technology application is the Knowledge-Based Engineering (KBE), which involves digital tools used for automation of design processes and reuse of standard knowledge (Montali et al. 2017). By using these tools, in fact, design teams can start to understand the limitations of designing a solution that will eventually be produced by a specific manufacturer, while expressing their design intent (Montali et al. 2017). This way, ETO products could be seen as closer to a MTO type, where an existing package of knowledge is available and ready to be used. (Montali et al. 2017). As product development moves increasingly towards mass customization, the use of KBE systems might appear to be counterintuitive, given the reduction in design freedom. However, Montali et al. 2017 believe that products, which have not yet been manufactured, should be considered as highly engineered products with some a priori design knowledge that takes into account some limitations.

2.3 LEAN AND INDUSTRY 4.0

a) <u>Screening process</u>

In order to inspect how current literature presents possible interrelation between Industry 4.0 and Lean Manufacturing, papers related to the aforementioned subject were searched on Scopus database using the keywords presented in *figure 7*.

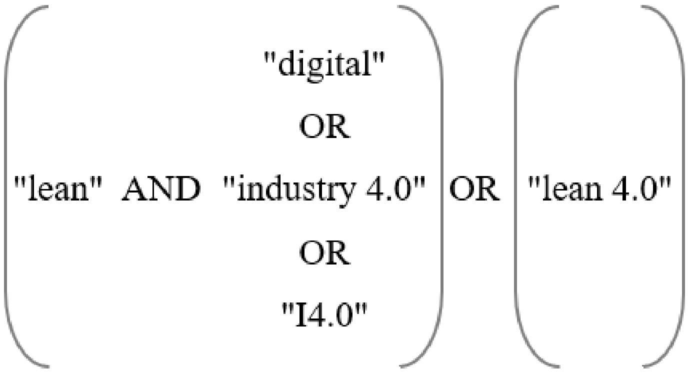


Figure 7: Research keywords of Lean and Industry 4.0

The formula used in the research has the following syntax:

TITLE-ABS-KEY (“lean” AND “digital”)

Combining the aforementioned keywords, research generated a result of 1175 inherent papers. Due to the different combinations used (i.e. “lean” AND “digital” OR “lean” AND “I4.0”), the same paper could be resulted in different researches. For this reason, from the total number of articles founded, the duplicated papers were eliminated. Moreover, to narrow the research, other three filters were applied:

- Only journal articles
- Only English language
- Only Business and Engineering area of interest

Only 227 papers respected the filters applied. At this stage, a first screening was conducted by reading the abstract of each one of them. Only 59 papers were considered relevant in relation to the aforementioned subject. The second screening, based on the selection of articles published on Q1 journals (ranked by Scimago) in order to guarantee the reliability of the references, highlighted only 16 relevant papers. Each one of these 16 papers was read and, finally, only the 7 papers presented in table 3 were considered relevant to understand the guideline of this research.

Article Title	Journal	Journal Rank	Authors	Year
Towards a lean automation interface for workstations	International Journal of Production Research	Q1	D. Kolberg, J. Knobloch, D. Zühlke	2016
The interrelation between Industry 4.0 and lean production: an empirical study on European manufacturers	The International Journal of Advanced Manufacturing Technology	Q1	M. Rossini, F. Costa, G.L. Tortorella, A. Portioli-Staudacher	2019
Human-robot collaborative work cell implementation through lean thinking	International Journal of Computer Integrated Manufacturing	Q1	D. Stadnicka, D. Antonelli	2019
Industry 4.0 and lean manufacturing practices for sustainable organisational performance in Indian manufacturing companies	Industry 4.0 and lean manufacturing practices for sustainable organisational performance in Indian manufacturing companies	Q1	S. Kamble, A. Gunasekaran, N. C. Dhone	2019
Implementation of Industry 4.0 and lean production in Brazilian manufacturing companies	International Journal of Production Research	Q1	G.L. Tortorella, D. Fettermann	2018
The link between Industry 4.0 and lean manufacturing: mapping current research and establishing a research agenda	International Journal of Production Research	Q1	S.V. Buer, J. O. Strandhagen, F.T.S. Chan	2018
The evolution of production systems from Industry 2.0 through Industry 4.0	International Journal of Production Research	Q1	Y. Yin, K.E. Stecke, D. Li	2018

Table 3: Relevant papers concerning Lean and Industry 4.0

All these 7 papers are published later than 2011, year in which the concept of Industry 4.0 first appeared at the Hanover Fair, and are faithful to the definition of Lean Manufacturing given by American Production and Inventory Control Society (APICS) Dictionary:

"*Lean Manufacturing refers to an approach to management that focuses on reducing or eliminating waste in all facets of the manufacturing system*"

and to the definition of Industry 4.0 given in "The Fourth Industrial Revolution" by Klaus Schwab (2018):

"*range of new technologies that are fusing the physical, digital and biological worlds, impacting all disciplines, economies and industries, and even challenging ideas about what it means to be human*"

b) From Lean Automation to Lean 4.0

Since the mid-1990s, authors studied the correlation between Lean Manufacturing and automation technologies and named their integrated implementation Lean Automation (Kolberg, Knobloch and Zühlke, 2016). However, according to its founder Ohno (1988), Lean Manufacturing already involves automation practices. Autonomation (Jidoka) can be applied to each process that owns value-adding and repetitive tasks that can be performed with the passive employees' supervision (Ohno, 1988; Bilberg and Hadar, 2012). The idea that a process may be automated and supervised by operators was recalled by Industry 4.0 (Schlick et al., 2014; Gorecky et al., 2014).

Although in the last quarter-century the term and concept of Lean Automation was overlooked, the combination between Lean Manufacturing and Industry 4.0 technology allows to develop new solutions (Kolberg, Knobloch and Zühlke, 2016). The competitive advantage reached with the joint implementation of Industry 4.0 and Lean Manufacturing may allow companies to enhance their operative performances, by going beyond their traditional barriers (Portioli-Staudacher et al., 2019).

So, nevertheless current literature treats rarely about the term "Lean 4.0", it is possible to identify mentions about the interrelationship between Lean Manufacturing and Industry 4.0.

c) The market evolution and the need of Lean 4.0

Over time, production systems implemented by companies have been forced to evolve in relation with customer demand transformation in terms of volume, variety, time, quality, price, brand and design (Yin, Stecke and Li, 2018). First industrial revolution, thanks to mass production, was able to satisfy a high products' volume (Zhou, Liu, Zhou, 2015).

The research of variety was introduced by the second industrial revolution and was guaranteed by Flow line, TPS (Toyota Production System), Job shop, Cell and FMS (Flexible Manufacturing System) (Yin, Stecke and Li, 2018). These production systems, in addition to SERU (Shared Electronics Resource Understanding), were also able to satisfy the growing request of delivery time flexibility during the third industrial revolution (Yin, Stecke and Li, 2018). Finally, Industry 4.0, combining information and communication technologies (ICT) and smart industrial tools, allowed to establish the smart factory system (Kagermann, et al. 2013) and to satisfy the increasing demand of customization. (Yin, Stecke and Li, 2018)

Nowadays, in a world that is continuously changing and in which the market is unstable in terms of demand and products, the new requirement of flexibility can be satisfied by integrating modern Industry 4.0 to Lean Manufacturing (Kolberg, Knobloch and Zühlke, 2016). This joint implementation of the aforementioned approaches can be adapted for each industry and even for each single part production since wastes elimination is common goal for every company (Stadnicka and Antonelli, 2019). Interrelating Industry 4.0 with Lean Manufacturing, supply chain may become more flexible, lean and transparent, production system may be more automated and autonomous and decision-making system may turn into a more decentralised process (Takeda 2006; Dickmann 2007; Zühlke 2010). Moreover, thanks to the correlation between Industry 4.0 and Lean practices, the effects of some contextual factors (i.e. firm size, Lean Manufacturing implementation experience, type of ownership and business operating model) can be decreased (Portioli-Staudacher et al., 2019).

d) <u>Different visions about Lean 4.0</u>

Buer et al. (2018) proposed a conceptual framework to categorize papers related to Lean 4.0; according to the way in which Lean Manufacturing and Industry 4.0 interact, literature presents three different perspectives:

- **Industry 4.0 supports Lean Manufacturing:** Industry 4.0 may allow to develop new opportunities and to overcome limitations of Lean Manufacturing, which processes can be stabilized and refined (Wagner et al. 2017, Pokorni et al. 2017).

Indeed, usually companies implement Industry 4.0 when they have already achieved high Lean results (Tortorella and Fettermann, 2018) since Lean practices have a higher influence on new operative performances than Industry 4.0 practices (Portioli-Staudacher et al. 2019). Thanks to a consolidated establishment of Lean philosophy and practices, companies may create an internal pool of knowledge that facilitate the introduction of Industry 4.0 (Buer, Strandhagena and Chanb, 2018). Indeed, companies that have implemented Lean practices by more than two years, are facilitated in the adoption of Industry 4.0 tools and may achieve major performance results (Tortorella and Fettermann, 2018). These advantages are created by a quicker understanding of customer demand and by a more agile information exchange that allow to efficiently combine Lean Manufacturing and Industry 4.0 (Tortorella and Fettermann, 2018). Novel technologies can enhance Lean practice efficiency (Buer et al., 2018) and allow companies to deal with higher complexity (Blöchl and Schneider, 2016; Wang et al., 2016). Indeed, Industry 4.0 technologies allow companies to reach higher levels of flexibility in order to cope with the rising market complexity and its fluctuating demand (Mayr et al.,2018).

For example, although value stream mapping (VSM) is a basilar Lean tool that allows to map the current process and study the value stream, it is a manual support and represents only a snapshot of the situation (Sanders, Elangeswaran, and Wulfsberg, 2016). With real-time data collection the efficiency of the VSM tool can be enhanced (Chen and Chen 2014; Meudt, Metternich, and Abele 2017; Mrugalska and Wyrwicka 2017). As a consequence, thanks to autonomous data collection, the likelihood of errors is reduced and the speed of monitoring increases (Chen and Chen 2014). Thanks to 3D printing, just-in-time deliveries and one-piece flow objectives can be reached (Chen and Lin, 2017) and, thanks to cyber physical system technologies, Jidoka can become smarter (Wang, and Zhao, 2017). Other authors (Kolberg and Zühlke 2015; Wagner, Herrmann, and Thiede 2017) support this perspective, but state that not each Lean company may be able to sustain this change towards Industry 4.0 because of their immaturity.

- **Lean Manufacturing supports Industry 4.0:** Wagner et al. (2017) and Pokorni et al. (2017) describe that, thanks to Industry 4.0, Lean processes can be stabilized and refined. Hence, Industry 4.0 contributes to addressing limitations of Lean

Manufacturing by coping with a fluctuating market demand (Mayr et al. 2018). Indeed, a Lean process is simpler to be controlled (Wang et al., 2016) and facilitate further efforts of digitalization (Buer et al., 2018).

- **Combined Industry 4.0 and Lean Manufacturing integration enhance Lean 4.0 performances:** Lean Manufacturing and Industry 4.0 can coexist and complementary support each other (B. Mrugalska and M. K. Wyrwicka, 2017). Indeed, many convictions, like employees' relevance and complexity reduction, are common to both approaches (Mayr et al.,2018). Thanks to the combined ability to improve productivity and reduce costs (Sanders, Elangeswaran, and Wulfsberg, 2016), many authors approve the general compatibility of Lean Manufacturing and Industry 4.0 (Wang et al. 2016; Ghi and Rossetti, 2016; Jayaram, 2016; Kolberg et al., 2017; Ma et al., 2017; Sanders et al., 2016). In particular, Kolberg and Zühlke (2015) describe how SMED techniques, combined with smart manufacturing lines, can decrease set-up time and how autonomous Kanban can reduce inventory level.

These three perspectives, proposed by Buer et al. 2018 and Mayr et al. 2018, show that literature agrees about the potential benefits of Lean 4.0, but is still uncertain about how Lean Manufacturing and Industry 4.0 can be combined efficiently.

e) <u>Digitalization areas and Lean 4.0 implications</u>

A smart manufacturing system able to connect customers, suppliers, assemblers and other service providers is organized in different application domains according to the different technologies, in order to keep the pace of the market (Yin, Stecke and Li, 2018). The first part is an information system which represent the brain of the smart manufacturing system and is constituted by processes, products and cloud computing (Yin, Stecke and Li, 2018). Cloud computing, by providing rental storage space, allows companies to manage and process huge amount of data generated by smart objects (Aazam, Hung and Huh, 2014). The information system of smart manufacturing companies should be able to process quickly different and customized customer orders, through artificial intelligence solutions and machine learning algorithms (Yin, Stecke and Li, 2018). The second part is constituted by a unified communication system used to support interface processes among companies (Kolberg, Knobloch and Zühlke, 2016). Through the Cyber Physical System, workstations can be linked to vendor-independent third-party solutions, and, through digital Kanban, supply chain areas of different actors can be integrated (Kolberg, Knobloch and Zühlke, 2016). The third part is constituted by technologies such as robotics, automation, digital manufacturing and sensors which allow companies to change the operational procedures of their production system, by adapting them to the environment, in order to deal with variable customer demand dimensions (Yin, Stecke and Li, 2018). The introduction of robotics and automation is a critical step and has to be supported by Lean concepts, tools and methods in order to favour the reorganization of the factory and the adoption of new Industry 4.0 tools and avoid inefficiency and losses of quality (Stadnicka and Antonelli, 2019).

Buer et al. (2018), tried to map where industry 4.0 tools can be applied in a Lean Manufacturing company. In particular, Bortolotti, Boscari, and Danese 2015 studied which “Hard” (related to analytical and technical procedures) and “Soft” (concerning people and relations) Lean practices can be improved by Industry 4.0 technologies:

- **Hard Practices:** Industry 4.0 supports process factors (pull system, continuous flow and set-up time reduction), control factors (total productive/preventive maintenance and statistical process control) and interface processes with customers and suppliers (Buer et. al., 2018). A digital Kanban can understand the charging level of the stock and report it to manage the inventory system or send orders to third-party suppliers (Kolberg, Knobloch and Zühlke, 2016). A flexible material supply system can digitalize Heijunka by automatically converting customer orders into smaller, recurring batches: this is done through displays with Graphical User Interface (GUI) connected with the production line (Kolberg, Knobloch and Zühlke, 2016). Moreover, Industry 4.0 tools that enable real-time information are useful in identifying process wastes with higher accuracy and speed and in preparing accurate value stream maps (S. Kamble, A. Gunasekaran, N. C. Dhone, 2019).
- **Soft Practices:** These practices are important to sustain change, through Lean Manufacturing, in the long term (Bortolotti, Boscari, and Danese, 2015). It is important to involve employees, avoiding to laid them off, and be sure that automation ennoble their tasks, without replacing workers (Buer et. al., 2018). Continuous learning, education and training allows the workforce to have the qualification requirements to deal with Industry 4.0 tools (Bonekamp and Sure

2015). Given the increased complexity of processes, employee's job satisfaction can be enhanced through Kaizen events (Smith, 2003). Without involving employees and enhancing their tasks, the situation can degenerate in a continuous improvement paradox, in which employees, through optimising the process, make themselves redundant (Buer et. al., 2018).

Finally, Lean 4.0 can be visible in each singular cyber-physical workstation, by combining Hard and Soft Lean practices: the e-Kanban-system helps to digitalize the distributed production and to avoid lost Kanban, wearables and sensors allow employees to directly receive notifications when a breakdown is going to occur and advanced analytics support the continuous improvement by reporting and analysing data. (D. Kolberg, J. Knobloch, D. Zühlke, 2016)

2.4 LEAN 4.0 AND PRODUCTION STRATEGY

a) <u>Screening Process</u>

In this section, current literature was analysed in order to inspect the relationship between Production Strategy and Lean 4.0. As the analysis in the previous sections, Scopus was the only database used to conduct this study. In *figure 8* are presented the keywords that were used to build the syntax for the research.

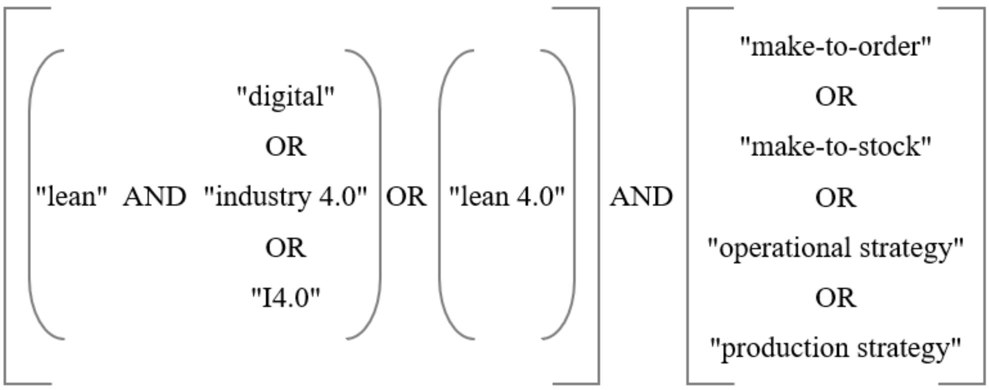


Figure 8: Research keywords of Lean, Industry 4.0 and Production Strategy

An example of the syntax used can be:

TITLE-ABS-KEY ("lean" AND "digital" AND "make-to-stock")

Only 6 inherent papers resulted from the research of the admitted combination of aforementioned keywords. No duplicated articles were found among these 6 papers, but only 3 of them remained after the application of the following three filters:

- Only journal articles
- Only English language
- Only Business and Engineering area of interest

After the reading of the abstracts of these 3 papers, no one of them was identified as important to describe the relation between Lean 4.0 and Production Strategy. The absence of papers in this research highlights the gap we want to cover with our analysis.

2.5 CONCLUSION

Figure 9 represents the research procedure followed in the systematic literature review for each one of the four area of interest, highlighting the number of papers processed at each screening phase.

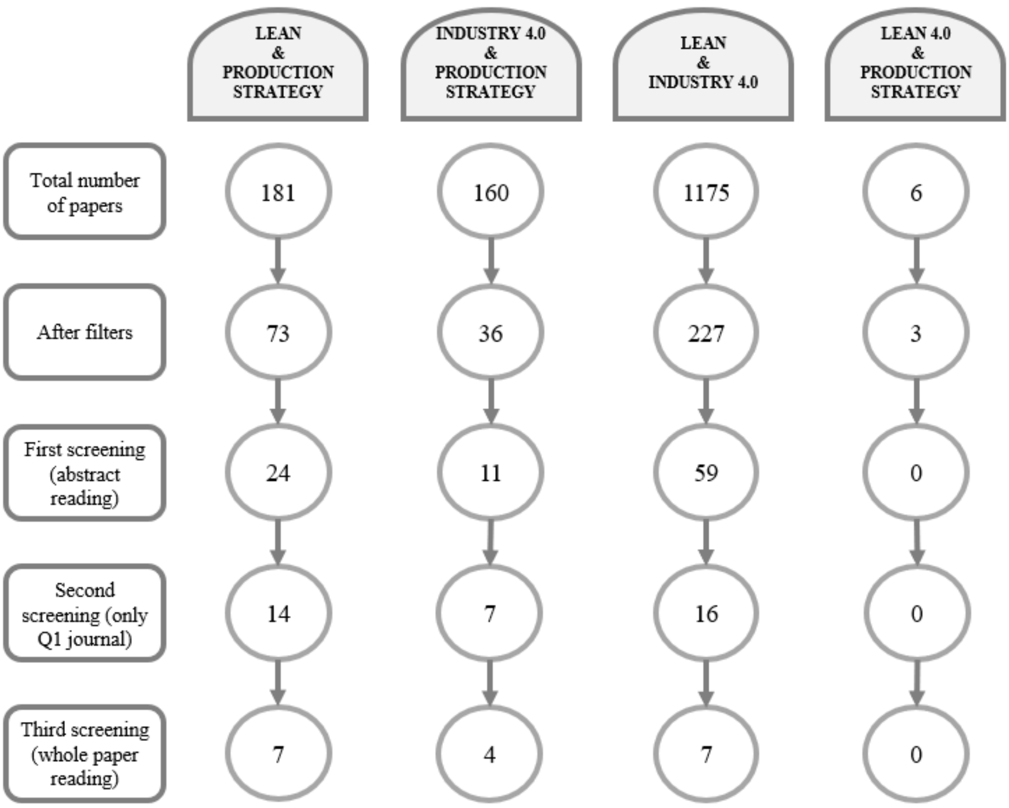


Figure 9: Literature review screening procedure

Summarizing the main findings of the literature review, the current scenario presents the application of Industry 4.0 and Lean Manufacturing concepts in different Production Strategy's environments, but the relationship between the latter and Lean 4.0 has not been deeply studied yet. Although authors demonstrate that the combination between Lean

Manufacturing and Industry 4.0 could enhance Operational Performances, no particular mention to Production Strategy was done. However, despite traditionally Lean tools have been developed and applied to mass production, they can be successfully applied also in mass customization environments (Birkie and Trucco, 2016; Abdulmalek and Rajgopal, 2007). Even though high demand variability may influence the introduction of Lean Manufacturing in a non-repetitive plant (Thurer et.al 2012), it is not studied if a company achieves lower results whether the Lean adoption level is the same and Production Strategy differ. In addition, even in the Industry 4.0 field, it is difficult to find information regarding its possible relationship with Production Strategy.

3. RESEARCH QUESTION

Drawing conclusions from the previously presented framework, the main aim of the research is to inspect the presence of synergies and trade-offs between Lean 4.0 and Production Strategy on Operational Performance. However, from a theoretical point-of-view three different perspectives emerged, unveiling an absence of shared vision in building Lean 4.0 construct (Buer et al. 2018 and Mayr et al. 2018). The first research question seeks to inquire the link between Lean Manufacturing and Industry 4.0:

> *RQ1: How does Lean Manufacturing and Industry 4.0 are related one to another in building Lean 4.0 construct?*

Secondly, in order to study which production environment is more suitable for introducing Lean 4.0, the research analyses how Lean Manufacturing and Industry 4.0 are individually related to Production Strategy. Indeed, according to Olhager and Prajogo (2011), some improvement initiatives and techniques are more applicable in certain manufacturing environments. Starting from this thesis, the second research question can be stated as follow:

> *RQ2: Do Lean Manufacturing and Industry 4.0 have a relationship with Production Strategy?*

Furthermore, literature demonstrates that exists an interrelation between Lean Manufacturing and Industry 4.0, which allows companies to go beyond their traditional barriers (Portioli-Staudacher et al., 2019) and to develop new solutions (Kolberg, Knobloch and Zühlke, 2016). Operational Performances are so influenced by the implementation of Lean 4.0, but, since in Italy the enterprise panorama is widely different, a further step of the analysis was performed investigating how and if the specific contextual factors of each firm could have an impact on such implementation. Therefore, the third research question inspected can be defined as follow:

> *RQ3: Does contextual factors affect Lean 4.0 adoption?*

Finally, once further analysed what is evident in prior literature, the study moves to inspect the most significant gap. Production Strategy, in fact, has never been analysed in relation with Lean 4.0. As reported in section 2 “Literature Review”, no papers were found searching a relationship between the aforementioned themes. Therefore, to fill the highlighted gap, possible synergies and trade-offs between Lean 4.0 and Production Strategy were investigated in the fourth research question:

RQ4: Are there any synergies or trade-offs between Lean 4.0 and Production Strategy on Operational Strategy?

The research questions' framework built is presented in *figure 10*.

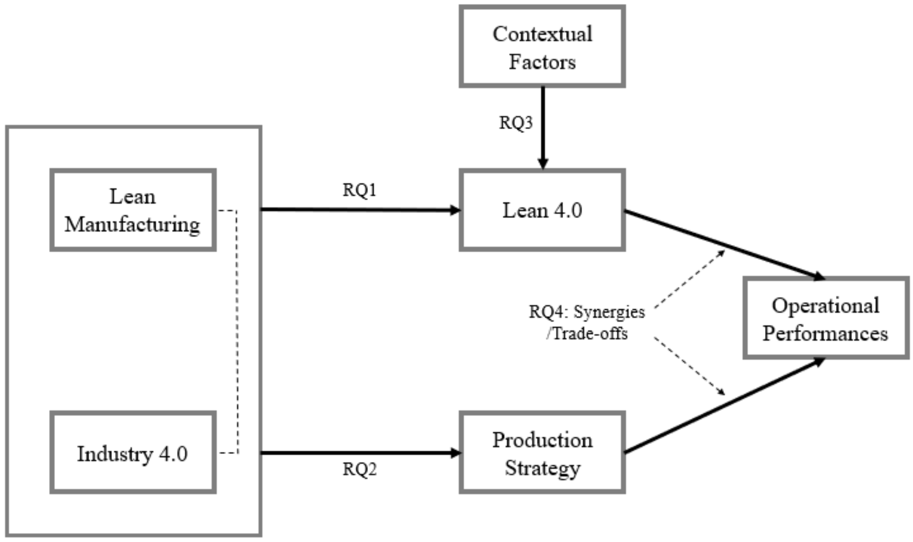


Figure 10: Research questions' diagram

Considering the research question framework, the study is structured according to the two main methodologies used. The first phase is based on a survey and inquires RQ1, RQ2 and RQ3; the second phase, instead, is based on semi-structured interviews in which RQ4 is inspected.

4. RESEARCH METHODOLOGY

This chapter aims at clarifying the procedure followed to conduct the study, the methodologies used (i.e. survey and semi-structured interviews) and their implications. First of all, in paragraph 4.1, it is presented an overview on the terminology used, explaining the clusters and the classifications adopted to analyse information. Secondly, the modalities and techniques used to collect these data are described and the reasons beyond their adoption are discussed (i.e. paragraph 4.2). Hereafter, in paragraph 4.3 and 4.4, it is shown the procedure followed to encode the information gathered and the model used to build Lean Manufacturing, Industry 4.0 and Lean 4.0 indexes. Finally, in paragraph 4.5, an overview of the statistical models' theory is presented.

4.1 STUDY TERMINOLOGY

The first two sections (i.e. section 4.1.1 and 4.1.2) aim at presenting a clear classification and definition of Lean and Industry 4.0 bundles. The paragraph ends by showing how literature helps to define Production Strategy's clustering (i.e. section 4.1.3) and most relevant Operational Performances (section 4.1.4).

4.1.1 Lean Bundles

This section aims at clarifying which are the main Lean bundles used to define Lean Manufacturing in a unique and clear manner. According to Furlan et al. 2011, Lean bundles are defined as a set of interrelated and internally consistent Lean practices.

Since Shah and Ward (2007) points out an absence of common definition of Lean Manufacturing due to the multitude of descriptions and terms used with respect to this concept, as main reference for the identification of Lean bundles, the contribution of Shah & Ward "Lean Manufacturing: context, practice bundles, and performance", published on the Journal of Operations Management in 2003, is adopted. In their study, the authors attempt to clarify the semantic confusion surrounding Lean Manufacturing by conducting an extensive literature review using a historical evolutionary perspective in tracing its main components (Shah & Ward, 2003).

Indeed, a review of the literature reveals that there is a multiplicity of descriptions, terms and practices used with respect to Lean Manufacturing. The ambiguity stems from different sources which could be classified into three main categories:

- Lean Manufacturing has evolved over a long period of time (Hopp and Spearman, 2004; Womack et al., 1990; Spear and Bowen, 1999)
- Lean Manufacturing disagreement on what it comprises and how it can be measured operationally (Shah and Ward, 2007).
- Lean Manufacturing is sometimes confused with other related approaches like DMAIC, Six Sigma, Lean Management and Lean Start-up. The main difference between Lean Manufacturing and the aforementioned approaches is that the first focuses on the improvement of the entire value stream and the elimination of non-value adding activities, the others are focused on individual processes and the efficiency or productivity improvement (A. Anvari et al., 2011).

The sources of ambiguities are caused by a wide range of applicability of Lean Manufacturing, that is generally described from two points of view: from a philosophical perspective related to guiding principles and overarching goals (Womack and Jones, 1996; Spear and Bowen, 1999); and from the practical perspective of a set of management practices, tools, or techniques that can be observed directly (Shah & Ward, 2003; Li et al., 2005).

To solve these issues, Shah & Ward (2003) developed measures for Lean Manufacturing and operationalized it as bundles of practices related to Just in Time (JIT), Total Quality Management (TQM), Total Preventive Maintenance (TPM), and Human Resource Management (HRM). The authors limit their analysis to four bundles that are oriented internally to reflect a firm's approach to manage its manufacturing operation. In Shah & Ward 2007, instead, even the suppliers and customer management bundles are considered, since the authors define Lean Manufacturing as an integrated socio-technical system whose main objective is to eliminate waste by concurrently reducing or minimizing supplier, customer, and internal variability. But, in this study, less relevance was given to external bundles (i.e. customer and supplier management) for two main reasons:

- The focus of the whole research is on internal manufacturing production processes and so there is no reason to consider external actors.
- Operational Performances, considered in the whole study, are related to companies' internal efficiency and effectiveness.

According to what has been stated before and Shah and Ward (2003), the grouping of Lean practices and the classification of Lean bundles is presented below:

- **Just in Time (JIT):** manufacturing program that aims at reducing and, ultimately, eliminating all forms of waste (Sugimori, et al., 1977). The major wastes that need to be contrasted are work-in-process (WIP) inventory, that can be reduced by applying practices of lot size reduction, quick changeover techniques and cycle time reduction, and delays in flow time, that can be reduced by implementing bottleneck removal, cellular layout and production process reengineering (Shah and Ward, 2003).
- **Total Quality Management (TQM):** it includes practices related to process capability measurement, management programs sustainability of quality products and processes and continuous improvement (Shah and Ward, 2003).
- **Total Productive Maintenance (TPM):** this bundle is related to activities involving technology acquisition and new process equipment (Cua et a., 2001). The main practices applied are predictive and preventive maintenance and maintenance optimization techniques (Shah and Ward, 2003).
- **Human Resource Management (HRM):** it includes lower level practices like job rotation, job design, job enlargement, formal training programs, cross-training programs, work teams, problem solving groups, and employees involvement, that are organized in higher level practices: self-directed work teams and flexible, cross-functional work force (Shah and Ward, 2003). According to Furlan et al. (2011), HRM practices can be considered at the same level of other more technically oriented practices or bundles.

This complete set of bundles is considered appropriate to cover each Lean Manufacturing practice that a company can implement in its manufacturing floor.

4.1.2 Industry 4.0 Bundles

This section aims at clarifying the reasons beyond the choice of Industry 4.0 bundles: using the literature as a starting point, the highest-level framework is presented; down in the detail, by verifying digital tools citations in technological and consultancy reports, a final bundle framework is proposed.

From a technological point of view, Industry 4.0 framework is characterized by four fundamental conceptual approaches (R. Anderl, 2014):

- **Cyber-Physical Systems (CPS)**: this concept involves mechanisms monitored or controlled by software algorithms, integrated with users via the Internet. Physical components and software algorithms penetrate mutually on different spatial and temporal scales, interacting in ways that change the context of the whole system (A Stăncioiu, 2017). This interpenetration results in two complementary approaches: cyberizing the physical and physicalizing the cyber (R. Anderl, 2014). In Industry 4.0 environment, each machine is a collaborative CPS entity that communicates with other machines physically and virtually (P. Zheng et al., 2018).
- **Internet Technology:** Internet Technology comprises the concepts of Internet of Things (IoT), Internet of Services (IoS) and Internet of Data (IoD) (R. Anderl, 2014). Thanks to IoT, objects are converted into Smart Manufacturing Objects (SMOs) that can intelligently interact and communicate in real time (Pai Zheng et al. 2018). IoS involves new service paradigms such as SOA (Service Oriented Architecture) and REST (Representational State Transfer) technologies that allow to identify resources and develop a software architecture based on systems interoperability for the Web Services usage (R. Anderl, 2014). IoD allows to enable the analysis, the interpretation, the management and the transfer of huge amount of data, generated from IoT and IoS (R. Anderl, 2014).
- **Manufacturing objects as information carriers:** components are connected in a network of communicating instances that allows to identify, localize and address them (R. Anderl, 2014). Moreover, manufacturing objects can control their own manufacturing processes and flow, thanks to their connection to process planning and product model structures (R. Anderl, 2014).
- **Cybersecurity:** Cyber-Physical Systems and Internet Technologies require to ensure safety, privacy, security and knowledge protection (R. Anderl, 2014). These issues acquire importance with the increased connectivity and data sharing across sites and company boundaries (F. Othman at al. 2016). Cybersecurity-related services can generate additional revenue and help companies to increase their competitive positioning, through enhanced security features (M. Podrecca et al., 2019).

Going more in detail to this high level framework and concentrating on the manufacturing field, Osservatori Digital Innovation's report "Industria 4.0: la rivoluzione si fa con le persone!" displays that 42% of the projects are developed in the area of Smart Factory (e.g. maintenance, quality control, logistic, production, security and regulation respect), 33% in Smart Lifecycle (e.g. suppliers management, product development and life cycle management) and 25% in Smart Supply Chain (e.g. planning of financial and physical flows). Although national economies, according to their ability to capitalize future production opportunities and challenges, can influence the results of Industry 4.0 adoption (A. Batchkova et al., 2018), Politecnico di Milano's Osservatori Digital Innovation considers Industry 4.0 as a revolution, still in evolution everywhere, that nowadays is present in each part of the company. However, Industry 4.0 tools can be classified in consistent bundles in order to group homogeneous practices.

With the aim of finding out this clustering, a systematic report analysis was conducted. The research was carried on Google, using the following keywords: "Industry 4.0", "Industry 4.0 Bundles", "Smart Manufacturing", "Industry 4.0 Technologies", "Digital Technologies 4.0" and "Industry 4.0 Categories". Among the results, only technological and consulting reports and whitepapers were analysed. Considering that companies operating in the fields of technology and consultancy have a wide view on all the industries, have direct contact with the market and are up with the times of technological progress and innovations, there was not the need to analyse scientific papers in this phase.

In Annex A, the information about the 40 technological and consultancy reports analysed are presented. For each document in the list, the citations to the main Industry 4.0 technologies were collected. The level of analysis, kept during the whole procedure, was at the bundle level: indeed, the objective of the analysis was not to find out digital tools and applications, but to understand the bundles in which these Industry 4.0 tools and applications were classified. In table 4, are displayed the technology categories' citations for each document analysed:

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
Advanced Analytics		X	X	X	X	X	X	X	X	X	X	X		X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	
Digital Manufacturing	X	X	X	X	X	X	X	X	X	X		X	X	X		X	X	X	X	X	X		X	X	X	X	X	X	X	X	X	X	X	X	X		X	X	X	X
Internet of Things	X	X	X	X	X	X	X	X		X	X	X	X	X			X	X	X	X	X		X	X	X	X	X	X		X	X	X	X	X	X	X	X	X	X	X
Robotics	X	X	X	X	X	X	X		X	X		X	X	X		X	X	X	X	X	X	X	X	X	X	X	X	X	X		X	X		X	X			X		X
Virtual and Augmented Reality	X		X	X	X	X	X	X			X	X	X		X	X	X		X	X	X		X	X	X		X		X			X	X	X	X	X				X
Cloud Computing		X		X	X	X	X	X	X	X		X						X	X	X	X		X	X	X	X	X	X		X	X		X	X						
Cybersecurity				X			X	X			X				X	X		X	X	X	X				X	X	X							X				X		
Autonomous Vehicles	X		X	X								X	X	X						X			X			X	X	X	X			X		X						
Simulation				X		X	X		X			X						X		X	X		X				X					X		X						
Horizontal & Vertical System Integration				X			X		X											X							X	X				X		X				X		
Blockchain											X				X		X					X							X				X		X	X	X			
Mobile Device					X			X				X																	X		X									
Smart Sensors						X		X				X														X		X												
Biotechnology & Nanotechnology			X															X										X							X					
Smart Materials																		X								X		X							X					
Predictive Maintenance	X																															X						X		
Process Automation																	X	X				X																		
Social Business Media	X																													X										
Geoengineering			X																																X					
Neurotechnology			X																																X					
Energy Storage					X																												X							
Quantum Computing															X																				X					
Advanced Materials																																		X						X
Digital Twins																																							X	X
Crowdfunding			X																																					
GPS Technology								X																																
New Marketplaces									X																															
5G Technology																X																								
Rapid Prototyping																																				X				

Table 4: Technology citations in the 40 papers analysed

Summing up, in table 5, it is presented the number of citations for each Industry 4.0 bundle mentioned in the 40 reports analysed.

Technology	Citations
Advanced Analytics	37
Digital Manufacturing	36
Internet of Things	35
Robotics	32
Virtual and Augmented Reality	27
Cloud Computing	23
Cybersecurity	15
Autonomous Vehicles	14
Simulation	12
Horizontal & Vertical System Integration	9
Blockchain	9
Mobile Device	5
Smart Sensors	5
Biotechnology & Nanotechnology	4
Smart Materials	4
Predictive Maintenance	3
Process Automation	3
Social Business Media	2
Geoengineering	2
Neurotechnology	2
Energy Storage	2
Quantum Computing	2
Advanced Materials	2
Digital Twins	2
Crowdfunding	1
GPS Technology	1
New Marketplaces	1
5G Technology	1
Rapid Prototyping	1

Table 5:Summary of technology citations in the 40 papers analysed

To identify the bundles, the following procedure was applied:

- If a technology is cited in at least one-third of the reports (i.e. 13 papers), the technology is considered effectively as a bundle.

- If a technology is cited in less than 13 reports, the technology is not considered as a bundle.

According to this analysis, the identified bundles' framework is:

- **Advanced Analytics:** methodologies and tools used to analyse and extract values from data gathered from the productive and logistic flows, that are usually too complex and large (i.e. Big Data) to be managed by traditional data-processing application software. In this category are included technologies and techniques of simulation, machine learning, business intelligence, visualization, forecasting and data analytics (Osservatori Digital Innovation, 2019)
- **Internet of Things (IoT) and Cloud Computing:** tools that deals with the interconnectivity of smart objects across the company. Indeed, smart objects, connected through a smart network, are able to send and receive information and take actions based on data. In particular, each smart object has to own the properties of self-awareness, interaction, processing and communication, and a smart network has to be multifunctional, accessible and based on open technological standards (Osservatori Digital Innovation, 2019). Since data, generated by these interconnected smart objects, are increasing, storing information locally is not possible anymore. Thanks to Cloud Computing, companies may use rental storage space to process and manage this data. Indeed, it allows, through the Internet, to make available the accessibility to computer system resources (i.e. computing power and storage capacity at different levels: IaaS, PaaS and SaaS), with a simple and on-demand service (M. Aazam et al., 2014).
- **Autonomous Vehicles:** Autonomous means of transport (i.e. without a driver actively operating) used to transport people, animals or things, with capabilities to interpret signals and perceive external environment. Drones, cargo ships and self-driving cars are the major examples of this category (Osservatori Digital Innovation, 2019).
- **Digital Manufacturing:** technologies which allow, through 3D printing, to "create" objects, thanks to the manipulation of plastics and metals (Osservatori Digital Innovation, 2019).
- **Robotics:** Robots that can autonomously move themselves without human intervention. These solutions (i.e. industrial robots and co-bots) are characterized

by processing, learning, reasoning, planning and interaction capabilities (Osservatori Digital Innovation, 2019).

- **Virtual and Augmented Reality:** this bundle includes wearables and tools able to insert digital elements to a live view (AR) and able to shout out the physical world by creating a virtual one (VR) (Osservatori Digital Innovation, 2019).

The only exception to this scheme is presented by Cybersecurity, which, as previously mentioned, is considered as a part of the high-level framework and is linked to concepts of safety, privacy, security and knowledge protection (R. Anderl, 2014). Indeed, since Cybersecurity is closer to the field of Information and Communication Technology (ICT) rather than the manufacturing one, it is not considered as a bundle. Moreover, it involves also strategy definition since managers should approach this issue by leveraging cyber resilience and risk management (M. Podrecca et al., 2019).

4.1.3 Production Strategy

In a world that is demanding high level of customization, positioning the Customer Order Decoupling Point (CODP) correctly allows companies to identify the optimal balance between productivity and flexibility (Rudberg and Wikner, 2004). As such, CODP can be the means for a thorough analysis for establishing operational processes in mass customization (Rudberg and Wikner, 2004). A literature review conducted by Wikner and Rudberg (2001) reveals that four CODPs are most frequently used: Engineer-To-Oorder (ETO), Make-To-Order (MTO), Assemble-To-Order (ATO) and Make-To-Stock (MTS). These four CODPs define the four different Production Strategies that are used in this study.

Mass and series production, high-volume-low-variety production (i.e. MTS) are characterized by repetitive production steps while low-volume-high-variety production described by different and mainly unique projects (i.e. ATO, MTO, ETO) are characterized by non-repetitive production steps (Matt and Rauch et al.. 2014).

4.1.4 Operational Performance

As already stated, this research aims at studying relationship between Lean 4.0 implementation and company's Production Strategy. In order to evaluate this relation, the effect on Operational Performance originated by Lean 4.0 implementation was studied. Operational Performances metrics, analysed in the research, were the ones proposed by Shah and Ward, 2003:

- Finished-product first-pass quality yield;
- Scrap and rework costs;
- Productivity, defined as euro volume of shipments per employee;
- Per unit manufacturing costs, excluding purchased material;
- Manufacturing cycle time;
- Customer lead-time.

In addition to these six metrics, in order to broaden the portfolio, two other measures were included, due also to their relevance for the Lean Manufacturing approach:

- Total inventories monetary value;
- Set-up time.

The whole set of Operational Performances selected displays a wide and complete overview of the effects of the combined implementation of Lean Manufacturing and Industry 4.0.

4.2 DATA COLLECTION

Data collection is a fundamental part of a scientific research, since conducting this phase in the proper way will enhance the accuracy, validity and reliability of research findings, carrying out high-quality results. In this study two main data collection techniques were used: survey and semi-structured interviews. The information gathered from these two different approaches were used to build and structure two different datasets:

- The first dataset (presented in section 4.2.1) is composed by data collected through a survey in a study conducted in 2018 by a research team composed by researchers from Politecnico di Milano, Oxford and KLU University. According to Cifone et al. 2019, the survey provided information classified in a dataset of 105 respondents (i.e. sample's population=105).
- The second dataset (presented in section 4.2.3), instead, is composed by information gathered from 20 direct interviews conducted from 3 to 17 September

2019. The interviews, conducted through telephone or Skype, enabled to gather more reliable information, discussing directly with companies' managers.

In the following sections, the two datasets are presented showing their structure, their data collection process and their sample's characteristics. Moreover, in section 4.2.2 are highlighted the reasons that lead us to move from a survey-based to an interview-based research.

4.2.1 Survey

a. Survey Data Collection Process

As mentioned in paragraph 4.2 *Data Collection*, the dataset was structured in 2018, starting from a questionnaire developed by a research team composed by researchers from Politecnico di Milano, Oxford and KLU University. According to the study conducted by Cifone et al. (2019), survey methodology has been adopted since it is the most suitable quantitative methodology to conduct exploratory studies. The sample was limited to Lean experts (i.e. Green Belt or Black Belt was a mandatory requisite), and to the Italian manufacturing sector, with plants as unit of analysis. The final dataset, after the elimination of service sector (i.e. 56 answers) and random (i.e. 1 answer) responses, was composed by 105 respondents, referring to 88 different companies.

b. Survey Structure

The aim of the survey was to widely inspect Lean 4.0 topic going through different themes:

- Potential influence of contextual variables on both Lean Manufacturing and Industry 4.0 implementation;
- Implementation level of Lean Manufacturing practices and Industry 4.0 tools and their relative maturity degree;
- Digitalization level of Lean Manufacturing practices;
- Improvement of Operational Performances resulting from Lean 4.0 adoption.

To efficiently inspect the previous themes, survey was designed with a pertinent structure, divided in the following sections:

i. Company's Profile

The first section aims at identifying general information regarding respondents and their companies:

- Name of the company;
- Sector in which the company operates;
- Role of respondents.

This information was used to classify the sample. Since some respondents could work in the same company, in case of conflictual responses, their role was used to understand the validity of answers given.

ii. Contextual Factors

This second section aims at collecting information about contextual variables that could potentially influence Lean Manufacturing practices adoption and the digitalization of the plant. Production process, age of the plant, plant size and industry were the contextual variables considered in the research.

iii. Lean Manufacturing Implementation

The purpose of the third section is to understand the level of implementation of Lean Manufacturing and its maturity degree. Respondents had to declare the time period of implementation of Lean Manufacturing, and the level of a list of Lean bundles giving values in a range from 0 (equal to not implemented) to 5 (which represents the total implementation) where 3 represents partially implemented. The list of Lean Manufacturing bundles inspected is the following:

- Just in Time (JIT);
- Total Quality Management (TQM);
- Total Productive Maintenance (TPM);
- Human Resource Management (HRM).

iv. Industry 4.0 Implementation

The fourth section is structed as the third one but aims at understanding the maturity degree and the level of implementation of Industry 4.0. Respondents had to declare the time period of implementation of Industry 4.0, and the level of a list of Industry 4.0 bundles giving values in a range from 0 (equal to not implemented) to 5 (which represents the total implementation) where 3 represents partially implemented. The list of Industry 4.0 bundles inspected is the following:

- Advanced Analytics
- Internet of Things (IoT) and Cloud Computing;
- Autonomous Vehicles;
- Digital Manufacturing;
- Robotics;
- Virtual and Augmented Reality.

v. Operational Performances

The last section is dedicated to inspect the effects on Operational Performances of Industry 4.0 tools implementation with respect to Lean practices. As stated in *section 4.1.4 Operational Performances*, according to Shah and Ward (2003), the metrics considered are the following:

- Finished products first-pass quality;
- Scrap and re-work cost;
- Productivity, defined as volume per year;
- Per unit manufacturing cost excluding purchase material;
- Customer Lead Time;
- Manufacturing Cycle Time;
- Total inventories monetary value;
- Set-up time.

c. <u>Survey Sample Characteristics</u>

The data collected through the survey, provided several information which could be used to perform a preliminary analysis describing the sample's characteristics. The categories used to classify the different companies are the following:

- Industrial sector;
- Age of the plant;
- Number of employees.

According to the industry in which operate, companies are clustered into five sectors. Most of them, as shown in table 6, are characterized by Machinery and metal products (32% of companies) and Automotive (25% of the sample) industry.

Industrial Sector	Count	Percentage
Machinery and metal products	33	31%
Automotive	26	25%
Chemicals and pharmaceuticals	21	20%
Electric and electronic equipment	13	12%
Miscellaneous manufacturing (i.e. Food and beverages, Apparel and other textile, Rubber and miscellaneous plastic)	12	11%
Total	105	100%

Table 6: Survey industry's characteristics

The second metric analysed aims at understanding the maturity of the plant considered in the research. In table 7 is easily visible that the 80% of the sample is represented by companies with a plant age equal to more than 20 years; while only the 6.7% of companies has less than 10 years.

Plant age	Count	Percentage
Less than 9 years	7	7%
From 10 to 20	14	13%
More than 20	84	80%
Total	105	100%

Table 7:Survey plant age's characteristics

According to many studies (Birkie 2016, Portioli-Staucher 2018, Furlan 2011 et al.) the size of the companies, represented in table 8, is measured considering the number of employees. The 40% of the plants can be classified as Small-Medium Enterprise (from 0 to 250 employees) according to the definition given by European Union in EU recommendation 2003/361. The remain 60%, instead, are represented by large enterprise (more than 250 people employed).

Number of Employees	Count	Percentage
Less than 50	7	7%
From 51 to 250	35	33%
More than 250	63	60%
Total	105	100%

Table 8: Survey number of employees' characteristics

Table 9 and 10, instead, clustered the companies according to their maturity level of Lean Manufacturing and Industry 4.0. It is immediately visible that Lean Manufacturing is a deeply rooted approach in Italy since the 62% of companies has been implemented this approach from more than 6 year. On the opposite, due to the novelty of Industry 4.0, the 41% of companies has just started to implement Industry 4.0 technologies (i.e. less than 1 year of implementation).

Years of Lean implementation	**Count**	**Percentage**
Less than 1	12	11%
From 2 to 3	11	10%
From 4 to 5	17	16%
From 6 to 10	31	30%
Higher than 10	34	32%
Total	105	100%

Table 9: Survey Lean maturity's characteristics

Years of Industry 4.0 implementation	**Count**	**Percentage**
Less than 1	43	41%
From 2 to 3	25	24%
From 4 to 5	14	13%
More than 5	23	22%
Total	105	100%

Table 10: Survey Industry 4.0 maturity's characteristics

This preliminary analysis was useful to describe sample's characteristics but needs to be integrated with statistically relevant analysis (*chapter 5 Analysis*) in order to provide significant findings.

4.2.2 Reasons Beyond Case-Study Research

This section aims at clarifying the reasons that let us move from a survey-based methodology to an interview-based methodology.

According to current literature, the survey approach presents different criticalities:

- Since the structure of the survey is univocally designed for each respondent, there is a lack of flexibility and ability to deeply inspect the most interesting answers (Akbayrak, 2000);

- Although survey is characterized by uniformity of measurement and high reliability, respondents could not be satisfied by none of the proposed answer alternatives and be forced to give inappropriate responses (Cohen and Manion, 1994);
- Since the researcher force the respondent to choose among predetermined alternatives, the latter is pushed to think about answers and connections that he would have never given in a dialogue (Akbayrak, 2000);
- Online surveys are completed during time convenient for the respondent but are often filled out in the midst of other activities (i.e. reading and answering emails, video streaming, web surfing, and social sharing) that could bring to inaccurate and misleading data (DeFranzo et al., 2014).
- Although a survey may be simply submitted to respondent, there is no control on their responses and there is no possibility to keep track of the logical path followed to answer (Akbayrak, 2000);

In addition, in our research, the survey used to build the dataset for the analysis presents the following criticalities:

- Production Strategy of each company was not inspected; only an Internet research on companies' website was performed. This procedure will be deeply described in paragraph 4.3 *Data Encoding*.
- Given the novelty and the scarce diffusion of Industry 4.0, respondents may have overlapped and confused Industry 4.0 tools with digital technologies concepts.
- Lean Manufacturing and Industry 4.0 implementation level could be difficult to evaluate due to the subjectivity of respondents: without having a term of comparison, respondents could have misleading values of bundles implementation.
- Survey research is characterized by poor response rate (Austin 1981, Cormack 1984, Treece & Treece 1986, Bailey 1987). The result of 105 manufacturing respondents corresponded to a response rate of 31,46%.

According to Akbayrak (2000), the disadvantages of the survey are the advantages of the interviews and so one technique could be used to resolve the issues of the other. The combination of survey and interviews techniques may provide a powerful research strategy and allow the researcher to know, not only respondents' thoughts, but also their feelings and ideas (Akbayrak, 2000). Indeed, case study research, on one side, can bring to a deeper understanding of a complex and elaborated issue and, on the other side, can add strength to what was found out in the previous research (i.e. the survey-based statistical analysis) (Dooley, 2002). The case study research method is defined as "*scholarly inquiry that investigates a contemporary phenomenon within its real-life context, when the boundaries between phenomenon and context are not clearly evident; and in which multiple sources of evidence are used*" (Yin, 1994). Obviously, the inquiry of one company, was followed by the inquiry of another, and so on. From a single observation, the theory can begin to be formed and the researcher is brought to study the same phenomenon of another company, combining the findings (Dooley, 2002). However, the case study research method is not a theory-building methodology (L.M. Dooley, 2002), which is defined as "*the process of modelling real-world phenomena*" (Torraco, 1997). Despite that, case-study research can be used as a support of theory-building (Eisenhardt, 1989, Yin, 1994 and Soy, 1996) whether it is conducted using both quantitative and qualitative methodologies (i.e. document analysis, surveys, questionnaires, interviews, Delphi processes and others) (Dooley 2002). Indeed, case-studies information may be analysed with a statistical model, even if the small sample can arise some criticalities, in order to give relevant findings.

In particular, in order to deeper understand the complex Lean 4.0 topic, add strength to what was found out in the previous research and capture verbal and non-verbal cues (Dooley, 2002; DeFranzo et al.., 2014), direct interviews were conducted. Indeed, through the telephone, interviewers, interpreting the voice and intonation of respondents, are able to understand the level of enthusiasm or discomfort with the questions (Opdenakker et al. 2006). Through Skype-call, instead, even the body language can be used as source of extra-information. Capturing non-verbal cues is not possible in online or mobile surveys. By observing non-verbal indicators, which is particularly useful when discussing sensitive issues, there is the opportunity to evaluate the validity of the respondent's answers (Gordon 1975). Another advantage of this synchronous communication is that answers of the interviewee are more spontaneous and are given without an extended reflection. But due to this synchronous characteristic, the interviewer must concentrate much more on the questions to be asked and to the answers given in order to be able to reply (Opdenakker et al. 2006). Especially when an unstructured or semi structured interview list is used, and the interviewer has to formulate questions as a result of the interactive nature of the communication. Wengraf (2001) even speaks about "double attention", which is the priority of the interviewer that has to "*both listen to the informant's responses to understand what he or she is trying to get at and, at the same time, bear in mind his needs to ensure that all the questions are liable to get answered within the fixed time at the level of depth and detail needed*".

In addition, interview allows a more accurate screening. In fact, while the subjectivity of the answer of respondents is impossible to be completely eliminated, direct interviews enable the interviewer to control and keep the interviewee focused and on track to completion, avoiding as much as possible errors during all phases of the research in order to increase the credibility of the results (Brink 1989). Interviewer also ensures that the respondent is unable to receive assistance from others while formulating a response (Bailey 1987). Moreover, interviews have the potential to overcome the poor response rates of a questionnaire survey (Austin 1981, Cormack 1984, Treece & Treece 1986, Bailey 1987) and help in getting more precise information clarifying meaning of questions, ambiguities. Perhaps, face to face contact with a researcher can motivate respondents to participate in a survey research (Gordon 1975).

In conclusion, with interviews approach, each criticality of the survey could be solved and the real knowledge about the correlation between Lean Manufacturing and Industry 4.0 could be grasped. By forcing respondents to compare their level of implementation with the best-in class level, more reliable information could be gathered, and data could be compared.

In our case, the approach followed was the one of semi-structured interviews, because, according to Mann and Stewart (2000), this typology of interviews gives several benefits in comparison with surveys and structured interviews:

- First, semi-structured interviews are well suited for the exploration of the perceptions and opinions of respondents regarding complex and sensitive issues and enable the researchers to deeply inspect answers and ask for clarification (Barriball and White et al. 1993);
- Second, semi-structured interviews allow to design a flexible interview structure that preclude the use of a standardized interview schedule for varied

professional, educational and personal histories (Barriball and White et al. 1993);

- Third, semi-structured interviews achieve validity and reliability, not upon the repeated use of the same words in each question, but upon conveying equivalence of meaning (Denzin 1989) which helps to standardize the structure and facilitate comparability. Indeed, not every word has the same meaning to every respondent and not every respondent uses the same vocabulary (Treece and Treece 1986).

However, according to Cohen and Manion (1994), the greater flexibility and freedom of semi-structured interviews does not allow the researcher to dedicate less attention to the interview's structure design, which has to be carefully planned (as shown in section 4.2.3 *Interviews*).

4.2.3 Interviews

a. Interview Data Collection Process

Cross-case study research is the approach used to deeply inspect the relationship between Production Strategy and Lean 4.0. This technique allows the researcher to study the same phenomenon within the boundaries of another case and then another, as the theory begins to take shape between individual cases (Dooley, 2002). Indeed, closer interviews can overcome the poor response rates of a questionnaire survey (Austin 1981) and, in our case, help to investigate more deeply the relation between Industry 4.0 and Lean Manufacturing practices implementation in respondents' company.

According to Yin (1994), Eisenhardt (1989) et al., case study research has well-defined steps. The procedure of cross-case study, presented in "Case Study Research and Theory Building" by Dooley (1989), is divided in six main steps. The first four steps describe the data collection process and the last two steps stand for the analysis and the representation of the results:

1. **Determine and define the research questions**

   The starting point is the theory studied through a systematic literature review presented in chapter 2 *Literature Review*. The literature review can add validity and scientific worth to the project and helps to identify the research questions (i.e. how and why relationships are formed) (Dooley, 2002). Once understood the previous theory and found the gap, this study aims at mind it.

2. **Select the cases and determine data-gathering and analysis techniques**

   In this phase, the technique of interview was used in order to gather qualitative and quantitative information through a cross-case study. According to Dooley (2002), although multiple cases are selected, each case has to be treated individually, but the conclusion of each one has to be considered as a part of a multiple-case phenomenon. According to Blair and Presser (1989), to gather all the necessary information and properly conduct each interview, a great attention has been dedicated to their structure design as wider explained in section 4.2.3 *Interviews*.

3. **Prepare to collect data**

   To organize the interviews, a logical scheme was followed, proceeding through different steps. Among all the survey respondents, were individuated the companies which could be part of a second further analysis based on case studies: from a total of 105 plant's managers that answered to the survey, only 66 left their e-mail or phone number to be informed about the outcome of the analysis. These 66 respondents were re-contacted three times through e-mail, with the aim to fix a date for an interview. The first email was sent at the end of August 2019. The ones which no answer to the first mail were re-contacted a second time at the beginning of September 2019. In the middle of September 2019, a third solicit was sent. Each e-mail was sent specifying the aim of the interview, the modalities of data acquisition and the scope of the whole analysis. Indeed, brief comments by the researcher about his background, purpose and experiences may deeply involve the respondent and facilitate data collection (Gall et al., 1996).

   To people that answered to the e-mail was sent a calendar, through Doodle application, with a set of possible dates and hours at which the interview could take place. Moreover, to interviewees was asked to express a preference among the communication means (i.e. phone call or Skype video-call). People had the opportunity to propose a new date, if they were not available in the proposed ones. Among the 66 people contacted, 20 answered to the e-mail (i.e. 30% of response rate) and have made themselves available for the interview.

4. **Collect data in the field**

   Information is collected systematically, but, according to Dooley (2002), some changes could be made in order to make the research flexible. Indeed, although the interviewer prepares a predefined questions' structure, semi-structured interviews offer the possibility to explore issues that participants feel are important (Clifford et al., 2010). For these reasons, respondents were permitted to probe beyond the answers to the prepared questions.

   Each one of the 20 interviews was treated as a single-case study and lasted about one hour, with the aim of collecting as much more information to nurture the analysis. In table 11, are presented the descriptive information about the people interviewed. Further data (i.e. name of the respondent and company) were hidden. As can be understood from the table, Respondent N.20 does not work in any manufacturing company but he has founded a Lean consultancy company. Taking advantage of his role as Lean coach, his interview was useful to inspect more widely the Lean Manufacturing environment and the Italian panorama, but his data were not used in further statistical analysis.

Respondent	Company Industry	Production Strategy	Plant Employees	Plant Age	Respondent Role	Lean years	Industry 4.0 years
Respondent N.1	Alluminium lamination	MTO	30	Less than 9 years	Operations and supply chain value stream manager	From 2 to 3	Less than 1
Respondent N.2	Drive automation solutions	ATO	50	More than 20	Lean Specialist	Mmore than 10	From 2 to 3
Respondent N.3	Machinery	ETO	380	More than 20	Lean coordinator	Higher than 10	Less than 1
Respondent N.4	Packaging and Converting	MTO	470	More than 20	Head Of Operational Excellence (MASTER BLACK BELT)	From 6 to 10	From 2 to 3
Respondent N.5	Home appliances	MTS	700	More than 20	Manufacturing Quality Manager	Higher than 10	From 2 to 3
Respondent N.6	Cosmetics and Packaging	MTO	376	Less than 9 years	Production Manager	Higher than 10	From 2 to 3
Respondent N.7	Metallurgical Industry	MTS	300	More than 20	Project manager	Higher than 10	From 4 to 5
Respondent N.8	Oil and Gas	ETO	270	More than 20	Industrial Engineer	From 6 to 10	From 2 to 3
Respondent N.9	Aerospace machinery	MTO	50	More than 20	Quality Project Manager	Less than 1	Less than 1
Respondent N.10	Elevator and Escalator	MTO	200	From 10 to 20	CIOI (Engineering & Lean Manager)	From 6 to 10	From 4 to 5
Respondent N.11	telecommunication	ATO	600	More than 20	Operation Manager/Lean Program Manager	Higher than 10	From 4 to 5
Respondent N.12	Automotive (Tractors and bulldozers)	MTS	250	More than 20	CEO	From 2 to 3	From 4 to 5
Respondent N.13	motion and control technologies and systems	MTS	380	More than 20	Operations Manager	Higher than 10	Less than 1
Respondent N.14	Automotive Machinery	ATO	31	From 10 to 20	Operations & Purchasing Manager	From 6 to 10	From 2 to 3
Respondent N.15	Medicines and drugs	MTS	700	More than 20	Manufacturing Excellence Transformation Leader	Higher than 10	From 2 to 3
Respondent N.16	Home appliances	MTS	700	More than 20	Global Director Digital Industrial Operations	Higher than 10	From 2 to 3
Respondent N.17	Oil and Gas	ETO	375	More than 20	Manufacturing Manager	Higher than 10	Less than 1
Respondent N.18	Printing inks and pigments	MTS	350	More than 20	Business Improvement Europe and Latin America	Higher than 10	From 2 to 3
Respondent N.19	Heating systems	MTO	160	More than 20	Operation Manager	From 2 to 3	From 2 to 3
Respondent N.20	Operational Consultancy	-	-	-	Lean Coach	-	-

Table 11: Descriptive information of interviewees

5. **Evaluate and analyse the data**

   After having analysed each interview individually, a cross-case analysis was performed in order to develop the possible implications of such analysis. According to paragraph 5.4 *Preliminary Interview Analysis* and paragraph 5.5 *Interview Analysis*, data were analysed with both qualitative (i.e. Nvivo) and quantitative (i.e. SPSS Statistics and Minitab) tools. It is important to sort and analyse data in as many ways as possible in order to look for hidden meanings and seek unintended finding (Dooley, 2002).

6. **Prepare the report**

   A report was prepared in order to present the methodology adopted and the conclusions extrapolated.

b. Interview Structure

Interviews' structure follows the framework of the survey and, as the latter, consists of five sections: (i) Company's Profile; (ii) Contextual Factors; (iii) Production Strategy; (iv) Lean Bundles Implementation; (v) Industry 4.0 Bundles Implementation; (vi) Operational Performances.

Some questions were the same asked during the survey, but the interview was used as proof of them, and as an opportunity to ask more information about ambiguous data. In order to be able to compare in a more appropriate way the information captured, examples of Lean Manufacturing practices and Industry 4.0 tools implementation were inquired and, where it was possible, KPIs and objective results derived by those implementations were inspected.

The interview structure was designed in the following way:

i. **Company's Profile**

   The first section holds approximately the same questions of the survey and aims at acquiring information about the structure of the company and of the plant in which the respondent work, and his role inside the enterprise.

ii. **Contextual Factors**

   This second section aims at gathering information about contextual variables that could potentially influence Lean Manufacturing and Industry 4.0 adoption.

Contextual factors (i.e. age of the plant, plant size and industry sector) may also have an impact on company's Operational Performance.

iii. Production Strategy

This specific section is dedicated to inspecting company's Production Strategy in order to understand possible synergies between the latter and Lean 4.0. By evaluating company's variety and volume of production and its relationship with customers and suppliers, Production Strategy was investigated.

iv. Lean Bundles Implementation

This fourth section aims at widely inspecting the application of Lean Manufacturing bundles. In order to better understand how each tool was effectively applied, real examples of such implementations were asked to respondents. Examples enable to demonstrate the degree of Lean Manufacturing bundles' implementation, guaranteeing the reliability of data and ensuring that answers (which can assume values in a range from 0 to 5) can be compared one to another. In other words, this approach reduces the subjectivity of the answers. Indeed, the same value may have different meaning for different respondent.

As in the survey, the bundles investigated were the ones proposed by Shah and Ward 2003:

- Just in Time (JIT);
- Total Quality Management (TQM);
- Total Productive Maintenance (TPM);
- Human Resource Management (HRM).

v. Industry 4.0 Bundles Implementation

This fifth section aims at widely inquire the application of Industry 4.0 bundles. Due to the novelty of the argument and to the low diffusion of digital competence in the workforce, as shown in *figure 3*, a wider investigation through direct interview could provide more reliable results. In fact, it is emerged that an overlapping between digital technology and Industry 4.0 terminology is still present in Italian panorama (e.g. barcode reader is a digital technology but not belongs to Industry 4.0). Following the same approach used to validate Lean Manufacturing bundles' implementation, real examples of Industry 4.0 technologies applied were asked to interviewees.

Asking the respondents to provide real example of Industry 4.0 tools applied, the validity of answers given by respondents is proved.

The following list is the complete set of bundles asked:

- Advanced Analytics
- Internet of Things (IoT) and Cloud Computing;
- Autonomous Vehicles;
- Digital Manufacturing;
- Robotics;
- Virtual and Augmented Reality.

vi. Operational Performance

The last section, dedicated to Operational Performances, enables us to gather information about the changes in performances and about the level of each metric inspected (i.e. performances stay stable after the Lean 4.0 implementation and are equal to 93%).

In addition, discuss directly with people working in companies enable to verify that the delta performance was referred to Lean 4.0 implementation and not to Lean Manufacturing.

According to Shah and Ward 2003 the Operational Performances asked are the following:

- Finished products first-pass quality;
- Scrap and rework cost;
- Productivity, defined as volume per year;
- Per unit manufacturing cost excluding purchase material;
- Customer Lead Time;
- Manufacturing Cycle Time;
- Total inventories monetary value;
- Set-up time.

The detailed interviews’ structure design is presented in Annex B.

c. Interview Sample Characteristics

Following the same classification proposed in the survey-based dataset, companies are clustered, in table 12, according to the sector in which they operate.

Industrial sector	Count	Percentage
Machinery and metal products	9	47%
Automotive	2	11%
Electric and electronic equipment	3	16%
Chemicals and pharmaceuticals	2	11%
Miscellaneous manufacturing (i.e. Food and beverages, Apparel and other textile, Rubber and miscellaneous plastic)	3	16%
Total	19	100%

Table 12: Interview industry's characteristics

In table 13 is shown that almost 80% of the sample is represented by companies with a plant age equal to more than 20 years; while, only 10% of companies has less than 10 years. The interview-based dataset is distributed as the survey-based sample, since the proportions and characteristics are still the same. This guarantee the faithful of the interviews sample, even if it is smaller, to the survey sample.

Age of the plant	Count	Percentage
Less than 9 years	2	11%
From 10 to 20	2	11%
More than 20	15	79%
Total	19	100%

Table 13: Interview age of the plant's characteristics

The size of the companies, instead, is represented in table 14 through the "number of employees" metrics. Even though the sample is heterogeneous, using as a reference the study conducted by Furlan, Vinelli, and Dal Pont in 2011 in which authors demonstrate that firm age and size does not have a significant impact on Operational Performances, the dataset can be considered reliable in order to perform our analysis.

Number of employees	Count	Percentage
Less than 50	4	21%
From 51 to 250	4	21%
More than 250	11	58%
Total	19	100%

Table 14: Interview number of employees' characteristics

In the end, companies were classified according to their Production Strategy. In table 15, it is visible that each one of the different configurations are present in the sample. Most of them were MTS companies (37%) or MTO companies (31%), while few firms had ATO or ETO strategy (i.e. 16% each configuration).

Production Strategy	Count	Percentage
MTS	7	37%
ATO	3	16%
MTO	6	32%
ETO	3	16%
Total	19	100%

Table 15:Interview Production Strategy's characteristics

4.3 DATA ENCODING

In this paragraph the technique used to encode each variable (i.e. contextual factors, production strategy, Lean and Industry 4.0 bundles and Operational Performance) is presented. The encodings will be used in Chapter 5 *Analysis* in order to conduct statistical analysis.

A) **Contextual factors**

Although during interviews was possible to inspect the precise age of the plants, the exact years of Industry 4.0 and Lean implementation and the precise size, in the survey-based data collection this information were collected using a ordinal scale, that differs for each contextual factor. So, for each contextual factor inspected in the survey, a different approach was used to encode information.

i. Age of the plant

In the survey, three levels of maturity were used to inspect plant’s age:

- New: plants with less than 10 years
- Adolescent: plant between 10 and 20 years
- Old: plants with more than 20 years

To conduct the analysis, these three levels were encoded in the following two labels:

- Plants with less than 20 year
- Plants with 20 or more years

ii. Size of the plant

In the survey, the size of the plant was measured in terms of number of employees:

- Small sized: plants with less than 50 employees
- Medium sized: plants between 50 and 250 employees
- Large sized: plants with more than 250 employees

Even this scale was encoded in two different labels, according to the definition given by European Union in EU recommendation 2003/361:

- Plants with less than 250 employees (i.e. small-medium plant)
- Plants with 250 or more employees (i.e. large plant)

iii. Industry of the company

Since respondents were allowed to indicate their industry without choosing among proposed answers, a multitude of different descriptions of the same sector were given. Although the goodness of the analysis can be supported by a heterogeneous and complete manufacturing sector coverage, answers were clustered in the following five industries in order to structure the dataset:

- Machinery and metal products
- Electric and electronic equipment
- Automotive
- Chemicals and pharmaceuticals
- Miscellaneous manufacturing (i.e. Food and beverages, Apparel and other textile, Rubber and miscellaneous plastic)

iv. Years of Lean implementation

According to the survey, the number of years of Lean implementation can be classified in these groups:

- Less than 1 Lean years
- From 2 to 3 Lean years

- From 4 to 5 Lean years
- From 6 to 10 Lean years
- Higher than 10 Lean years

In accordance with Morodin et al. (2016), Lean Manufacturing implementation experience was classified into two categories:

- Up to 5 years
- More than 5 years

v. Years of Industry 4.0 implementation

According to the survey, Industry 4.0 implementation experience can be classified in these groups:

- Less than 1 digital years
- From 2 to 3 digital years
- From 4 to 5 digital years
- Higher than 5 digital years

Given that Industry 4.0 is a subject present since 2011, the threshold used to divide different implementation experiences is lower:

- Up to 3 years
- More than 3 years:

Thanks to this encoding, analysis on SPSS and Minitab could be performed.

B) <u>Production Strategy</u>

In order to mind the lack of information regarding Production Strategy in the survey-based database, we collected these data investigating companies' websites. This research provided us the information required, but in some cases, it was difficult to perfectly understand which strategy was followed by the company. By conducting interviews, instead, we were able to directly inspect company's Production Strategy. The interview sample covers all the possible configurations but Assemble-to-Order (ATO) and Engineer-to-Order (ETO) strategies characterize only a few number of plants (i.e. 3 plants out of 19 for each configuration).

Considering that drawing any conclusions on a so small cluster (i.e. ATO and ETO counts only 3 observations each one) could lead to misleading results, companies are rearranged according to these two variables:

- **Repetitive:** this label refers to MTS strategy (high volume-low variety) and represent the 37% of the sample;
- **Non-Repetitive:** this label refers to ATO-MTO-ETO strategy (low volume-high variety) and represent the 63% of the sample.

Indeed, mass production and series production are characterized by repetitive production steps (MTS strategy) while ATO, MTO and ETO manufacturing are characterized by different and mainly unique projects and non-repetitive production steps (Matt and Rauch et al. 2014).

C) <u>Lean and Industry 4.0 bundles</u>

Concerning Lean and Industry 4.0 bundles, respondents were required to self-evaluate their degree of implementation using a scale from 0 to 5 (where 0 represented not implemented, 3 represented partially implemented and 5 represented totally implemented) as is widely explained in section 4.2.1 *Survey* and 4.2.3 *Interviews*.

No additional actions were done to encode the information gathered, since the variables were already in the form of ordinal numbers: the scale from 0 to 5 was directly used to make the analysis of chapter 5 *Analysis*.

D) <u>Operational Performance</u>

As explained in section 4.1.4 *Operational Performances*, Interview-based and survey-based information about Operational Performance was collected following the group-scheme proposed by Shah & Ward (2003). A six-item scale was adopted to measure the operational performance of companies that apply Industry 4.0 tools to already implemented Lean Manufacturing practices:

- Operational performance decreased more than 40%
- Operational performance decreased from 21% to 40%
- Operational performance decreased from 1% to 20%

- Operational performance stable
- Operational performance increased from 1% to 20%
- Operational performance increased from 21% to 40%
- Operational performance increased more than 40%

In order to use the information gathered in this part, these operational performance ranges were encoded in discrete ordinal numbers. *Table 16* shows the encoding procudere for "direct metrics" (e.g. productivity), which means that the higher the performance's indicator is, the better it is. On th opposite, considering "inverse metrics" (e.g. manufacturing cycle time), which means that the lower the perdormance's indicator is, the better it is, the encoded numerical values were associated in an opposite direction (e.g. "operational performance decreased more than 40%" equal to +3).

Operational Performance Scale	**Encoding**
Operational performance decreased more than 40%	-3
Operational performance decreased from 21% to 40%	-2
Operational performance decreased from 1% to 20%	-1
Operational performance stable	0
Operational performance increased from 1% to 20%	+1
Operational performance increased from 21% to 40%	+2
Operational performance increased more than 40%	+3

Table 16: Operational Performances encoding

Thanks to this data encoding, analysis performed in chapter 5 *Analysis* were possible since the operational performance variable was translated from string to ordinal number.

4.4 INDEXES BUILDING

This section aims at clarifying the approach used to create Industry 4.0, Lean and Lean 4.0 indexes.

As said in section 4.1.2 *Industry 4.0 Bundles*, six Industry 4.0 bundles were identified:

- Advanced Analytics;
- Internet of Things (IoT) and Cloud Computing;
- Autonomous Vehicles;

- Digital Manufacturing;
- Robotics;
- Virtual and Augmented Reality.

According to the model developed by Soriano-Meier and Forrester (2002), Industry 4.0 commitment level can be computed as the average value of self-evaluation values of the implementation of several Lean practices. The same approach was adopted to calculate the Lean Manufacturing commitment level for each company, considering the Lean bundles identified in section 4.1.1 *Lean Bundles*:

- Just in Time (JIT)
- Total Quality Management (TQM)
- Total Productive Maintenance (TPM)
- Human Resource Management (HRM)

Summarizing, Lean Manufacturing and Industry 4.0 indexes were built using the formulas displayed in equation 1 and 2.

$$Lean\ Manufacturing\ index = \frac{\sum_1^N Lean\ bundle_i}{N}$$

Equation 1: Lean Manufacturing index building

$$Industry\ 4.0\ index = \frac{\sum_1^N Digital\ bundle_i}{N}$$

Equation 2: Industry 4.0 index building

In order to understand how to measure the Lean 4.0 level for each company the most relevant factors, influencing this response variable, were identified. As will be demonstrated in paragraph 5.3 *Contextual Factors Analysis*, in accordance with Portioli-Staudacher et al. 2019 and Furlan et al. 2011, the interrelation of Industry 4.0 and Lean Manufacturing may overcome the effects of some contextual factors (e.g. age of the plant, industry of the company, size of the plant, years of Lean implementation, years of Industry 4.0 implementation). For this reason, only the level of commitment of Lean and Industry 4.0 bundles impact on the latter. According to the model developed by Soriano-Meier and Forrester (2002), Lean 4.0 level can be computed as the average value between its underlying elements (i.e. Lean and Industry 4.0).

As a proof of the goodness of this approach, a factor analysis was conducted, keeping as relevant factor, as described in section 4.5.2 *Factor Analysis*, just the factor with a variance higher than 1. Two factors were extracted but, since the second factor's variance was lower than 1 (i.e. 0,4486), it was eliminated. The factor analysis rearranges the total variance according to the new factor extracted; the weight of the first factor is 1,5514 and represents 78% of the overall variability.

As shown in table 17 and 18, the relative weight of each variable, Lean and Industry 4.0, in the component in a factor analysis is identified by the factors score coefficients. The weight on Factor 1, which it will be called Lean 4.0, is 0,568 for both the variables. This indicates that the importance of the corresponding variables, Lean and Industry 4.0 in the component (i.e. Lean 4.0), is the same.

Variable	**Factor1**	**Communality**
Lean	0,881	0,776
Industry 4.0	0,881	0,776
Variance	1,5514	1,5514
%Var	0,776	0,776

Table 17: Lean and Industry 4.0 unrotated factor loadings and communalities

Variable	**Factor1**
Lean	0,568
Industry 4.0	0,568

Table 18: Lean and Industry 4.0 factor score coefficients

The relevance of the mean method used in the literature and the equivalence of the factors' weights, allowed to build the Lean 4.0 factor as presented in equation 3.

$$Lean4.0 = \frac{Lean + Digital}{2}$$

Equation 3: Lean 4.0 index building

Annex C provides an illustrative example of the Lean Manufacturing, Industry 4.0 and Lean 4.0 indexes building.

4.5 DATA ANALYSIS: Theory of the analysis

In this section, all the statistical methods used in the paper are presented, explaining in detail the hypothesis, the structure and the purpose of each analysis.

4.5.1 ANOVA: analysis of variance

ANOVA is a statistical test that aims at analyzing the results of the experiments, comparing more than two sample means of the same factor.

In this study, ANOVA is carried out to determine if the main effect of two factors and their interaction are significant on a response variable.

The response variable should be continuous. If the response variable is categorical, the model is less likely to meet the assumptions of the analysis, to accurately describe the data, or to make useful predictions. In order to perform such analysis, different hypothesis need to be verified:

i. **Interdependence of residuals**

   Each observation should be randomly selected and independent from all other observations. Random samples are used to make generalizations, or inferences, about a population. If data are not collected randomly, results might not represent the population. In addition, since dependent observations could provide not valid results, observation must be independent (i.e. an observation must provide no information about the value of another observation).

   In order to check this assumption, it is necessary to look at the residuals versus order plot. Independent residuals show no trends or patterns when displayed in time order. Patterns in the points may indicate that residuals which are closer each other may be correlated, and thus, not independent.

ii. **Normality of residuals**

   The method is based on a statistical test proofing whether any of the population means are different.

   As showed below, the null hypothesis is that all the population means are the same, while the alternate hypothesis is that at least one of them is different.

$$H_0: \mu_1 = \mu_2 = \cdots = \mu_a$$

$$H_a: At\ least\ one\ \mu_k\ is\ different,\ \text{with}\ k = 1,2,..,a$$

ANOVA analyses three sources of variability:

- Total variability which is the total variability among all observations (equation 4).

$$SS_{TOT} = \sum_{i=1}^{a}\sum_{j=1}^{b}(Y_{ij} - \overline{\overline{Y}})^2$$

Equation 4: Sum of squares total

- Factor variability which is the variation between group means. In other words, it is calculated as the difference between observed treatment means and the grand mean (equation 5).

$$SS_{factor} = b\sum_{i=1}^{a}(\overline{Y_i} - \overline{\overline{Y}})^2$$

Equation 5 Sum of squares of factors

- Error variability which is a random variation within each group (noise, or statistical error). In other words, it is calculated as the difference of observations within a treatment from the treatment mean (equation 6).

$$SS_{error} = \sum_{i=1}^{a}\sum_{j=1}^{b}(Y_{ij} - \overline{Y_i})^2 = SS_{TOT} - SS_{factor}$$

Equation 6: Sum of squares of errors

There are two ways to estimate the variance of each population:

- A first method is based on the error variability (equation 7).

$$\sigma^2_{estimated} = \sum_{i=1}^{a}\frac{\sum_{j=1}^{n}(Y_{ij} - \overline{Y_i})^2}{n-1} \times \frac{1}{a} = \frac{SS_{error}}{a(n-1)} = MS_{error}$$

Equation 7: MS error variance estimation

- A second method based on factor variability (equation 8).

$$\sigma^2_{estimated} = \frac{n\sum_{i=1}^{a}(\overline{Y_i} - \overline{\overline{Y}})^2}{a-1} = \frac{SS_{factor}}{a-1} = MS_{factor}$$

Equation 8:MS factor variance estimation

Where:

a: $number\ of\ factor\ levels$

n: $number\ of\ observation$

i: $1,2,\dots,a$

j: $1,2,\dots,n$

If the null hypothesis is true the ratio between MS_{factor} and MS_{error} is almost 1, and so the two variances estimated are equal. If the null hypothesis is true, so, all observations are taken from a normal distribution (i.e. $Y_i \sim N(\mu, \sigma^2)$). The test performed in the analysis to check the hypothesis is the Kolmogorov-Smirnov (KS) test:

$$H_0: E(\varepsilon_i|x_i) = 0, var(\varepsilon_i|x_i) = \sigma^2$$

$$H_1: E(\varepsilon_i|x_i) \neq 0, var(\varepsilon_i|x_i) \neq \sigma^2$$

iii. <u>Test of equal variances</u>

The test for equal variances is used to determine whether the variances or the standard deviations of two or more groups differ, considering at least one categorical factor and a continuous response. To estimate the standard deviation of each population based on the categorical factors, the Bonferroni confidence intervals is used. A confidence level of 95% for the simultaneous confidence intervals is considered reliable. The simultaneous confidence level is the percentage of times that the entire set of confidence intervals contains the true standard deviations for all group comparisons, if the study is repeated multiple times.

With 95% Bonferroni confidence intervals, we can be 95% confident that the entire set of confidence intervals includes the true population standard deviations for all groups.

The hypothesis used for a test for equal variances are as follows:

$$\mathrm{H_0}: The\ population\ standard\ deviations\ are\ all\ equal$$

$$\mathrm{H_A}: Not\ all\ population\ standard\ deviations\ are\ equal$$

The calculation method, used to verify these hypotheses, is the Levene's test, which is a modification of Levene's procedure (Levene, 1960) that was developed by Brown and Forsythe (1974). The method used on Minitab, in fact, considers the distances of the observations from their sample median rather than their sample mean (equation 9). Using as a reference the sample median rather than from the sample mean makes the test more robust for smaller samples and makes the procedure asymptotically distribution-free. If the p-value is smaller than α-level (i.e. 0,05), the null hypothesis, that the variances are equal, is rejected.

$$S_i{}^2 = \sum_{j=1}^{n_i} \frac{(x_{ij} - \overline{x})^2}{(n_i - 1)}$$

Equation 9: Levene's test

Where:

$$i: 1,2, \dots, k$$

$$j: 1,2, \dots, n_i$$

Once verified all the hypothesis, an Analysis of Variance can be carried out to determine if the main effect of a factor is significant, examining whether different levels of factors and their interaction impact a response variable.

The hypothesis we want to test with this analysis are the following:

$$\mathrm{H_0}: Factor\ does\ not\ have\ a\ significant\ impact\ on\ response\ variable$$

$$\mathrm{H_A}: Factor\ has\ a\ significant\ impact\ on\ response\ variable$$

Assuming that all the assumption previously described are true, the ANOVA tests are based on Fisher distribution (equation 10):

$$F_0 = \frac{MS_{factor}}{MS_{error}} \approx F(a-1, a(b-1))$$

Equation 10: Fisher distribution

Where:

$$MS = \frac{SS}{DoF}$$

$$DoF_{total} = N - 1$$

$$DoF_{error} = (n_{r1} - 1) + (n_{r2} - 1) + \cdots + (n_{rN} - 1)$$

$$DoF_{factor} = DoF_{total} - DoF_{error}$$

$$r: number\ of\ runs\ with\ r = 1,2, \ldots N$$

$$n_r: number\ of\ replications\ per\ run$$

To understand the relationship between the F distribution and the p-value used to accept or reject the null hypothesis, it is presented a graph (*figure 11*) that shows on the x-axis the F values and on the y-axis the probability of F (i.e. P(F)).

Figure 11: Relationship between Fisher distribution and p-value

According to the *figure 11*, to determine whether the association between the response and each term in the model is statistically significant, the p-value for the term need to be lower than the significance alpha level (i.e. 0,05) (equation 11).

$$\mathrm{F}_0 < \mathrm{F}_\propto(a - 1, a(b - 1))$$

Equation 11: null hypothesis of ANOVA

A significance level of 0.05 indicates a 5% risk of concluding that an association exists when there is no actual association.

Once the model is created is fundamental to determine how well the model fits the data. The model should provide a good fit to the data, because if the model does not fit the data, the results can be misleading.

The main metrics used to understand the goodness of the model (equation 12) is the coefficient of determination (i.e. R^2), which represents the percentage of variation in the response explained by the model. It is calculated as 1 minus the ratio between the error sum of squares (which is the variation that is not explained by model) and the total sum of squares (which is the total variation in the model).

$$R^2 = 1 - \frac{SS_{error}}{SS_{total}} = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \overline{y})^2}$$

Equation 12: Coefficient of determination

The higher the R^2 value, the better the model fits your data. A criticality is that R^2 always increases when additional predictors are added to a model, so can happen that a model seems good due to the huge number of factors introduces. In order to overcome this problem, it is better to use the $R - sq\ (adj)$. Adjusted R^2 (equation 13) is the percentage of the variation in the response that is explained by the model, adjusted for the number of predictors in the model relative to the number of observations. The adjusted R^2 value incorporates the number of predictors in the model to help you to choose the correct model. Adjusted R^2 is calculated as 1 minus the ratio of the mean square error (MSE) to the mean square total (MS_{total}).

$$R^2_{adj} = 1 - \frac{MS_{error}}{MS_{total}} = 1 - \left[\frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \overline{y})^2}\right]\left(\frac{n-1}{n-p-1}\right)$$

Equation 13: Adjusted coefficient of determination

Where:

$$y_i = i^{th} observed\ response\ value$$

$$\hat{y}_i = i^{th}\ fitted\ response$$

$$\overline{y} = mean\ response$$

$$n = number\ of\ observations$$

$$p = number\ of\ terms\ in\ the\ model$$

The last measure showed by Minitab is R-sq (pred), which is the ability to determine how well your model predicts the response for new observations. In fact, even if R^2 is 100%, the model does not necessarily predict new observations well. Models that have larger predicted R^2 values have better predictive ability. A predicted R^2 that is substantially less than R^2 may indicate that the model is over-fitted. An over-fit model occurs when you add terms for effects that are not important in the population. The model becomes tailored to the sample data and, therefore, may not be useful for making predictions about the population.

4.5.2 Factor Analysis

The Factor analysis is applied with the aim of grouping the sample-variables in order to keep together those that are more similar and/or are used together.

The study wants to discover the pattern of intercorrelations among variables evaluating the correlations between them.

Factor analysis is used to describe variability among observed, correlated variables in terms of a potentially lower number of unobserved variables called factors, which are not directly measured or observed, but which may be easier to interpret.

The analysis searches for such joint variations in response to unobserved-latent variables. The observed variables are modelled as linear combination of the potential factors, plus “error" terms.

There are several methods of extraction of data and the one selected in this analysis is the Principal Components. This option is used if it is not known the number of factors to extract, and if it is not possible to assume that the factors and errors obtained after fitting the factor model follow a normal distribution.

In the Principal Components’ extraction method, the $\mathrm{j^{th}}$ loadings are the scaled coefficients of the $\mathrm{j^{th}}$ principal components. The factors are related to the first m components. In the unrotated solution, we can interpret the factors as you would interpret the components in Principal Components analysis. However, after rotation, we can no longer interpret the factors as principal components.

In this study, since variables are two and the factor to be extracted is only one, a rotation can not be applied: the unrotated solution is adopted.

The principal component factor analysis of the sample correlation matrix R is specified in terms of its eigenvalue-eigenvector pairs $(\lambda_i, e_i), i = 1, \ldots, p$ and $\lambda_1 \leq \lambda_2 \leq \ldots \leq \lambda_p$. Let $m < p$ be the number of common factors.

Minitab, through this method calculate the unrotated factor loadings which indicate how much a factor explains a variable, since it is the projection of each variable on the new factor. Examining the loading pattern, it is possible to determine which factor has the most influence on each variable. Factor loading can range from -1 to 1. Loadings close to -1 or 1 indicate that the factor strongly influences the variable, while loadings close to 0 indicate that the factor has a weak influence on the variable.

The matrix of estimated factor loadings (*equation 14*), L, is a $p \times m$ matrix whose i^{th} column is $i = 1, \ldots, m$.

$$L = \left[\sqrt{\hat{\lambda}_1 \hat{e}_1} \sqrt{\hat{\lambda}_2 \hat{e}_2} \ldots \sqrt{\hat{\lambda}_m \hat{e}_m} \right]$$

Equation 14: Estimated factor loading matrix

To determine the number of factors to be extracted using the Principal Components method, the variance equals the eigenvalue.

The higher the variance, the more the factor explains the variability in the data. According to the Kaiser criterion, only factors with eigenvalues that are greater than 1, which means at least equal to the contribution of the original variable, are retained in the analysis as relevant factors.

The proportion of variance explained by j^{th} factor is computed in *equation 15*.

$$\frac{\hat{L}_{1j}^2 + \hat{L}_{2j}^2 + \cdots + \hat{L}_{pj}^2}{tr(R)} = \frac{\lambda_j}{tr(R)}$$

Equation 15: Proportion of variance explained by j-th factor

To determine, instead, how well those factors explain each variable, the communality is a reliable metric.

Examining its values, it is possible to assess how well each variable is explained by the factors, calculating the percentage of the variance explained by each variable within the m factors (*equation 16*). The closer the communality is to 1, the better the variable is explained by the factors.

$$h_i^2 = L_{i1}^2 + L_{i2}^2 + \cdots + L_{im}^2$$

Equation 16: Communality

Where:

$i = 1,2, \ldots , p$

$L: matrix\ of\ factor\ loadings$

$\lambda_j: j^{th} eingenvalue$

$tr(R): trace\ of\ correlation\ matrix$

$(\hat{\lambda}_i \hat{e}_i): eigenvalue - eigenvector\ pairs$

Finally, the relative weight of each variable in the component in a factor analysis is identified by the factors' score coefficients. The larger the absolute value of the coefficient, the more important the corresponding variable is in calculating the component.

4.5.3 Chi-Squared

The chi-squared test is an analysis which is performed when data are categorized by one or more categorical variables. The analysis aims at investigating the relationship between such variables.

A cross tabulation displays the joint frequency of data values, determining the counts or percentages for combinations of categories across two or more categorical variables.

The joint frequency data can be then analysed with the chi-squared statistic to evaluate whether the variables are associated or independent.

In order to ensure that the results are valid, during the collection of data, the following guidelines have to be considered:

- The sample should be selected randomly: random samples are used to make generalizations, or inferences, about a population. If the sample is not randomly selected, the results may not be valid.
- Each observation should be independent from all other observations: independence of the observations is a critical assumption for the chi-squared test of association.

- All the data must be categorized into mutually exclusive row and column categories: The chi-squared test of association cannot be performed when categories of the variables are overlapped. Thus, each observation must be categorized into one and only one category.
- The expected counts must not be too small: each sample should be large enough so that there is a reasonable chance of observing outcomes in every category. If the expected counts are too low, the p-value for the test may not be accurate.

The chi-squared test can be used to determine whether or not the variables are associated considering the following hypotheses:

$$\mathrm{H}_0\colon Variables\ are\ indipendent;\ no\ association\ between\ variables\ exists$$

$$\mathrm{H}_1\colon Variables\ are\ not\ indipendent;\ an\ association\ between\ variables\ exists$$

In order to determine whether to reject or accept the null hypothesis, which states that the variables are independent, the p-value can be used. If the p-value is less than or equal to the significance level, the null hypothesis is rejected, and it is possible to conclude that there is a statistically significant association between the variables. On the other side, if the p-value is larger than the significance level, there is not enough evidence to conclude that the variables are associated.

The p-values are calculated according to the two tests performed by Minitab:

- **Pearson Chi-squared test**: the Pearson chi-squared statistic (χ^2) involves the squared difference between the observed and the expected frequencies (*equation 17*).

$$X^2 = \sum_{i=1}^{r}\sum_{j=1}^{c}\frac{\left(O_{ij} - E_{ij}\right)^2}{E_{ij}}$$

Equation 17: Pearson chi-squared test

- **Likelihood-ratio Chi-squared test**: the likelihood-ratio chi-squared statistic (G^2) is based on the ratio of the observed to the expected frequencies (*equation 18*).

$$G^2 = 2\sum_{i=1}^{r}\sum_{j=1}^{c} O_{ij}\ln\left(\frac{O_{ij}}{E_{ij}}\right)$$

Equation 18: Likelihood-ratio chi-squared test

In addition, even the adjusted residuals for each cell are displayed. Adjusted residuals are the raw residuals divided by an estimate of the standard error. The adjusted residual values are the differences between the observed and expected frequencies for a group and are used to indicate the significance level of each relationship (*equation 19*). Positive values of adjusted residuals mean that observed values are larger than the expected ones, while negative ones mean that observed values are fewer than the expected ones.

$$Adjusted\ Residual = \frac{O_{ij} - E_{ij}}{\sqrt{\left[N_i \times N_j \times \frac{(1 - N_i N^{-1})}{N} \times \left(1 - \frac{N_j}{N}\right)\right]}}$$

Equation 19: Adjusted Residual

Where:

$O_{ij}: observed\ frequency\ in\ cell\ (i, j)$

$E_{ij}: expected\ frequency\ in\ cell\ (i, j)$

$N_i: number\ of\ observations\ in\ the\ i^{th} row$

$N_j: number\ of\ observations\ in\ the\ j^{th} column$

$N: total\ number\ of\ observations$

$$E_{ij} = \frac{N_i N_j}{N}$$

4.5.4 Correlation

The correlation analysis is used to measure the strength and direction of the association between two variables. The most common method is the Pearson correlation method (also known as r) which measures the linear relationship between two continuous variables (e.g. x_j and x_k).

The correlation coefficient can range in value from −1 to +1. The larger the absolute value of the coefficient, the stronger the relationship between the variables. The sign of the coefficient, instead, indicates the direction of the relationship. If both variables tend to increase or decrease together, the coefficient is positive, while if one variable tends to increase as the other decreases, the coefficient is negative. A low Pearson correlation coefficient does not mean that no relationship exists between the variables. The variables may have a non-linear relationship.

The Pearson Coefficient is defined as the ration between the covariance v_{jk} of the two attributes and the product of the two sample standard deviations $\overline{\sigma}_j$ and $\overline{\sigma}_k$ (*equation 20*).

$$r_{jk} = corr(x_j, x_k) = \frac{v_{jk}}{\overline{\sigma}_j \overline{\sigma}_k}$$

Equation 20: Pearson coefficient

The strength of the correlation can be labelled in three categories according to the following scheme:

- if $0 < |r_{jk}| < 0{,}4$ there is a weak correlation;
- if $0{,}4 < |r_{jk}| < 0{,}7$ there is a moderate correlation;
- if $0{,}7 < |r_{jk}| < 1$ there is a strong correlation.

4.5.5 Bayesian Network

The interview analysis uses the Bayesian inference approach to systematically study encoded data from firms assessing the causal relationship between Lean4.0 and operations strategy on weighted performance.

The Bayesian Network (BN) is a compact representation of joint probability distribution over variables of interest and popularly used for reasoning and decision making under uncertainty (McNaught and Chan, 2011), which makes it an interesting and efficient approach for this study.

The use of the Bayesian approach provides the benefit of making a synergy/trade-off analysis with a relatively small sample size, handling uncertainties well (Birkie, 2016).

The required sample size for obtaining significant results would have been much larger if a regression-based approach had been used, as in Furlan et al. 2011.

Each node in the BN (*figure 12*) represents random variables, and an arch between two nodes shows a stochastic dependency among them.

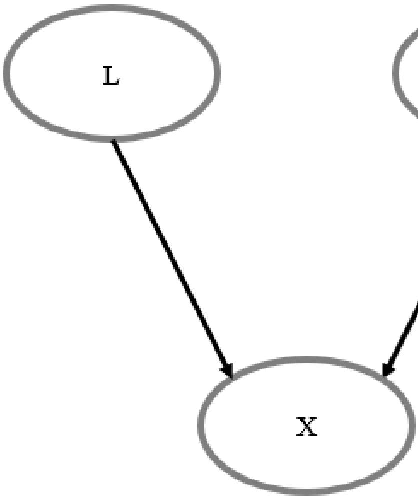


Figure 12: Bayesian Network

If there is a directed edge in the network (*figure 12)* from node L to node X, L is said to be a parent of X; likewise, X is called a child of L. Each variable, represented by a node, is understood to be conditionally independent of the set of all its predecessors in the network (*figure 12),* given the values of its parents. In other words, the absence of a directly connecting arrow between any two nodes implies that these two variables are independent given the values of any intermediate nodes.

In particular, in this study, Lean 4.0 and Production Strategy represent independent variables (i.e. parent nodes), while Operational Performances a dependent one (i.e. child node).

Variables in a BN can take continuous values, nevertheless they are often discretized so that they take fewer mutually exclusive states. In most of the cases, the variables will have binary forms (e.g. 0,1)

In addition, the BN method requires to determine a set of conditional probabilities distribution taking into account the available (prior) information.

This way the Bayesian approach enables the causal relationship between the variables of interest based on probability values estimated using the adopted encoding mechanism to be represented.

In addition, the method has a sequential use: when more data become available, is possible to calculate the posterior distribution of the parent nodes; subsequently, the posterior data becomes the next prior.

According to Badurdeen et al., 2014, in fact, posterior probabilities of parent nodes can be estimated as if they occurred with hard evidence by considering evidence on the occurrence of the child node.

The Bayesian approach, in order to inspect independency between variables and to captures the joint influence of two variables on a common successor at a particular value (i.e. product synergy), has to graphically design a diagram showing the nodes and edges considered in the study.

Considering three variables (L,R,X) of which two independent (L,R) and one dependent (X), the Bayesian inference synergy models interaction among them could be inquired.

The sign of the inter-causal influence (of L and R on X) is captured by the product synergy (Y^{δ}) associated with the variables.

If two or more causes or predictors interact with positive product synergy, their joint occurrence is a more likely explanation than either one alone. L negative product synergy of and R on X is observed when, given X, a high value of L makes a high value of R less likely; negative product synergy is a popularly known pattern of "explaining away" (Wellman and Henrion, 1993).

The mathematical theorem on the indirect evidence (*equation 21*), presented by Wellman and Henrion in 1993, says:

"Let L and R be predecessors of X, and let z denote an assignment to X other predecessors, if any. Variables L and R exhibit negative product synergy with respect to a particular value x_0 of X, written as Y^- ({L,R}, X), if, for all $l > \bar{l}$, $r > \bar{r}$:"

$$P\,(x_0 \mid lrz) \times P\,(\,x_0 \mid \bar{l}\bar{r}z\,) \leq P\,(x_0 \mid \bar{l}rz) \times P\,(x_0 \mid l\bar{r}z)$$

Equation 21: product synergy theorem

In the scheme used in this study, L and R are assumed as the only predecessor of X, so the *equation 21* can be written as *equation 22.*

$$P\,(x_0 \mid lr) \times P\,(\,x_0 \mid \bar{l}\bar{r}\,) \leq P\,(x_0 \mid \bar{l}r) \times P\,(x_0 \mid l\bar{r})$$

Equation 22: product synergy theorem with one predecessor

Positive product synergy, Y^+ , and zero product synergy, Y^0, are defined by substituting ≥ and =, respectively, for ≤ in *equation 22*. The indirect evidence theorem is also valid with either "+" or "0" in substitution of "-" in the intercausal product synergy Y^-. The negative product synergy represents a trade-off, while the positive product synergy is related to the concept of complementarity in operations management. If the product synergy, instead, is strictly zero, then the two variables are standalone without leveraging synergy or exhibiting

trade-off. Nevertheless, those relations are not exhaustive. The condition $Y^?$ indicates that the product synergy is ambiguous or that it is not known which, if any, of the relations hold (Wellman, Henriony et al. 1994).

5. ANALYSIS

In this chapter, the analyses conducted to inspect each research question are presented. In particular, in paragraph 5.1 and 5.2, survey-based analysis is disclosed in order to answer to RQ1 and RQ2. Furthermore, paragraph 5.3 aims at studying the influence of contextual factors on Lean 4.0 (i.e. RQ3). Finally, in the last two paragraphs (i.e. paragraph 5.4 and 5.5), it is studied the presence of synergies or trade-offs between Production Strategy and Lean 4.0 in increasing Operational Performances according to the interview-based dataset (i.e. RQ4).

5.1 PRELIMINARY SURVEY ANALYSIS

This section aims at providing a preliminary descriptive and qualitative analysis of the survey-based dataset. The following representations, in fact, are not used as a theory-building methodology, but aims at displaying the sample in a more relevant way.

Firstly, by plotting companies according to the answers given by respondents in the questionnaire, we can analyse which are the most affected performances by the adoption of Lean and Industry 4.0 bundles.

Table 19 and *table 20* show the percentage of companies that increase or decrease their performances according to the scale used to evaluate the changes in each metric analysed. As stated in *section 4.1.4 Operational Performance*, Operational Performances' information was gathered following the group-scheme proposed by Shah and Ward 2003.

	Finished products first-pass quality	**Scrap and rework cost**	**Productivity, defined as volume per year**	**Per unit manufacturing cost excluding purchase material**
Decreased more than 40%	0%	0%	0%	0%
Decreased 20 - 40%	0%	6%	0%	1%
Decreased 1 - 20%	3%	39%	4%	31%
Stayed the same	32%	39%	30%	40%
Increased 1 - 20%	34%	14%	47%	26%
Increased 21 - 40%	10%	2%	18%	2%
Increased more than 40%	20%	0%	2%	0%

Table 19: Operational Performances change (A)

	Total inventories monetary value	Manufacturing Cycle Time	Set - up time	Customer Lead Time
Decreased more than 40%	0%	0%	2%	0%
Decreased 20 - 40%	3%	5%	7%	7%
Decreased 1 - 20%	29%	61%	51%	39%
Stayed the same	47%	34%	40%	41%
Increased 1 - 20%	21%	0%	0%	13%
Increased 21 - 40%	1%	0%	0%	0%
Increased more than 40%	0%	0%	0%	0%

Table 20: Operational Performances change (B)

These tables provide an overview of Lean 4.0's effect on the whole dashboard of metrics inspected, while the impact on each performance is presented in Annex D.

In addition, according to *paragraph 4.3 Data Encoding*, in order to use the information gathered, these Operational Performances' ranges were encoded in discrete ordinal numbers, as presented in *table 21*.

Operational Performance Scale	Encoding
Operational performance decreased more than 40%	-3
Operational performance decreased from 21% to 40%	-2
Operational performance decreased from 1% to 20%	-1
Operational performance stable	0
Operational performance increased from 1% to 20%	+1
Operational performance increased from 21% to 40%	+2
Operational performance increased more than 40%	+3

Table 21: Operational Performances encoding recall

In accordance with the tables presented above, a weighted average was computed with the aim of understanding whether the combined effect of Lean Manufacturing and Industry 4.0 have different effect on specific performances.

By multiplying the percentage of companies belonging to a particular Operational Performances' range by its associated numerical value, the weighted average of each performance emerged according to *equation 23*.

$$Y_i = \sum_j w_{ij} \times v_j$$

Equation 23: Operational Performance weighted average

Where:

$$w_{ij} = percentage\ of\ companies\ in\ j^{th} cluster\ for\ i^{th} performance$$

$$v_j = \ encoded\ value\ for\ j^{th} cluster$$

Summarizing the results, *table 22* present the total value of each Operational Performance Y_i computed according to *equation 23*.

Performance i^{th}	**Total performances value Y_i**
Finished products first-pass quality	1.12
Scrap and rework cost	0.32
Productivity, defined as volume per year	0.85
Per unit manufacturing cost excluding purchase material	0.04
Total inventories monetary value	0.11
Manufacturing Cycle Time	0.70
Set - up time	0.70
Customer Lead Time	0.39

Table 22: Operational Performances values

From *table 22*, it is evident that the major metric affected in a positive way by Lean 4.0 implementation is "finished products first-pass quality", hence the percentage of parts that pass the quality control the first time (i.e. $Y_i = 1.12$). Secondly, other measures which are deeply affected by Lean 4.0 are "productivity", "manufacturing cycle time" and "set-up time". On the contrary, "per unit manufacturing cost" seems to be not influenced by Lean 4.0 implementation (i.e. $Y_i = 1.12$).

A further qualitative analysis performed on the survey-based dataset, aims at inspecting the Industry 4.0 bundles mostly implemented by Italian manufacturing companies at a different degree of Lean Manufacturing implementation (i.e. low and high level). In particular, in *figure 13*, the dimension of the bubbles represents the percentage of companies which have a specific Industry 4.0 bundle's level compared to the total of firms in the survey which have a low Lean Manufacturing's implementation level (i.e. adoption degree inferior to the average). It is clear that the majority of the companies have not adopted any Industry 4.0 technology, and that very few plants have a level higher than 3 in a single bundle (i.e. 3 plants have a level equal to 4 in Robotics bundle, 1 plant has a level equal to 4 in Digital Manufacturing bundle and 4 plants have a level equal to 4 or 5 in Autonomous Vehicles bundle). The mostly implemented bundle is, without no doubt, Advanced Analytics, since only 26% of respondents declare to not implement at all such technology. On the opposite, the bundles which are less adopted are Autonomous Vehicles and Digital Manufacturing, since respectively 81% and 72% of companies declared to have not implemented any technologies related to these applications.

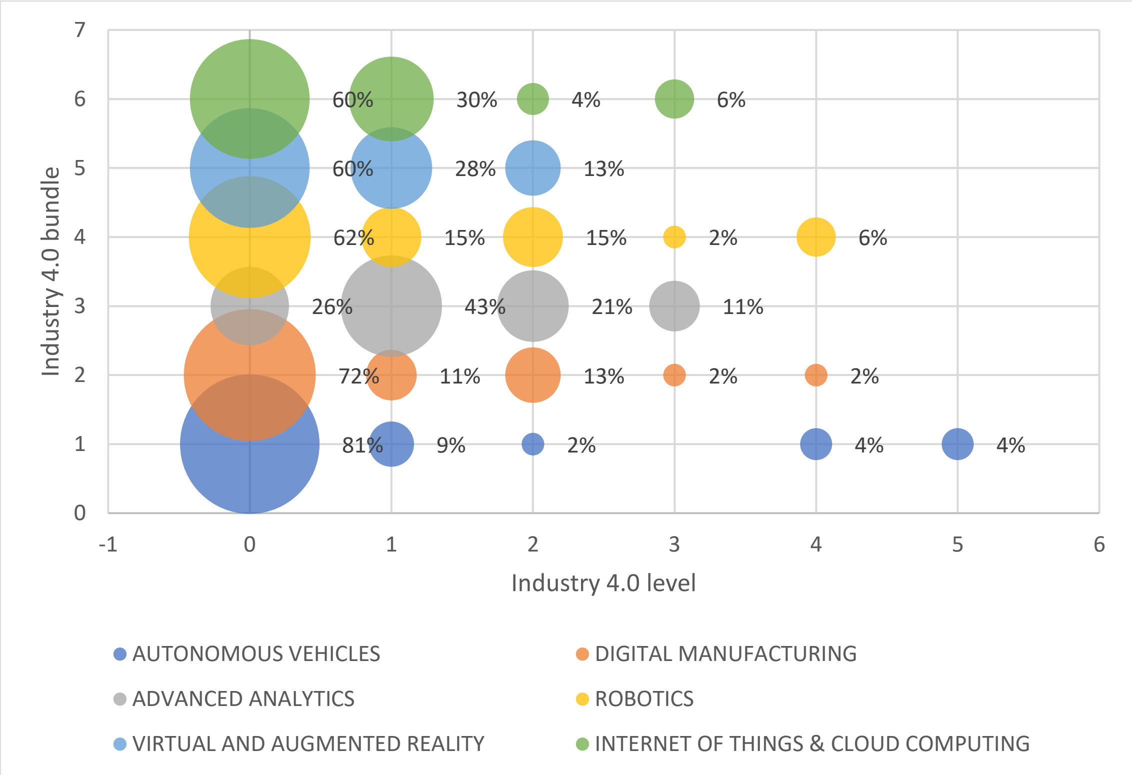


Figure 13: Industry 4.0 bundles implementation in low Lean Manufacturing implementation level environments

The same analysis was performed considering companies with a high degree of Lean Manufacturing adoption (i.e. implementation level superior to the average). In *figure 14*, it is evident that the distribution of Industry 4.0 technologies' adoption covers all the implementation level range in a wider way. With the increase of Lean Manufacturing level, Advance Analytics still remain the most implemented Industry 4.0 bundle (i.e. only 9% of plants have not adopted at all any technology associated to it) and the percentage of companies which implement it with a good degree level (i.e. 3) is pretty high (i.e. 28%). The bundles which mostly suffer of a smaller diffusion are Autonomous Vehicles, Virtual and Augmented Reality and Digital Manufacturing since respectively 48%, 40% and 45% of respondents declare to not implement such technologies. However, the latter, when it is adopted, is used in a pervasive way since in 34% of the cases Digital Manufacturing reaches a level equal to 4 or 5.

Figure 14: Industry 4.0 bundles implementation in high Lean Manufacturing Implementation level environments

These preliminary analyses open the road to conduct on the survey-based dataset more statistically robust analysis, which are discussed in the next section (*paragraph 5.2 Survey Analysis*).

5.2 SURVEY ANALYSIS

The literature review evidences a positive synergy between Lean Manufacturing and Industry 4.0 on Operational Performances since both impact on the improvement of the overall systems' flexibility and efficiency, reducing their complexity and making the company able to react to the current changes.

However, literature disagrees about the integration between Lean Manufacturing and Industry 4.0.

As stated in the *section 1 Introduction*, Buer et al. 2018 identified three different perspectives about the interrelation between Lean Manufacturing and Industry 4.0:

- Industry 4.0 supports Lean Manufacturing;

- Lean Manufacturing supports Industry 4.0;
- Combined Industry 4.0 and Lean Manufacturing integration enhance Lean 4.0 performances.

The data collected through the survey are presented in a scatter plot (*figure 15*) which represent the relationship between Lean Manufacturing and Industry 4.0 level.

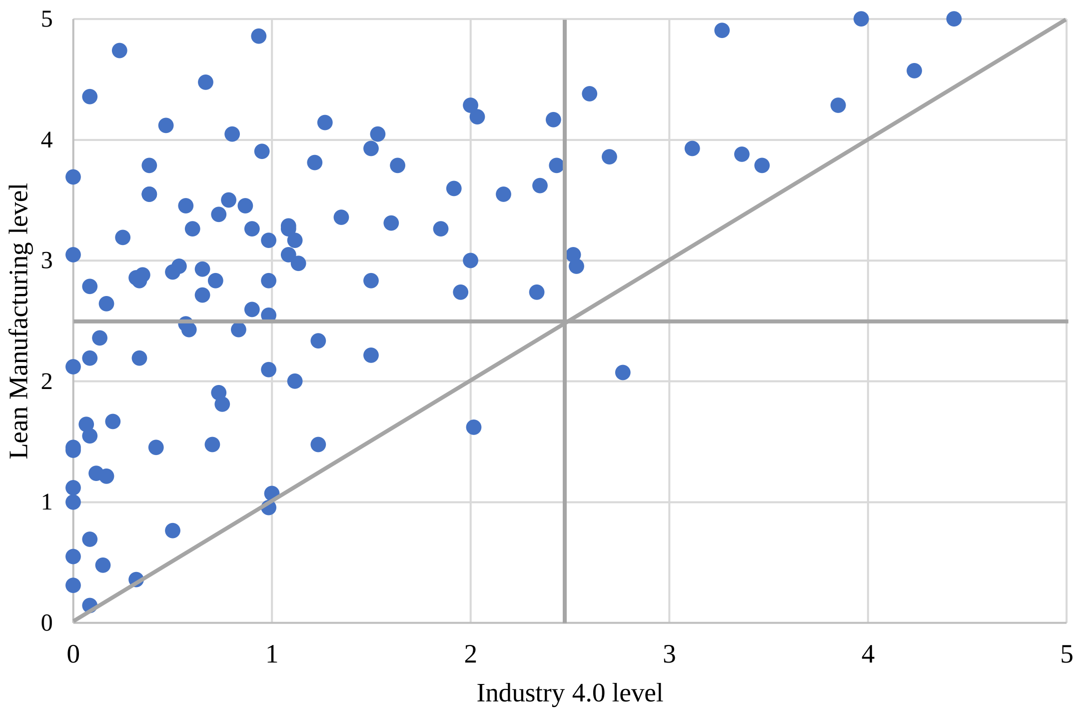


Figure 15: Industry 4.0 vs Lean Manufacturing scatter plot

The graph (*figure 15*), for a better understanding, was divided into four quadrants using the average value of the scale as cut-off (i.e. 2,5 is the average value in 0-5 scale) and was diagonally divided along the bisector.

From *figure 15*, two main considerations could be made:

- Only one observation belongs to the fourth quadrant (i.e. Industry 4.0 level higher than 2,5 and Lean Manufacturing level lower than 2,5).
- Only three observation are below the bisector, which means that the observation has a higher value of Industry 4.0 implementation than Lean Manufacturing implementation

The scatter plot suggests that Lean Manufacturing is an enabler for the digitalization (RQ1), as Huber (2016), Künzel (2016), Ketteler and König (2017) sustained, since processes, to enhance their performances, should be already standardized in order to be positively automated. In other words, when processes are not robustly designed and continuous improvement practices are not established, the introduction of Industry 4.0 may digitalize wastes and non-value adding processes (Portioli-Staudacher et al. 2019). These results, according to Tortorella and Fettermann 2018 and Buer et al. 2018 findings, reinforce that Lean Manufacturing' implementation may serve as a solid foundation on which Industry 4.0 technologies can consistently grow.

In addition, the box plot analysis was conducted (*figure 16*) to better understand how data related to Lean Manufacturing and Industry 4.0 level are distributed.

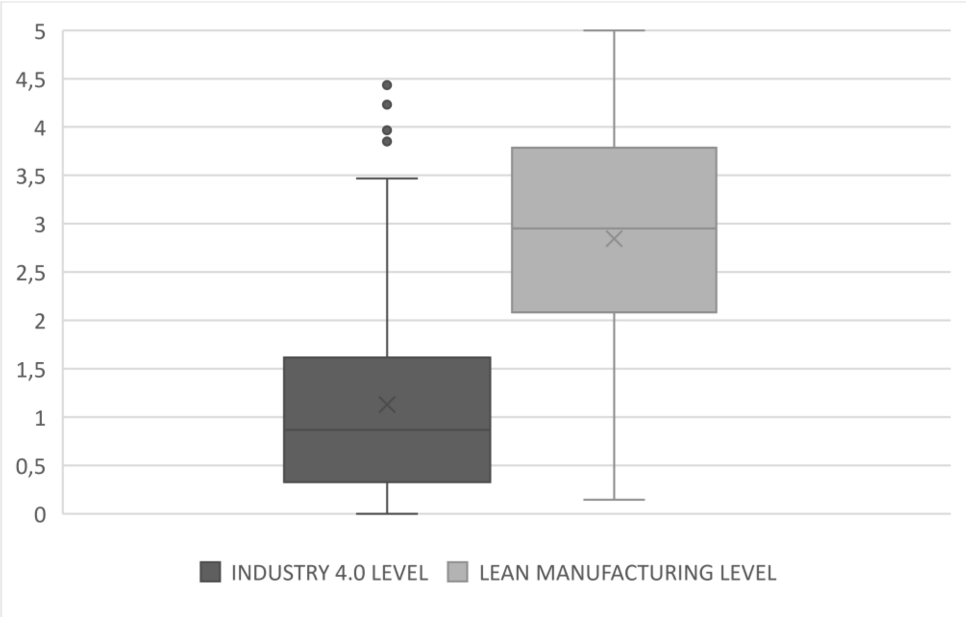


Figure 16: Industry 4.0 vs Lean Manufacturing box plot

The adoption level of Lean Manufacturing and Industry 4.0 is very different one to another since the sample presents an average value of Lean implementation of 2.85 and an average value of Industry 4.0 of 1.13.

Indeed, Industry 4.0 implementation is a new area of interest compared to the Lean Manufacturing: European companies' understanding and level of maturity of Lean Manufacturing is often higher than the level of implementation of Industry 4.0 tools (Portioli-Staudacher et al., 2019).

In other words, the scatter plot (*figure 15*) of the data may suggest a possible relationship between Lean level and Industry 4.0 level.

In addition, in order to investigate possible relationships between the level of Lean Manufacturing implementation and the Production Strategy adopted by companies and to understand if the latter is related to Industry 4.0 introduction level (RQ2), further analysis should be conducted.

Literature unveil that Lean Manufacturing can be implemented in any firm independently by contextual factors and company's strategy. Despite traditionally Lean tools have been developed and applied to mass production, empirical evidences support that they can be successfully applied in mass customization environments (Birkie and Trucco, 2016). Although high demand variability, that implies difficult demand levelling and complex kanban system implementation, may obstruct the implementation of Lean Manufacturing in a non-repetitive plant, Lean methodology and philosophy can be adapted to each environment (Thurer, Stevenson, Silva, Land, and Fredendall et.al 2012).

Thesis proposed by current literature are confirmed by the chi-squared analysis (*table 23*) performed on the survey-based dataset. Indeed, repetitive and non-repetitive companies seems to be equally distributed among different levels of Lean Manufacturing implementation. The adjusted residuals computed, in fact, are lower than the threshold of 1.64 (i.e. significance level of 10%) which mean that we could not reject the null hypothesis that frequencies in the contingency table are independent; in other words, no significant correlation emerged. Even the Pearson Chi-squared test shows a coefficient higher than the α-value (i.e. $0{,}914 > 0{,}05$) unveiling that there is not enough evidence to conclude that variables are associated.

		LEAN MANUFACTURING				Total Frequency
		LL		HL		
		Frequency	Adj. Resi.	Frequency	Adj. Resi.	
PRODUCTION STRATEGY	NON-REP	24	0,1084	29	-0,1084	53
	REP	23	-0,1084	29	0,1084	52
	Total Frequency	47		58		105

*Significant at 10% (adjusted residual > |1.64|); **significant at 5% (adjusted residual > |1.96|); ***significant at 1% (adjusted residual > |2.58|)

Table 23: Lean Manufacturing vs Production Strategy chi-squared analysis

On the other hand, current literature does not evidence that a particular Production Strategy is more suitable than others in adopting Industry 4.0 technologies. In other words, it is proved that the 82% of the organizations that have implemented Industry 4.0, indipendently from their Production Strategy, said to have experienced an increment of the efficiency in the fabrication's process (Orellana and Torres, 2019).

These findings are also verified by a chi-squared analysis, performed in *table 24*, which shows that no significant correlation between Industry 4.0 and Production Strategy was emerged. In fact, the adjusted residuals computed are not higher enough (i.e. $0.54 <$

1.64) to reject the null hypothesis that frequencies in the contingency table are independent.

Even the Pearson Chi-squared test shows a coefficient higher than the α-value (i.e. $0{,}589 > 0{,}05$) unveiling that there is not enough evidence to conclude that variables are associated.

		INDUSTRY 4.0				
		LD		HD		Total Frequency
		Frequency	Adj. Resi.	Frequency	Adj. Resi.	
PRODUCTION STRATEGY	NON-REP	33	-0,5409	20	0,5409	53
	REP	35	0,5409	17	-0,5409	52
	Total Frequency	68		37		105

*Significant at 10% (adjusted residual > |1.64|); **significant at 5% (adjusted residual > |1.96|); ***significant at 1% (adjusted residual > |2.58|)

Table 24: Industry 4.0 vs Production Strategy chi-squared analysis

Literature and chi-squared analysis unveil several findings:

- Industry 4.0 technologies implementation and companies' Production Strategy does not present evidences of dependency.
- Lean Manufacturing practices, thanks to Lean methodology and culture flexibility, can be adopted in each manufacturing context (Thurer et al. 2012; Birkie and Trucco, 2016).
- Given the complexity and the pervasiveness of the interrelation between Lean Manufacturing and Industry 4.0, factors (e.g. Production Strategy) may affect in a different way Lean 4.0.

The first two findings help the study to inspect RQ2, the third one needs to be further investigated with other researches (i.e. RQ4).

To inquire whether the main effect of Production Strategy and Lean 4.0 and their interaction are significant on Operational Performances (RQ4) an Analysis of Variance is performed.

Since the available dataset, gathered from the survey, did not provide any information regarding the Production Strategy followed by companies, a further step of data collection needs to be executed.

In order to gather Production Strategy information, an Internet research was conducted, searching information directly on companies' official websites. Since most of the enterprises did not present their Production Strategy on their webpage, looking at the company's industrial sector, at products and services offered and at customers' portfolio, the researched information was extrapolated. As stated to *section 4.1.3 Production Strategy*, companies were clustered according to two classifications: repetitive and non-repetitive Production Strategy.

Once the dataset is completed with the new information, an Analysis of Variance can be performed on Minitab to examine whether different levels of two factors (i.e. Lean 4.0 and Production Strategy) and their interaction impact the response variable (i.e. Operational Performances). The results of the analysis are summarized in *table 25, table 26, table 27 and table 28*.

Factor	**Type**	**Levels**	**Values**
Production Strategy	Fixed	2	Non-repetitive; Repetitive
Lean 4.0	Fixed	6	0; 1;2; 3; 4; 5

Table 25: Lean 4.0 and Production Strategy factor Information (N=105)

Source	**DF**	**Adj SS**	**Adj MS**	**F-Value**	**P-Value**
Production Strategy	1	2,05	2,05	0,18	0,675
Lean 4.0	5	121,64	24,329	2,10	0,072
Error	98	1134,25	11,574		
Lack-of-fit	4	61,10	15,276	1,34	0,262
Pure Error	94	1073,14	11,416		
Total	104	1260,91			

Table 26:Lean 4.0 and Production Strategy Analysis of Variance (N=105)

S	**R-sq**	**R-sq (adj)**	**R-sq (pred)**
3,40205	10,05%	4,54%	*

Table 27: Lean 4.0 and Production Strategy model summary (N=105)

Obs	**Op. Performance**	**Fit**	**Resid**	**Std Resid**	**Large Residual**	**Unusual X**
4	13,00	4,48	8,52	2,57	R	
23	11,00	3,88	7,12	2,12	R	
70	4,00	4,00	-0,00	*		X
89	11,00	3,45	7,55	2,28	R	

Table 28: Lean 4.0 and Production Strategy fits and diagnostics for unusual observations (N=105)

The model presents several criticalities:

- The interaction between Production Strategy and Lean 4.0 was not estimated by the model and so removed

- No factors significantly impact on the response variable since the p-value of both Production Strategy and Lean 4.0 are higher than 0,05 (i.e. respectively 0,675 and 0,072).
- The model does not provide a good fit to the data since the R^2 indicator is very low (10,05%) and the $R^2{}_{adj}$ is even worst (4,54%).
- The diagnostic statistic for unusual observations shows 3 large residuals and 1 leverage point which have a disproportionate impact on ANOVA model.

The criticalities presented, in particular the last two points, suggest that the results can be misleading.

To determine the effect of unusual observations, we decide to fit the model with and without such observations and compare model parameters.

Eliminating the unusual observations shown in *table 28*, a new analysis was performed. T*able 29*, *table 30* and *table 31* summarize the main parameters of the new model.

Factor	Type	Levels	Values
Production Strategy	Fixed	2	Non-repetitive; Repetitive
Lean 4.0	Fixed	5	0; 1;2; 3; 4

Table 29: Lean 4.0 and Production Strategy factor Information (N=101)

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Production Strategy	1	12,60	12,596	1,33	0,252
Lean 4.0	4	123,64	30,910	3,26	0,015
Production Strategy * Lean 4.0	4	83,43	20,858	2,20	0,075
Error	91	862,77	9,481		
Total	100	1078,04			

Table 30:Lean 4.0 and Production Strategy Analysis of Variance (N=101)

S	R-sq	R-sq (adj)	R-sq (pred)
3,07913	19,97%	12,05%	*

Table 31: Lean 4.0 and Production Strategy model summary (N=101)

The new model, so, is computed on a sample of 101 companies and it provides a better fit of data even though R^2 value (19,97%) and a $R^2{}_{adj}$value (12,05%) still remain low. This highlight that other factors, not considered in this analysis, may significantly impact on the response variable.

The new model is able to estimate the interaction between Production Strategy and Lean 4.0, but the interrelation of the aforementioned approaches is not considered relevant on the Operational Performances since the p-value is slightly higher than the 0,05. A p-value of 0,075, in fact, may suggest that the interaction, considering a significance level of 0,1, could become relevant with a 10% risk of concluding that an association exists when there is no actual association.

Looking at the main factors, instead, Lean 4.0 construct appears relevant because p-value is equal to 0,015, while it is no possible to conclude that the Production Strategy significantly impact on Operational Performances since the p-value is higher than α level (i.e. $0{,}252 > 0{,}05$).

To perform an Analysis of Variance, hypothesis presented in *section 4.5.1 ANOVA: analysis of variance* must be tested:

(i) **Independence of residuals**

In *figure 17*, the Residuals Versus Order plot shows no trend or specific pattern, therefore residuals can be considered as independent and the assumption is satisfied.

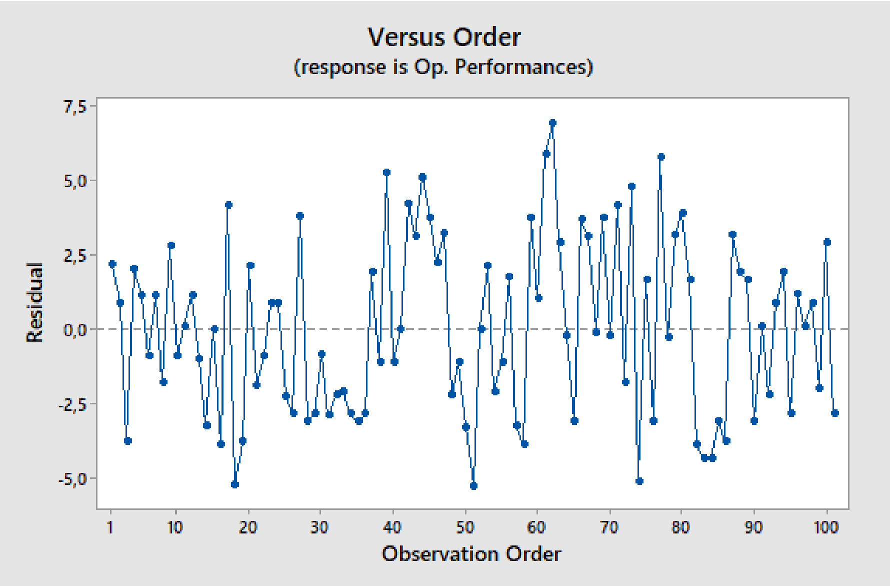


Figure 17: Residuals versus order plot

(ii) **Normality test on residuals**

To proceed with data analysis, the normality of response variable is checked upon the Kolmogorov-Smirnov (KS) test. The result (*figure 18*) shows that the dataset was not normally distributed since the p-value is lower than α (i.e. $0{,}014 < 0{,}05$).

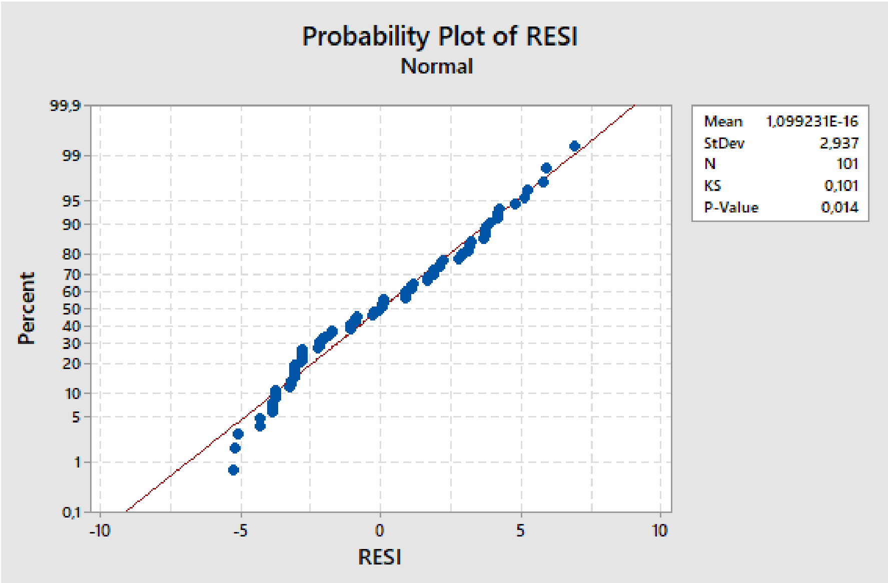


Figure 18: Probability plot of residuals

(iii) **Test of equal variances on residuals**

The Levene's test (*figure 19*) shows a p-value equal to 0,454, hence, the null hypothesis that variances are all equal can not be rejected.

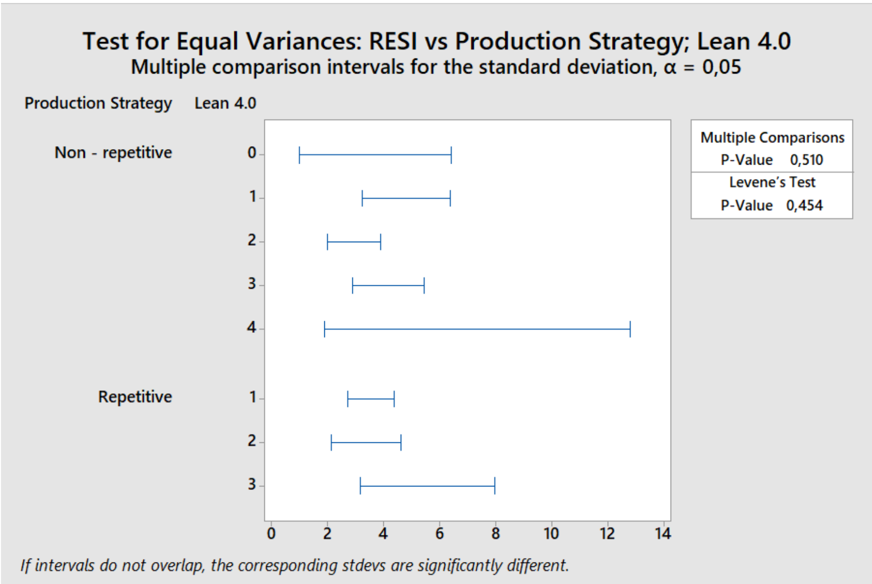


Figure 19: Test of equal variances

The effect of main factors on the Operational Performances, previously described, are plotted in *figure 20*. The graph (*figure 20)* appears to demonstrate a positive relationship of Lean 4.0 on the response variable: the higher is the Lean 4.0 level, the higher are the Operational Performances. Instead, even if it is not proved that Production Strategy variable impact on performances, the graph (*figure 20)* seems to show that repetitive companies have higher performances.

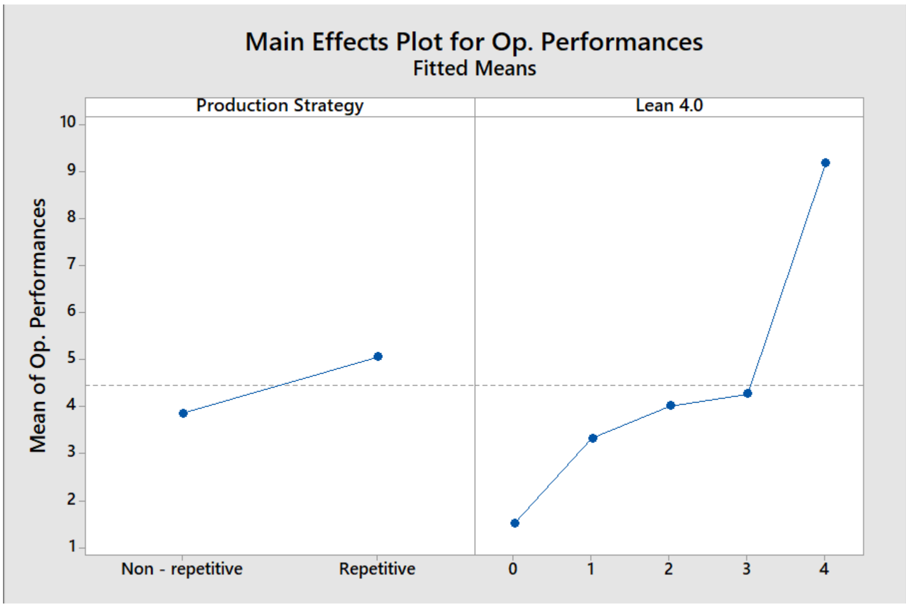


Figure 20: Main effects plot for Operational Performances

However, since residuals are not normally distributed, it is not possible to state that a linear combination between Lean4.0 and Operations Strategy factors exists.

In addition, in order to further investigate the effect of Lean 4.0 on Operational Performances, a correlation analysis on SPSS Statistics was performed. The Pearson coefficient (i.e. $r = 0{,}224$) unveil a weak correlation between factors. Although the correlation is not strong, the p-value lower than the α value (i.e. 0,022 < 0,05) guarantee that the correlation is significant.

Summarizing the outcome of the survey-based statistical analysis, the following findings emerged:

- A relationship between Lean Manufacturing level and Industry 4.0 level occur, and Lean Manufacturing is an enabler for digitalization.
- According to Portioli-Staudacher et al. 2019, when processes are not robustly designed and continuous improvement practices are not established, companies may not be focused on adopting novel technologies: indeed, according to *figure*

15, just one company has an high level of Industry 4.0 implementation (i.e. higher than 2,5) combined with low level of Lean Manufacturing (i.e. lower than 2,5).

- On one hand, Lean Manufacturing represents a preliminary step for Industry 4.0 implementation, on the other hand, the implementation of both Lean and Industry combined may influence each other (Nyhuis et al., 2017).
- Repetitive companies seem to achieve higher Operational Performances, enhancing companies' results (*figure 20*).

However, these findings are characterized by some criticalities:

- In the model, some significant factors, that impact on Operational Performances, may have not been considered.
- Statistical models used do not provide a good fit to the data. This criticality could be given by some information in conflict. Indeed, some questions in the survey could be misunderstood or not well comprehended. According to Knetsch (1984), in survey-based research there is the likelihood to get misleading answers to wrong questions or not-well formulated questions.
- The survey, given the absence of a precise question in the survey-structure, does not inspect the Production Strategy (i.e. MTS, MTO, ATO, ETO) of the respondent's company and its relationship with Lean 4.0 level. To partially mind this gap, companies were clustered, conducting an analysis on companies' webpages, according to two categories: repetitive and non-repetitive Production Strategy.

For these reasons, the model can not provide statistically significant results, however it suggests possible relationships between Lean 4.0 and Production Strategy.

The data entered in the analysis, in fact, depends on the way used to collect them. Indeed, the survey has the advantage to reach respondent without geographical limits, while on the other side questions can be misunderstood, leading to misleading data. In addition, the information collected on Production Strategy could be not reliable at 100%.

For these reasons and the ones wider explained in *section 4.2.2 Reasons Beyond Case-Study Research*, we decide to conduct semi-structured interviews to gather more precise and reliable information inspecting situations from a closer point of view (Mann and Stewart et al. 2000).

5.3 CONTEXTUAL FACTORS ANALYSIS

As stated in *section 4.2.1 Survey*, different information was collected through the survey: contextual factors, Lean Manufacturing and Industry 4.0 level of implementation and maturity and Operational Performances.

The different contextual factors gathered were used in *section 4.2.1 Survey* in order to classify the sample, while in this section they are analysed with the aim of understanding if they could influence the Operational Performances and/or the degree of Lean 4.0 implementation (RQ3).

5.3.1 Contextual factors vs Operational Performances

First of all, an analysis was performed with the aim at inspecting the relevance of an influence of some contextual factors on company's Operational Performances.

Since the dimensions identified were deemed as categorical, a chi-squared analysis on the survey-based dataset was performed testing the hypothesis that frequencies in the contingency table are independent (Portioli-Staudacher et al. 2019, Tabachnick and Fidell 2013).

In *table 32*, it is shown, for each contextual factor analysed (i.e. size, age of the plant, industry, Lean and Industry 4.0 maturity level), the frequencies and the adjusted residuals. Each contextual factor, except for industry which present 5 levels, was split into two level according to *paragraph 4.3 Data Encoding* (e.g. SME and Large companies for the size). Operational Performances, instead, was encoded into binary values (i.e. low-high value) using the average value as threshold.

The chi-squared test, applied in this section, aims at inferencing whether one factor is correlated with another one.

The adjusted residual values, shown in contingency tables, are the differences between the observed and expected frequencies for a group and are used in order to indicate the significance level of each relationship. Positive values of adjusted residuals, in fact, mean that observed values are larger than the expected ones, while negative ones mean that observed values are fewer than the expected ones. The chi-squared test, in addition, present even the Pearson chi-squared statistic which, according to *section 4.5.3 Chi-Squared,* is computed as the squared difference between the observed and the expected frequencies, and its p-value associated. Adjusted residuals and p-value are associated one to another, in fact, significant associations were identified whenever the corresponding adjusted residual value was larger than |1.64|, |1.96|, and |2.58|, indicating a respective significance level of 0.10, 0.05, and 0.01.

		OPERATIONAL PERFORMANCES				
		LOW		HIGH		Total Frequency
		Frequency	Adj. Resi.	Frequency	Adj. Resi.	
SIZE	SME	22	0.7977	20	−0.7977	63
	LARGE	28	−0.7977	35	0.7977	42
	Total Frequency	50		55		105
AGE OF THE PLANT	≤ 20 years	11	0.4885	10	−0.4885	21
	> 20 years	39	−0.4885	45	0.4885	84
	Total Frequency	50		55		105
LEAN MATURITY	≤ 5 years	20	0.3832	20	−0.3832	40
	> 5 years	30	−0.3832	35	0.3832	65
	Total Frequency	50		55		105
INDUSTRY 4.0 MATURITY	≤ 3 years	34	0.6622	34	−0.6622	68
	> 3 years	16	−0.6622	21	0.6622	37
	Total Frequency	50		55		105
INDUSTRY	Automotive	14	0.7330	12	−0.7330	26
	Chemicals and pharmaceuticals	10	0.0000	11	0.0000	21
	Electric and electronic equipment	6	−0.1130	7	0.1130	13
	Machinery and metal products	14	−0.7216	19	0.7216	33
	Miscellaneous manufacturing	6	0.1755	6	−0.1755	12
	Total Frequency	50		55		105

*Significant at 10% (adjusted residual > |1.64|); **significant at 5% (adjusted residual > |1.96|); ***significant at 1% (adjusted residual > |2.58|)

Table 32: Contextual Factors vs Operational Performances chi-squared

According to *table 32*, no one of the contextual factors analysed present a correlation with Operational Performances since the adjusted residuals for any factor are lower that the threshold of 1.64, which means that we could not reject the null-hypothesis that frequencies in the contingency table are independent, hence, no significant correlation was emerged.

Given the absence of linear relations between operational performance and contextual variables, the same analysis is conducted among contextual factors and Lean Manufacturing and Industry 4.0 implementation level.

5.3.2 Contextual factors vs Lean Manufacturing and Industry 4.0 Level

Once evaluated the effect of contextual factors on Operational Performances, the study aims at evaluating whether an interdependence exists between these factors and the level of Lean Manufacturing and Industry 4.0 implementation.

According to Portioli-Staudacher et al. (2019), a chi-squared test, testing the hypothesis that frequencies in the contingency table are independent, is performed with the aim of identifying possible interdependence between the two construct (i.e. Lean Manufacturing and Industry 4.0 implementation’s level) and the size of the company, which appear to be the only contextual factor that could be relevant.

In the *table 33*, the contingency tables showing the frequencies and the adjusted residuals are presented.

Lean Manufacturing and Industry 4.0 technology adoption were re-arranged using the average value as threshold into low-high value (respectively LL and HL for Lean Manufacturing, LD and HD for Industry 4.0).

			LEAN MANUFACTURING				
			LL		HL		Total frequency
		INDUSTRY 4.0 TECHNOLOGY	Frequency	Adj. Resi.	Frequency	Adj. Resi.	
SIZE	SME	LD	31	1,8**	23	-1,8**	54
		HD	5	-1,8**	11	1,8**	16
		Total frequency	36		34		70
	LARGE	LD	8	2,7***	6	-2,7***	14
		HD	3	-2,7***	18	2,7***	21
		Total frequency	11		24		35

*Significant at 10% (adjusted residual > |1.64|); **significant at 5% (adjusted residual > |1.96|); ***significant at 1% (adjusted residual > |2.58|)

Table 33: Contextual Factors vs Lean 4.0 chi-squared

Table 33 shows a high significance level between large company size and the Lean and Industry 4.0 level of implementation (i. e |2.7|).

This result is in accordance with the result of Portioli-Staudacher et al. 2019 and confirm the interdependence of the size with Lean and Industry 4.0. In fact, HD frequencies showed that large-sized companies tend to implement Industry 4.0 much more than small-sized companies, and the same for Lean Manufacturing, since the frequency of HL is slightly greater in large-sized companies with respect to small-sized ones.

5.3.3 Contextual factors vs Lean 4.0

In this research the main focus is about Lean 4.0 which is represented as the combination of both Lean Manufacturing and the Industry 4.0. For this reason, once demonstrated the influence of size respectively on Lean Manufacturing and Industry 4.0, the aim of this section is to evaluate the possible relationship between the size and the Lean 4.0.

An empirical study conducted by Portioli-Staudacher et al. 2019, unveil the association between Lean Manufacturing and Industry 4.0 under different contextual factors.

The pervasiveness of the relationship between Lean Manufacturing and Industry 4.0 demonstrated in “The interrelation between Industry 4.0 and lean production: an empirical study on European manufacturers”, may overcome the effect of some contextual factors indicating that company size may not be a relevant contextual factor for influencing this association. In addition, on that paper it is highlight how managers from manufacturer companies can benefit from the conjoint implementation of both approaches by comprehending that Industry 4.0 is positively related to Lean Manufacturing, disregarding the context (e.g., company size) (Portioli-Staudacher et al. 2019).

5.4 PRELIMINARY INTERVIEW ANALYSIS

Once interviews’ data collection was completed, a preliminary analysis, with the information gathered from the 19 people interviewed, was conducted. This qualitative investigation was done performing words, sentiment and cluster analyses on the software NVivo.

First of all, considering the whole sample of the interviews, a word map (*figure 21)* was built by eliminating connections, verbs, adverbs and prepositions and by manually unifying synonymous (i.e. customizing, personalization, customization, personalizing). This way, the word map generated aims at understanding which are the main themes and arguments investigated and the main words used. Among the others, “Lean”, “Work”, “Management” “Time”, “Production”, “Improvement” and “Customer” may be considered the main areas of interest and may be used as input keywords for further qualitative analysis. The words found underline the effects of Lean 4.0: indeed, the relationship between Lean Manufacturing and Industry 4.0, combined with the right Production Strategy, may allow companies to produce more efficiently (production time and cost savings) and effectively (customer can obtain customized products).

Figure 21: Interviews word map

In *annex E*, are displayed the most common connections between words used by people interviewed. This cluster analysis shows that the word “Lean” is often associated to “Need” and “People”, highlighting the importance of Lean Manufacturing both at the level of process simplification and at the level of corporate culture. Indeed, by integrating hard and soft factors, processes can be managed by employees with certified skills and pervasive organizational culture in order to exploit innovativeness. Innovation management can be developed thanks to coaching leadership, learning culture, employee appreciation, learning routines, and collaborative networks (Solaimani et al., 2019). In combination to the present Lean culture that involves continuous improvement actions, a digital culture should be integrated among processes, employees and business units in order to drive new digitally enabled ways of working, thinking and interacting. Successful digital transformations are enabled by a correct process-culture-technology alignment (D. Romero et al., 2019). On the other hand, the word “Digital” is often used in connection with the words “Internal”, “Costs” and “Reduced”. Indeed, thanks to Industry 4.0 technologies companies can reach advantages and improvements in terms of production quality, supply chain reaction, materials savings, real-time detection, reaction to errors and anomalies, time spent and resource employment. Thanks to these advantages, investments in Smart Factory allow a very fast ROI. (L. Belli, 2019).

Since the approach followed was the one of semi-structured interviews, information regarding the same topic could be scattered all the test long: for this reason, each paragraph was coded, using the NVivo function "Coding", into different areas of interest:

- General Information
    - Company Information
    - Respondent Information
- Production Strategy
    - Demand Variability
    - Supply Chain Relationships
- Lean 4.0
    - Lean Bundles
    - Industry 4.0 Bundles
    - Lean 4.0 Delta Performances

The codes' division permits to conduct each analysis either on the father node or on the child's nodes, allowing to increase or decrease the degree of investigation.

Going deeply in detail of Lean 4.0 topic and in its interrelation with Production Strategy, a world map was created on the father nodes of these two themes.

In *figure 22*, it is clearly shown that, regarding Lean 4.0, the main words used by managers interviewed are "Lean", "Production", "System", "Time", "Management and "Work". Indeed, Lean 4.0 helps companies to reduce time, simplify work and enhance a simple operations management. Since European companies' understanding and level of maturity of Lean Manufacturing is often higher than the level of implementation of Industry 4.0 tools (A. Portioli-Staudacher, 2019), the word "Lean" is mentioned more frequently than the word "Digital".

Moreover, thanks to the word map are clearly visible the most used Lean Manufacturing practices, such as SMED and Kanban. On the other side, given the difference among companies and the high variety of tools used, in the world map are not displayed any Industry 4.0 technology.

Figure 22: Lean 4.0 word map

In *figure 23*, instead, the main keywords of Production Strategy' word map are displayed: the association of Lean 4.0 to repetitive and non-repetitive strategies appears to be the same, as stated by the same dimensions of the words "Order" and "Stock", which represent the two main adopted production strategy (i.e. MTO and MTS). However, the attention for the "Customer" seems to be a shared approach of both the methods.

Figure 23: Production Strategy word map

In the interviews, having to deal with people and so with their personal opinions, moods and emotions; the "human side" (i.e. subjective information) of the speeches was considered as important as the "professional side" (i.e. objective information).

Indeed, through the telephone, voice intonation and the structure of sentences allow to understand the level of enthusiasm of discomfort of a respondent with questions (Opdenakker et al. 2006).

A sentiment analysis, at the paragraph level (i.e. understanding the subjective or objectivity of an entire paragraph), was conducted to find out the way in which people interviewed have talked about the topic of Lean 4.0, helping to understand whether they are for or against the combined implementation of Lean Manufacturing with Industry 4.0.

This procedure was done by using the NVivo function "Case Classification", to divide the people interviewed by the interviewer, and the function "Auto Code", to implement the sentiment analysis.

Analysing the whole sample (*figure 24*), positive and negative thoughts are almost equivalent, while the higher number of "professional opinions" compared to "personal opinions" unveil a neutral point of view towards the Lean 4.0 theme. Finally, a considerable part of the interviews has a mixed opinion, which involves the coexistence of positive and negative opinions.

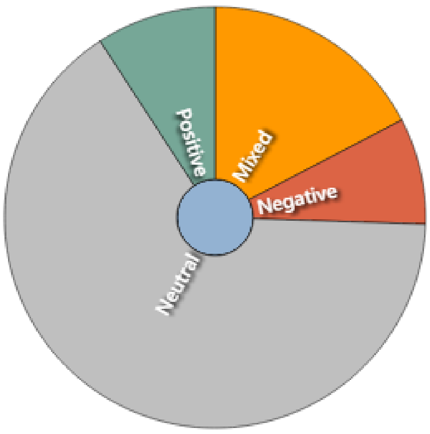


Figure 24: Overall sentiment analysis

Going further in detail, using the NVivo function "Case", a sentiment analysis for each person interviewed was conducted. From *figure 25*, it is evident that almost each respondent has a prevalence of neutral thoughts, combined with a smaller part of positive and negative thoughts. This indicates a prevalence of "professional opinion" compared to personal opinions (i.e. people usually do not express "personal opinions"). The only exception to this, is represented by Respondent N. 20 (i.e. Lean coach), that is really optimistic about the possibility to achieve higher results with the combination of Industry 4.0 and a correct application of Lean Manufacturing, no matter if the company is repetitive, non-repetitive, small, medium or big. However, on the other side, he is really pessimistic about the application of Lean tools in the Italian environment, since in companies there are no present figures like Lean Senseis with a right and proper Lean culture. This combination of positive and negative thoughts, regarding the chance to introduce Lean 4.0 in Italy, is represented in *figure 25* by the prevalence of the mixed opinion. The same reasoning is valid also for Respondent N.17 and Respondent N.1.

Figure 25: Sentiment analysis for each interviewee

In the end, in order to understand if Production Strategy can influence the application of Lean 4.0, repetitive companies' interviews and not-repetitive companies' interviews were divided. Although the approach of the interviews is semi-structured, given the low number of companies and the similarity of the questions, the previous analysis, applied to this new distinction, does not give further results in addition to what we have already stated before.

After having analysed qualitatively the interviews, in the following paragraph (*paragraph 5.5 Interview Analysis*) a more quantitative approach has been used.

5.5 INTERVIEW ANALYSIS

The interview analysis, conducted in this paragraph, aims at inspecting a possible synergy/trade-off relationship among variables (i.e. Lean 4.0 and Production Strategy) evaluating their impact on Operational Performances, which is our response variable (RQ4).

Due to the relatively small sample size (i.e. 19 companies), the statistical analysis performed on the survey-dataset can not be applied in a reliable way. Indeed, a sample not suficently large might bring to misleading results unveiling uncomplete and weak findings. Therefore, according to Birkie 2016, Bayesian approach was adopted to inquire interviews' sample.

Variables in a Bayesian Network can take continuous values but, most of the cases, they are rearranged to binary forms. With respect to the encoding procedure presented in *paragraph 4.3 Data Encoding*, a further step has to be computed.

Once the Lean 4.0 construct is formulated, according to the procedure shown in *paragraph 4.4 Indexes Building*, the continuous values obtained were recoded into low-high binary values using their respective sample average values as cut-off point (i.e. Lean 4.0 > 2,10 is high; all other values are regarded as low).

Considering the Operational Performances variable, in order to lead to a non-negative overall Operational Performance value (Birkie, 2016), the values obtained from interviews required a further encoding step. Since the metrics analyzed could have values ranging from -3 to +3, the interval of the total performances construct summing all the eight metrics is [−24; +24]. For this reason, values obtained from the interviews are transcoded into a positive value ranging from 0 to 48. Operational Performances construct was then recoded into low-high values following the same procedure used for Lean 4.0 (i.e. Operational Performance > 31,37 is high; all other values are regarded as low). In the study, the average values (e.g. 31,37) are encoded as low. However, changing the sign > to ≥ by considering so the average values as high, did not change the findings.

In *table 34*, the descriptive statistics of the sample are shown.

Construct	Average	Standard Deviation	Min	Max	Range
Lean 4.0	2,10	0,60	1,67	3,93	2,27
Operations Strategies					
Operational Performances	31,37	2,95	25,00	35,00	10,00

Table 34: Descriptive statistics

First of all, in order to perform the analysis, the Bayesian Network has to be designed. *Figure 26* perfectly represent the situation in which nodes L (Lean 4.0) and R (Production Strategy) are the independent parents' nodes of X (Operational Performances).

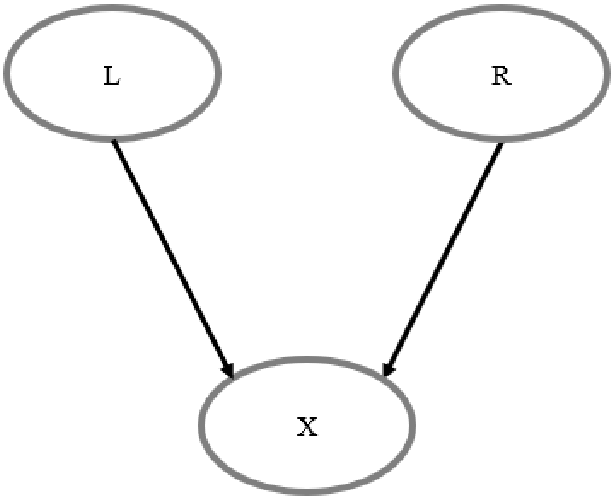


Figure 26: Bayesian Network

In this representation, the null hypothesis considered is that L and R are unconditionally independent. However, H_0 can be rejected whether some evidence about the dependency of L and R occur. In other words, supposed that X is observed to occur; if the event R arises and the probability of occurrence of the event L will increase compared to its relationship with the event X, the two events L and R are no more independent. Since the probability of occurrence of each node is positively dependent on whether the other occurs, the events are conditionally positive dependent on each other. The positive dependency is so demonstrated, and *equation 24* is satisfied:

$$P(L \mid X, R) > P(L \mid X)$$

Equation 24: Bayesian positive dependency

As already explained, in most of the cases, the Bayesian approach use binary data and, in this paper, according to the data encoding phase, "low" and "high" form are using the average value as cut-off.

This way, all the long of the section, l and $\bar{l}$ represent high and low values of Lean 4.0 construct, x and $\bar{x}$ represent high and low values of Operational Performances, while r and $\bar{r}$ represent respectively repetitive and non-repetitive Production Strategy.

Once defined the label-values and drawn the network (*figure 26*), a Bayesian Network can be considered fully specified if a table of conditional probabilities for all variables of interest, as *table 35* perfectly show, is included.

Lean4.0 (L)	l	Production Strategy (R)	r
P (L)	0,58	P (R)	0,37

Operational Performances (X)		
L	R	$P\ (x \mid L, R)$
l	r	1,00
l	$\bar{r}$	0,00
$\bar{l}$	r	0,60
$\bar{l}$	$\bar{r}$	0,14

Table 35: Prior conditional probabilities

The upper side of the table shows the percentage of companies in the dataset with, respectively, high value of Lean 4.0 and a repetitive strategy. The lower side, instead, shows the conditional probabilities computed by considering the occurrence of high value in Operational Performances (x) given each set of combination of L and R (e.g. high value of Lean 4.0 and repetitive strategy).

The network presented in *figure 26* and the table of conditional probability showed in *table 35*, were used to enable a causal relationship between the variables of interest. Moreover, the set of prior probabilities was used to estimate the posterior probabilities using the Bayesian statistics. Searching for posterior or conditional probabilities, the values presented in *table 36* have been obtained.

For example, the probability that a company has high Lean 4.0 given that its Operational Performance is high, is computed as reported in *equation 25*.

$$P\ (l\ |x) = \frac{P(l, r, x) + P(l, \bar{r}, x)}{P(l, r, x) + P(l, \bar{r}, x) + P(\bar{l}, r, x) + P(\bar{l}, \bar{r}, x)}$$

Equation 25: Conditional probability of l|x

Instead, the probability that company has high Lean 4.0 given that its Operational Persformance is high and its strategy is repetitive, is computed as in *equation 26*.

$$P\ (l\mid x,r) = \frac{P(l,r,x)}{P(l,r,x)+P(\bar{l},r,x)}$$

Equation 26: Conditional probability of l|x,r

These values are shown in *table 36*.

Lean 4.0 (L)		**Production Strategy (R)**	
P (L=High)	58%	P (R = Repetitive)	37%
P (L=High | X=High)	92%	P (R = Repetitive | X= High)	45%
P (L=High | X=High, R=Repetitive)	100%	P (R = Repetitive | X= High, L = High)	49%

Table 36: Conditional prior and posterior probabilities for repetitive production

The first row represents the probability that a company has high level of Lean 4.0, which means the percentage of companies in the dataset with high Lean 4.0 value over the total of the companies.

The second row, instead, is computed according to *equation 25* and shows that the probability that a company has high value of Lean 4.0 given that its Operational Performance is high, increase to 92 per cent compared to the prior probability of 58 per cent.

This probability increases to 100 per cent (applying *equation 26*) if it is also known that the company has a repetitive strategy (third row of *table 36*).

The same pattern of increase is also observed for Production Strategy. In fact, the prior probability of 37 per cent, increases to 45 per cent knowing that the performances are high. Furthermore, if it also known that the company has high Lean 4.0 implementation level, the probability increases to 49 per cent.

Table 36 confirms that, given the evidence of high Operational Performances and a repetitive strategy, the probability to obtain high Lean 4.0 value increases.

Equation 24, in fact, is respected and a positive dependency between Lean 4.0 and Production Strategy is demonstrated.

There is so evidence to reject the null hypothesis of unconditionally independence between L and R. It is so possible to state that Lean 4.0 and Production Strategy are conditionally dependent given the Operational Performance level, even though they were independent when there was no information about the performance outcome.

In *table 36* is shown the pattern of increase considering the repetitive Production Strategy.

On the contrary, of course, if we consider a non-repetitive strategy, a pattern of decrease is expected. Indeed, the prior probability that a company has a non-repetitive strategy (first row of *table 37*) decreases given that its Operational Performance is high (second row of *table 37),* and decreases even to lower values, if it also known that the company has high Lean 4.0 implementation (third row of *table 37),*.

Lean 4.0 (L)		**Production Strategy (R)**	
P (L=High)	58%	P (R = Non-Repetitive)	63%
P (L=High | X=High)	92%	P (R = Non-Repetitive | X= High)	55%
P (L=High | X=High, R=Non-Repetitive)	85%	P (R = Non-Repetitive | X= High, L = High)	51%

Table 37: Conditional prior and posterior probabilities for non-repetitive production

Once the positive dependency between Lean 4.0 and Production strategy is demonstrated through the analysis presented above, thanks to *equation 22* the positive product synergy between Lean 4.0 and Production strategy at high Operational Performance level could be proved:

$$1.00 \times 0.14 \geq 0.00 \times 0.60$$

Therefore the Y^+(positive product synergy) is demonstrated and so Lean 4.0 and Production Strategy interaction appears to synergistically increase company's Operational Performances.

Birkie 2016, in his study, in order to evaluate the robustness of findings against the selected encoding procedure, performed a sensitivity analysis changing the cut-off value between the range of data gathered. Following the same methodology, also in this research, the cut-off value of 31.37 for Operational Performances has been progressively changed between 25 and 35.

Results confirms that the positive product synergy holds for the whole range giving robustness to the analysis.

In order to graphically shows what the product synergy is presenting, an interaction plot between Lean 4.0 and Production Strategy on Operational Performances is performed on Minitab. As shown in *figure 27*, the two lines are not parallel, and this is expected to mean that the interaction between the two factors is relevant. In fact, the increase of Operational Performances, as Lean 4.0 increases from low to high, is much higher when Production Strategy is repetitive (red line) with respect to when it is non-repetitive (blue line).

*Figure 27: Lean 4.0*Production Strategy interaction plot*

However, given the small sample size, it is not possible to apply other statistical analyses like regression line, which should be addressed by a large-scale study. Nevertheless, as Birkie 2016 supports in his study, the positive gradient is a clear indication that trade-off is not the dominant relation.

Furthermore, plotting the data gathered from interviews, *figure 28* shows how repetitive companies have a higher degree of Lean Manufacturing and Industry 4.0, which is turned in higher results (i.e. Operational Performances).

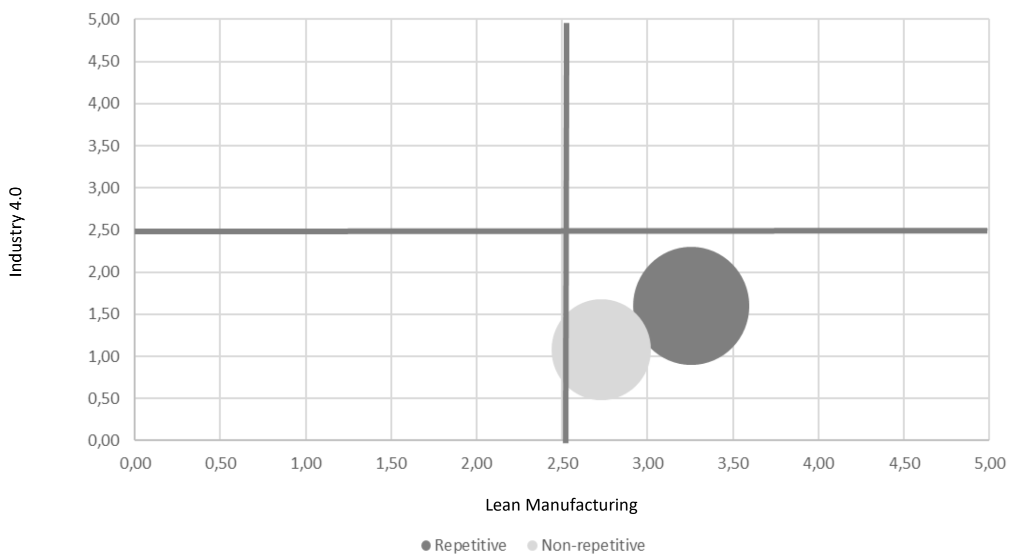


Figure 28: Performances of Lean and Industry 4.0 adoption in repetitive and non-repetitive environments

In this research even if the sample is not enough large, a Design of Experiment is performed in order to see possible insights for further researches. According to this analysis, in fact, many evidences appear regarding the relevance of Lean 4.0 construct on Operational Performances. In fact, p-value is almost zero and the main effect of Lean 4.0 factor on Operational Performances, as shown in *figure 29*, is huge. On the other side, the Production Strategy, seems to be not a significant factor on Operational Performances, since its main effect on company's results is stable changing from non-repetitive to repetitive strategy.

However, these considerations, given the small sample size, are just insights on which further investigate with future analysis. In any case, instead, the positive product synergy demonstrated through the Bayesian approach still remain meaningful independently to the sample-size

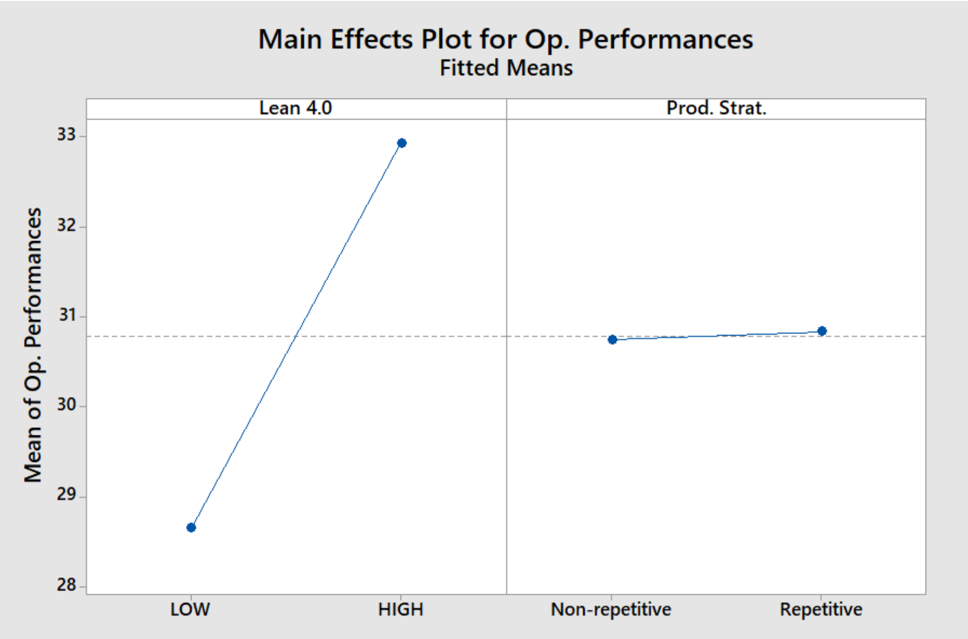


Figure 29: Lean 4.0 and Production Strategy main effect plot on Operational Performances

6. FINDINGS

This chapter aims at summarizing the results discussed in the previous sections in order to stress their contribute for the current state-of-the-art.

Although current literature reports that exist an interrelation between Lean Manufacturing and Industry 4.0, different perspectives emerged in understanding how the aforementioned elements are mutually related. According to Buer et al. 2018 and Mayr et al. 2018, authors disagree on the way in which they are combined, begging to differ about which is the enabler of the other (i.e. RQ1). By plotting information obtained in the survey (*figure 15*), it is evident that there are no plants characterized by high Industry 4.0 level and low Lean Manufacturing level. The absence of plants in the fourth quadrant (i.e. bottom-right corner of the graph in *figure 15*) unveils that high levels of Industry 4.0 may be reached only with a consolidated Lean implementation (Portioli-Staudacher et al. 2019). As a support of survey findings, the interviews' qualitative analysis, performed with the software NVivo, suggests, according to Portioli-Staudacher et al. 2019, that when processes are not robustly designed and continuous improvement practices are not established, companies may not be focused on adopting novel technologies. In other words, Lean Manufacturing, by reducing wastes and non-value adding activities, may be considered as an enabler of Industry 4.0.

Extant literature agrees that the combination of both topics yields in a positive result, namely Lean 4.0, but does not highlight which is the most appropriate production environment in which Lean Manufacturing and Industry 4.0 can individually be developed (i.e. RQ2). In order to inquire Production Strategy dependency, a chi-squared analysis on the survey-based dataset was performed in *paragraph 5.2 Survey Analysis*. Despite traditionally Lean tools have been developed and applied to mass production, chi-squared results (*table 23*) highlight that they can be successfully applied also in mass customization environments (Birkie and Trucco, 2016; Abdulmalek and Rajgopal, 2007). However, high demand variability may influence the introduction of Lean Manufacturing in a non-repetitive plant (Thurer et.al 2012). Statistical analysis also unveil that Industry 4.0 adoption is not related to company's repetitiveness or non-repetitiveness (*table 24*).

Furthermore, to inquire RQ3, the study has investigated whether other variables (i.e. contextual factors) impact Lean 4.0 implementation. To analyse contextual factors, since they have categorical values, a chi-squared test was performed (*paragraph 5.3 Contextual*

Factor Analysis). Results unveil that only the size of the company impacts Lean and Industry 4.0 implementation (*table 33*). Nevertheless, the pervasiveness of the interrelation between Lean Manufacturing and Industry 4.0 may overcome the effect of some contextual factors enabling manufacturers to benefit from the conjoint implementation of these approaches disregarding the context (Portioli-Staudacher et al. 2019).

Finally, the main aim of the study, as presented by RQ4, is to inspect and investigate whether there are evident synergies or trade-offs between company's Production Strategy and Lean 4.0 implementation in increasing Operational Performances. Analysis of Variance, performed on the survey-based dataset (*paragraph 5.2 Survey Analysis*), suggests that the only relevant factor, among the ones analysed, that impacts on Operational Performances is Lean 4.0 (i.e. $p - value = 0{,}015$). In addition, a weak correlation between the aforementioned topics (i.e. Lean 4.0 and Operational Performances) is present (i.e. $r = 0{,}224$). Although the correlation is not strong, the p-value lower than the α value (i.e. $0{,}022 < 0{,}05$) guarantees that the correlation is significant. On the other hand, Production Strategy does not have statistically significant impact on Operational Performances (i.e. $p - value = 0{,}252$), but it seems, from *figure 20,* that repetitive companies achieve higher Operational Performances, enhancing companies' results. Moreover, the estimation of the interaction between Production Strategy and Lean 4.0 done by the model, can not be considered significant on Operational Performances since the p-value is slightly higher than the α-value (i.e. $0{,}075 > 0{,}05$). This way, the model does not provide robust results but suggests evidence of a relationship between Lean 4.0 and Production Strategy.

In order to further inspect and inquire the existence of synergies or trade-offs between the aforementioned topics, semi-structured interviews were conducted. The Bayesian approach used to analyse the interviews-dataset, unveil a positive dependency between Lean 4.0 and Production Strategy. Indeed, the probability that a company might have a high value of Lean 4.0, knowing that the Operational Performances are high, increases with respect to prior probability that a company has high Lean 4.0 level. Moreover, if the company adopt a repetitive strategy, the probability of having high Lean 4.0 level is even higher. The same pattern of increase is also observed in Production Strategy, demonstrating that the latter and Lean 4.0 are conditionally dependent given the Operational Performances. Through *equation 22*, a positive synergy between Lean 4.0

and Production Strategy is proved unveiling that a company with a repetitive Production Strategy and a high level of Lean 4.0 implementation is more likely to obtain better Operational Performances. The faithful of findings was evaluated performing a sensitive analysis changing the cut-off value between the range of data gathered. Results prove that the positive product synergy holds for the whole range, giving robustness to the analysis. Accordingly, as shown in the interaction plot (*figure 27*), the increase in company's results, as Lean 4.0 is increased from low to high, is much higher when Production Strategy is repetitive compared to non repetitive Production Strategy, unveiling the relevance of the two factors. However, given the small sample size, it is not possible to perform other statistical analyses in order to further investigate this interrelation. Nevertheless, as Birkie (2016) supports in his study, the positive gradient is a clear indication that trade-off is not the dominant relation (i.e. synergy is demonstrated).

To summarize, the analysis started by investigating, through a survey-based dataset, the relationship between Lean Manufacturing and Industry 4.0. However, given the partiality of Production Strategy information in the survey, the analysis performed, with the aim of inspecting the role of the latter in regulating the impact of Lean 4.0 on Operational Performances, only suggests a possible relationship between Lean 4.0 and Production Strategy. To closely inquire the aforementioned topics and to better understand the interrelation between them, semi-structured interviews were conducted. Interviews proved the relationship between Lean Manufacturing and Industry 4.0 unveiling a positive product synergy between Production Strategy and Lean 4.0 in increasing Operational Performances.

7. DISCUSSION

This chapter is dedicated to discuss the already presented analysis and its related findings. In particular, study limitations are disclosed in *paragraph 7.1 Limitations* in order to provide, in *paragraph 7.2 Future Developments,* some suggestions and inputs for further future researches.

7.1 LIMITATIONS

Despite the original contribution to theory, the study presents some limitations due to the methodology adopted.

Firstly, survey and interviews both present criticalities (L.M. Dooley, 2002), but advantages of one approach can be used to solve disadvantages of the other (B. Akbayrak, 2000). Interviews can not be used as theory-building methodology but can provide valuable insights that can be adopted in quantitative analysis. Indeed, the small sample of interviewees did not allow us to perform sophisticated statistical analyses which could unveil more insightful findings. However, data enables the identification of positive synergies among variables which still provide meaningful results independently by the sample-size.

Secondly, the study is limited to Italian manufacturing enterprises. It is not excluded that, analysing Lean 4.0 implementation in other countries, interrelation among variables could change or be influenced by national Lean culture and national economies (Kull et al. 2014). Although, in *paragraph 5.3 Contextual Factors Analysis*, was verified that contextual factors do not impact on Lean 4.0 implementation, different countries may have different readiness to accept new techniques and approaches (A. F. Martins et al. 2015).

Thirdly, Lean Manufacturing’s underlying elements refer only to inter-related and internally consistent practices. According to Shah and Ward (2003), practices related to suppliers and customers management were not considered in building Lean bundles. This choice limits the study to the management of internal manufacturing operations and not of the whole supply chain. Consequently, despite internal oriented lean bundles are well analysed, supplier and demand variability aspects are not fully captured.

Fourthly, respondents of the survey are Lean experts, which do not imply that they have also a deeply knowledge about Industry 4.0 topic. In fact, while a lot of Lean's certifications exists as proof of the consciousness about the theme, regarding Industry 4.0 there is still a lack of certifications in worldwide panorama. This means that answers to the questions related to Lean Manufacturing bundles could be more accurate than the ones related to Industry 4.0 technologies. A direct discussion with respondents through semi-structured interviews could partially solve this problem thanks to a wider explanation of the technologies considered. Nevertheless, the analysis still suffered from subjectivity of answers. Furthermore, data collection significantly relies on the perceptions of a reduced number of interviewed key respondents, hence their subjectivity may represent another potential source of bias.

However, these limitations do not condition the faithful of the study and, on the contrary, given the wide field of the analysis, leave to practitioners and researchers the possibility to complete and develop it.

7.2 FUTURE DEVELOPMENTS

Future researches, by solving the aforementioned limitations of the analysis, can develop the study by adding solidity and robustness.

Firstly, future researches with larger sample sizes can be used to further investigate the findings. This may also help to improve the partially addressed interaction of Lean 4.0 and Production Strategy in a better way. By increasing the dataset-sample, the degree of freedom increases enabling further researches to perform more sophisticated multivariate data analysis techniques like structural equation modelling (e.g. SEM), which could unveil more insightful results. Such an analysis can reinforce the interrelation highlighted in this study and analyse the possible moderating effect of Production Strategy for Lean 4.0 and Operational Performances.

Secondly, with the increase of Industry 4.0 adoption, future researches could emphasize in a more assertive way the interrelation between Lean 4.0 and Production Strategy in increasing Operational Performances.

Thirdly, the geographical limitation can be extended to the European focus in which a different concentration of Lean Manufacturing and Industry 4.0 companies can unveil a different degree of interrelation between the two approaches and company's Production Strategy.

Fourthly, since this study examined the combined effect of the integrated implementation of Lean Manufacturing and Industry 4.0, Lean 4.0 construct was built considering that the two underlying elements have the same impact in defining the level of implementation of this variable. Further inquiries (i.e. regression analysis) can be performed in order to understand the weight of Lean Manufacturing and Industry 4.0 in regulating Lean 4.0 implementation level. In other words, using a weighted average of relevant factors, the study can build a more reliable response variable and favour the faithful of the analysis.

Finally, even if the chi-squared analysis indicates that contextual factors do not have an impact on company's Operational Performances, and that the positive relation between Lean Manufacturing and Industry 4.0 may overcome the effects of these contextual factors, the heterogeneity of the sample could represent a limitation to the analysis. For that reason, the effects of contextual factors on Lean 4.0 can be deeper investigated with larger study samples, investigating, in particular, the possible effect of company's size and industry and identifying the possible presence of further relevant variables that can affect Lean 4.0 implementation.

In conclusion, future researches can help to develop this study with two main aims: on one hand, enlarging the dataset sample in order to obtain insightful results through more sophisticated multivariate data analysis, on the other hand, wider investigating the construction of Lean 4.0 index and the effect of contextual factors.

8. REFERENCES

Shah R., Ward P. T. (2007), *Defining and developing measures of lean production*, Journal of Operations Management 25 785–805

Shah R., Ward P.T. (2003), *Lean Manufacturing: context, practice bundles, and performance*, Journal of Operations Management

Birkie S. E. (2016), *Operational resilience and lean: in search of synergies and trade-offs*, Journal of Manufacturing Technology Management

Soriano-Meier H., Forrester P. L. (2002), *A model for evaluating the degree of leanness of manufacturing firms, Integrating Manufacturing Systems*, 13/2 104-109

Portioli-Staudacher A., Tantardini M. (2011), *A Lean based ORR system for non-repetitive manufacturing*, International Journal of Production Research 50(12):3257-3273

Rossini M., Costa F., Tortorella G. L., Portioli-Staudacher A. (2019), *The interrelation between Industry 4.0 and lean production: an empirical study on European manufacturers*, The International Journal of Advanced Manufacturing Technology

Akbayrak B. (2000), *A comparison of two data collecting methods: interviews and questionnaires*, Hacettepe Üniversitesi Eğitim Fakültesi Dergisi 18: 1 - 10.

Kull T. J., Yan T., Liu Z., Wacker J. G. (2014), *The moderation of lean manufacturing effectiveness by dimensions of national culture: testing practice-culture congruence hypotheses*, International Journal of Production Economics 153, 1-12.

Mayr A., Weigelt M., Kuhl A., Grimm S., Erll A., Potzel M., Franke J. (2018), *Lean 4.0 - A conceptual conjunction of lean management and Industry 4.0*, 51st CIRP Conference on Manufacturing Systems

Cifone F. D., Hoberg K., Holweg M., Portioli-Staudacher A. (2019), *Lean 4.0: How can digital technologies support lean practices?*, Politecnico di Milano, Milano, Italy

Marodin G., Frank A., Tortorella G., Saurin T. (2016), *Contextual factors and lean production implementation in the Brazilian automotive supply chai*n, Supply Chain Management: An International Journal 21(4):417–432

Pero M., Cannas V. G., Pozzi R., Rossi T. (2018), *An empirical application of lean management techniques to support ETO design and production planning*, IFAC PapersOnLine 51-11, 134-139

Ohno T. (1988), *Toyota Production System: Beyond Large-Scale Production*, Productivity Press, 1988, ISBN 091529914

Furlan A., Vinelli A., Dal Pont G. (2011), *Complementarity and lean manufacturing bundles: an empirical analysis*, International Journal of Operations and Production Management, Vol. 31, n. 8, pp. 835-850

Matt D.T., Rauch E. (2014), *Implementing Lean in Engineer-to-Order Manufacturing: Experiences from a ETO Manufacturer*, Handbook of Research on Design and Management of Lean Production Systems

Mann C., Stewart F. (2000), *Internet communication and qualitative research: A Handbook for Researching Online*, London: SAGE Publications.

Cohen L., Manion L. (1994), *Research Methods in Education*, Routledge

Rudberg, M. and Wikner, J. (2004), *Mass customization in terms of the customer order decoupling point*, Production Planning & Control Vol. 15 No. 4, S. 445–458

Aazam M., Hung P. P., Huh E. N. (2014), *Cloud of Things: Integrating Internet of Things with Cloud Computing and the Issues Involved*, Proceedings of International Bhurban Conference on Applied Sciences & Technology

Bogoviz A. V., Osipov V. S., Chistyakova M. K., Borisov M.Y. (2018), *Comparative Analysis of Formation of Industry 4.0 in Developed and Developing Countries*, Industry 4.0: Industrial Revolution of the 21st Century

Romero D., Flores M., Herrera M., Resendez H. (2019), *Five Management Pillars for Digital Transformation Integrating the Lean Thinking Philosophy*, Conference: 25th International ICE-Conference on Engineering, Technology and Innovation

Talab A. H., Solaimani S., van der Rhee B. (2019), *An integrative view on Lean innovation management*, Journal of Business Research

Martins L. M., Costa Affonso M., Tamayo S., Lamouri S., Baldy Ngayo C. (2015), *Relationships between national culture and Lean Management: a literature Review*, 2015 International Conference on Industrial Engineering and Systems Management (IESM)

Belli L., Davoli L., Medioli A., Marchini P. L., Ferrari G. (2019), *Toward Industry 4.0 With IoT: Optimizing Business Processes in an Evolving Manufacturing Factory*, Technology Report

Ketteler D., König C. (2017), *Lean 4.0 – Schlank durch Digitalisierung*, Frankfurt am Main, Germany: BearingPoint GmbH

Huber W. (2016), *Industrie 4.0 in der Automobilproduktion: Ein Praxisbuch*, Wiesbaden, Germany: Springer Vieweg

Künzel H. (2016), *Erfolgsfaktor Lean Management 2.0: Wettbewerbsfähige Verschlankung auf nachhaltige und kundenorientierte Weise*, Berlin/Heidelberg, Germany: Springer Gabler

Dooley L. M. (2002), *Case Study Research and Theory Building*, Advances in Developing Human Resources

Knetsch J. L. (1994), *Environmental Valuation: Some Problems of Wrong Questions and Misleading Answers*, Environmental Values 3

Nyhuis P., Schmidt M., Quirico M. (2017), *Mythos PPS 4.0*, Handbuch Industrie 4.0: Geschäftsmodelle, Prozesse, Technik, G. Reinhart, Ed. München, Germany: Hanser,

McNaught K., Chan, A. (2011), *Bayesian networks in manufacturing*, Journal of Manufacturing Technology Management

Badurdeen F., Shuaib M., Wijekoon K., Brown A., Faulkner W., Amundson J., Jawahir I.S., Goldsby T.J., Iyengar D., Boden B. (2014), *Quantitative modeling and analysis of supply chain risks using Bayesian theory*, Journal of Manufacturing Technology Management

Wellman M.P., Henrion M. (1993), *Explaining 'Explaining Away'*, IEEE Transactions on Pattern Analysis and Machine Intelligence

Su C., Andrew A., Karagas M.R., Borsuk M.E. (2013), *Using Bayesian networks to discover relations between genes, environment, and disease*, Biodata Mining

Wagner T., Herrmann C., Thiede S. (2017) *Industry 4.0 Impacts on Lean Production Systems*, Procedia CIRP, vol. 63, pp. 125–131

B. Pokorni, Schlund S., Findeisen S., Tomm A., Euper D., Mehl D, Brehm N., Ahmad D., Ohlhausen P., Palm D. (2017), *Production assessment 4.0*, ZWF Zeitschrift für wirtschaftlichen Fabrikbetrieb, vol. 112, no. 1-2, pp. 20–24

Mrugalska B., Wyrwicka M. K. (2017), *Towards Lean Production in Industry 4.0*, Procedia Engineering, vol. 182, pp. 466–473,

Levene H. (1960), *Contributions to Probability and Statistics*, Stanford University Press, CA.

Brown M. B., Forsythe A. B. (1974), *Robust tests for the equality of variance*, Journal of the American Statistical Association, 69, 364-367

Opdenakker R. (2006), *Advantages and Disadvantages of Four Interview Techniques in Qualitative Research*, Forum: Qualitative Social Research, Volume 7, No. 4, Art. 11 September 2006

Wengraf T. (2001), *Qualitative research interviewing*, SAGE Publications, pag.194

Gordon R.L. (1975), *Interviewing: Strategy, Techniques and Tactics*, Dorsey Press, Illinois.

Austin E.K. (1981), *Guidelines for the Developing of Continuing Education offerings for Nurses*, Appleton-Century-Crofts, New York.

Barriball L., White A. (1993), *Collecting data using a semi-structured interview: a discussion paper*, Journal of Advanced Nursing

Cormack D.F.S. (1984), *An overview of the research process in nursing*, The Research Process in Nursing, Blackwell Scientific Publications, Oxford

Bailey K.D. (1987), *Methods of Social Research*, 3rd edn, The FreePress, New York

Treece E. W., Treece J. W. (1986), *Elements of Research in Nursing*, 4th edn, C.V. Mosby, St Louis

Mann P.H. (1985), *Methods of Social Investigation*, Basil Blackwell, Oxford

Denzin N.K. (1989), *The Research Act: A Theoretical Introduction to Sociological Methods*, 3rd edn, Prentice Hall, Englewood Chffs, New Jersey.

Nay-Brock R.M. (1984), *A comparison of the questionnaire and interviewing techniques in the collection of sociological data*, Australian Journal of Advanced Nursing 2(1), 14-23

Blair J., Presser S. (1989), *Survey procedures for conducting cognitive interviews to pretest questionnaires: a review of theory and practice*, Survey Research Center, University of Maryland

Williamson Y.M. (1981), *Research Methodology and Its Application to Nursing*, John Wiley and Sons, New York.

Dooley L. M. (2002), *Advances in Developing Human Resources Vol. 4*, No. 3 August 2002 335-354, Copyright 2002 Sage Publications

Yin R. K. (1994), *Case study research: Design and methods*, Applied Social Research Methods Series, 5, 2nd ed., Thousand Oaks, CA: Sage

Torraco R. J. (1997), *Theory building research methods*, R. A. Swanson & E. F. Holton (Eds.), Human resource development research handbook: Linking research and practice (pp. 114-138). San Francisco: Berrett-Kohler.

Eisenhardt E. M. (1989), *Building theories from case study research*, Academy of Management Review

Gall M. D., Borg W. R., Gall J. P. (1996), *Educational research: An introduction*, 6th ed., White Plains, NY: Longman

Clifford N., French S., Valentine G. (2010), *Key methods in Geography*, Sage Pubblication

Stăncioiu A. (2017), *The fourth industrial revolution "Industry 4.0"*, Fiabilitate si Durabilitate -Fiability & Durability, No 1/ 2017 Editura "Academica Brâncuşi", Târgu Jiu, ISSN 1844 –640X

Anderl R. (2014), *Industrie 4.0 - Advanced Engineering of Smart Products and Smart Production*, 19th International Seminar on High Technology, Piracicaba, Brasil

Fauzi O., Bahrin M. A. K., Azli N. H. N., Talib M. F. (2016), *Industry 4.0: A review on industrial automation and robotic*, Journal Teknologi, Vol. 78, No. 6-13, 2016, pp. 137–143

Batchkova I. A., Popov G.T., Ivanova T. A., Belev Y.A. (2018), *Assessment of Readiness for "Industry 4.0",* University of Chemical Technology and Metallurgy, Sofia, Bulgaria

Zheng P., Wang H., Sang Z., Zhong R. Y., Liu Y., Liu C., Mubarok K., Yu S., Xu X. (2018), *Smart manufacturing systems for Industry 4.0: Conceptual framework, scenarios, and future perspectives*, Frontiers of Mechanical Engineering, Volume 13, Issue 2, pp 137–150

Podrecca M, Culot G., Fattori F., Sartor M. (2019), *Addressing Industry 4.0 Cybersecurity Challenges*, IEEE Engineering Management Review 47(3):79-86

Anvari A., Ismail Y., Hojjati S. M. H. (2011), *A Study on Total Quality Management and Lean Manufacturing: Through Lean Thinking Approach*, World Applied Sciences Journal 12(9)

Li S., Subba R. S., Ragu-Nathan T.S., Ragu-Nathan B. (2005), *Development and validation of a measurement instrument for studying supply chain management practices*, Journal of Operations Management 23 (6), 618–641

Pine B.J. (1993), *Mass Customization: The New Frontier in Business Competition*, Harvard Business Press, Cambridge, MA, 1993

Wang B., Zhao J., Wan Z., Ma J., Li H., Ma J. (2016), *Lean Intelligent Production System and Value Stream Practice*, 2016 3rd International Conference on Economics and Management (ICEM 2016), ISBN: 978-1-60595-368-7

Metternich J., Müller M., Meudt T., Schaede C. (2017), *Lean 4.0 - zwischen Widerspruch und Vision*, ZWF Zeitschrift für wirtschaftlichen Fabrikbetrieb, vol. 112, no. 5, pp. 346–348

Quasdorff O., Bracht U. (2016), *Die Lean Factory*, ZWF Zeitschrift für wirtschaftlichen Fabrikbetrieb, vol. 111, no. 12, pp. 843–846

Bick W. (2014), *Warum Industrie 4.0 und Lean zwingend zusammengehören*, VDI-Z, vol. 156, no. 11, pp. 46-47

Zühlke D. (2010), *SmartFactory—Towards a factory-of-things*, Annual Reviews in Control, vol. 34, no. 1, pp. 129–138

Rüttimann B. G., Stöckli M. T. (2016), *Lean and Industry 4.0—Twins, Partners, or Contenders? A Due Clarification Regarding the Supposed Clash of Two Production Systems*, Journal of Service Science and Management, vol. 9, no. 6, pp. 485–500

Kolberg D., Zühlke D. (2015), *Lean Automation enabled by Industry 4.0 Technologies*, IFAC-PapersOnLine, vol. 48, no. 3, pp. 1870–1875

Spath D., Ganschar O., Gerlach S., Hämmerle M., Krause T., Schlund S. (2013), *Produktionsarbeit der Zukunft – Industrie 4.0*, Stuttgart, Germany: Fraunhofer Verlag

Sanders A. Elangeswaran C., Wulfsberg J. (2016), *Industry 4.0 implies lean manufacturing: Research activities in industry 4.0 function as enablers for lean manufacturing*, Journal of Industrial Engineering and Management, vol. 9, no. 3, pp. 811

Vogel-Heuser B., Bauernhansl T., Ten Hompel M. (2017), *Handbuch Industrie 4.0,* Bd.4: Allgemeine Grundlagen, 2nd ed. Berlin/Heidelberg, Germany: Springer Vieweg

Pool A., Wijngaard J., Van der Zee D. (2011), *Lean planning in the semi-process industry, a case study*, International Journal of Production Economics, Vol. 131 No. 1, pp. 194-203

Abdulmalek F.A., Rajgopal J. (2007), *Analyzing the benefits of lean manufacturing and value stream mapping via simulation: a process sector case study*, International Journal of Production Economics, Vol. 107 No. 1, pp. 223-236

Raghavan V., A., Yoon S., Srihari K. (2014), *Lean transformation in a high mix low volume electronics assembly environment*, International Journal of Lean Six Sigma, Vol. 5 No. 4

Jina J., Bhattacharya A. K., Walton D. (1997), *Applying lean principles for high product variety and low volumes: some issues and propositions*, Logistics Information Management Volume 10 Number1

Ehrhardt R. (1997), *A model of JIT make-to-stock inventory with stochastic demand*, Journal of the Operational Research Society, Volume 48, Issue 10, pp 1013–1021

Webster S., Weng Z. K. (2001), *Improving repetitive manufacturing systems: Model and insights*, Operations Research, 49(1), pp 99-106

Matzka J., Di Mascolo M., Furmans K. (2012), *Buffer sizing of a heijunka kanban system*, Journal Intelligent Manufacturing 23(1):49–60

Bilberg A, Hadar R. (2012), *Manufacturing Concepts of the Future – Upcoming Technologies Solving Upcoming Challenges*, Enabling Manufacturing Competitiveness and Economic Sustainability

Bonekamp L., Sure M. (2015), *Consequences of Industry 4.0 on Human Labour and Work Organisation*, Engineering Journal

Hodgkinson G. P., Ford J. K. (2014), "*Narrative, meta-analytic, and systematic reviews: What are the differences and why do they matter?*", Journal of Organizational Behavior 35(Special Issue):S1-S5

Rousseau D. M. (2012), *The Oxford Handbook of Evidence-Based Management*, New York: Oxford University Press

Rousseau D. M., Manning J., Denyer D. (2008), *Evidence in management and organizational science: Assembling the field's full weight of scientific knowledge through reflective reviews*, Annals of the Academy of Management, Vol. 2, No. 1, 475–515

Zhou K., Liu T., Zhou L. (2015), *Industry 4.0: Towards Future Industrial Opportunities and Challenges*, Published in 12th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD)

Tabachnick B., Fidell L. (2013), *Using multivariate statistics*, Pearson, Upper Saddle River, NJ

DeFranzo S. (2014), *Advantages and Disadvantages of Face-to-Face Data Collection*, Available at https://www.snapsurveys.com/blog/advantages-disadvantages-facetoface-data-collection/

Soy S. K. (1996), *The case study as a research method*, University of Texas, Graduate School of Library and Information Science Web

Cybertec (2018), *La pianificazione della produzione 4.0. Gestire la mass production*

Melchert E. R., de Mesquita M. A., Francischini P. G. (2006), *Lean manufacturing on make-to-order suppliers: a case study*, XII ICIEOM, Fortaleza, CE, Brasil

Commission Recommendation of 6 May 2003 concerning the definition of micro, small and medium-sized enterprises, notified under document number C (2003) 1422, Official Journal of the European Commission

2018 SBA Fact Sheet, European Commission, Italy

Okoli C., Schabram K. (2010), *A guide to conducting a systematic literature review of information systems research*, Work Pap Inf Syst, 10 (2010), pp. 1-51

Synchrono manufacturing software (2016), *Demand driven manufacturing in the Engineer-to-Order space.*

Serlenga P., Leppavuori I., and Moraes I. (2019), *Digital lean: a guide to manufacturing excellence*, Bain & Company.

Gerbert P., Lorenz M., Russmann M., Waldner M., Justus J., Engel P, Harnisch M. (2015), *Industry 4.0: the future of productivity and growth in manufacturing industry*, The Boston Consulting Group

Albiani C. (2017), *Lean management e industria 4.0*, Digital Innovation Hub.

Kupper D., Kuhlmann K., Kocher S., Dauner T., Burggraf, P. (2016), *The factory of the future,* The Boston Consulting Group

Kupper D., Heidermann A., Strohle J., Spindelndreier D., Knizek C.. (2017), *When lean meets industry 4.0,* The Boston Consulting Group

Staiano A. (2018), *Lean production e industry 4.0: la combinazione vincente per una azienda competitiva*, Ernst & Young

Faioli S., Bellini C. (2017), *L'Industria 4.0 e le nuove frontiere del Lean*, McKinsey

Scaramuzzi V., Casale M., Tirelli M. (2018), *Italia 4.0: siamo pronti?,* Deloitte

Osservatori Digital Innovation (2019), "Industria 4.0: la rivoluzione si fa con le persone!"

9. APPENDIX

ANNEX A - Technologies bundles' reports review

In *appendix table 1* is presented the information about the 40 technological and consultancy reports analysed in order to identify the main cited Industry 4.0 bundles.

	DOCUMENT TITLE	AUTHOR	REFERENCE COMPANY OR ORGANIZATION	YEAR
1	Time to accelerate in the race toward industry 4.0	M. Russmann, M. Lorenz, P. Gerbert, M. Waldner, J. Justus, P. Engel, A. Bause	Boston Consulting Group (BCG)	2016
2	Industry 4.0: The Capgemini Consulting View	J. Bechtold, C. Lauenstein, A. Kern, L. Bernhofer	Capgemini	2014
3	Industry 4.0: challenges and solutions for the digital transformation and use of exponential technologies	D. Schlaepter, M. Koch, P. Merkofer	Deloitte	2015
4	Industry 4.0: The future of productivity and Growth in Manufacturing Industries	M. Russmann, M. Lorenz, P. Gerbert, M. Waldner, J. Justus, P. Engel, M. Harnisch	Boston Consulting Group (BCG)	2015
5	Industry 4.0: How to navigate digitalization of the manufacturing sector	D. Wee, R. Kelly, J. Cattell, M. Breunig	McKinsey	2015
6	Industry 4.0: Digitalization for productivity and growth	European Parliament Team	European Parliament	2015
7	Investimenti, produttività e innovazione	European Parliament and Confindustria Teams	European Parliament and Confindustria	2016

8	Industry 4.0: Building the digital enterprise	R. Geissbauer, J. Vedso, S. Schrauf	PricewaterhouseCooper (PWC)	2016
9	Crafting the future: a roadmap for industry 4.0 in Mexico	M. Rios, O. Correa, E. Acuna, A. Gonzalez	Mexican Ministry of Economy	2015
10	Information economy report	A. Guterres, M. Kituyi	United Nations Conference on Trade and Development (UNICTAD)	2017
11	Redefine your company based on the company you keep	P. Daugherty	Accenture	2018
12	Shaping the Future of Construction: Breakthrough in Mindset and Technology	P. De Almeida, M. Z. Solas	World Economic Forum and BCG	2018
13	Industry 4.0 and Smart manufacturing market report 2018-2023	M. Wopata, J. Rickert, K. Lueth, P. Scully	IoT Analytics	2018
14	Planning for the warehouse of the future	Swisslog Team	Swisslog	2018
15	The post-digital era is upon us: are you ready for what's next?	P. Daugherty	Accenture	2019
16	Top 50 emerging technologies: growth opportunities of strategic imperative	R. Kumar, L. O'Connor, A. S, A. Shukla	Frost & Sullivan	2016
17	Emerging technologies: changing how we live, work and play	M. Makhija	Ernst & Young	2019
18	Industry 4.0 for the future of manufacturing in the EU	M. Tiraboschi	European Commission	2016

19	A reality check for today's C-suite on industry 4.0	P. Harris, M. Hendricks, E. Logan, P. Juras	KPMG	2018
20	Industry 4.0 – opportunities and challenges for SMEs in the North Sea Region	Interreg North Sea Region Team	Interreg North Sea Region	2018
21	HFS Blueprint guide: Industry 4.0 services	P. Jain, T. Mondal	Accenture	2017
22	Industry 4.0: engaging with disruption	N. Bhatt	Ernst & Young	2018
23	Industry 4.0: Go fourth insights into the next industrial revolution	D. Peters	Irwin Mitchell	2018
24	Industry 4.0 and ICS sector report	European Cyber Security Organisation (ECSO) Team	European Cyber Security Organisation (ECSO)	2018
25	Industry 4.0: India Inc. gearing up for change	KPMG Team	KPMG	2018
26	INDUSTRY 4.0: The new industrial revolution: How Europe will succeed	M. Blanchet, T. Rinn, G. V. Thaden, G. De Thieulloy	Roland Berger	2014
27	*India's Readiness for Industry 4.0*	M.M. Singh, S. Mehra	Grant Thornton	2017
28	Industry 4.0: A new industrial model	Dr. Philipp Hoff, Dr k. S. Schober	Roland Berger	2016
29	Industry X.0 Combine and conquer	D.Abood, A. Quilligan	Accenture	2017
30	The 2018 World Manufacturing Forum Report	Editorial Board	World Manufacturing Forum	2018
31	Industry 4.0: Making your business more competitive	team of senior experts at CGI	CGI Group	2017

32	Man and Machine in Industry 4.0	M.Lorenz, M. Rubmann, R.Stack, K. L. Lueth, M. Bolle	Boston Consulting Group (BCG)	2015
33	INDUSTRY 4.0 OPPORTUNITIES BEHIND THE CHALLENGE	Dr. Mirjana Stankovic, Ravi Gupta, Dr. Juan E. Figueroa	United Nations Industrial Developmnet Organization (UNIDO)	2017
34	INDUSTRY 4WRD: National policy on industry 4.0	Ministry of International Trade and Industry Team	Ministry of International Trade and Industry	2018
35	Readiness for the Future of Production Report 2018	C. Martin, R. Samans, F. Betti, M. Drzeniek-Hanouz, T. Geiger	World Economic Forum and A.T. Kearney	2018
36	Accelerating clean energy through industry 4.0	T. Pillay, C. Beier, G. Frietzsche, K. Pougel, F. Takama, T. The, K. Bobashev	United Nations Industrial Developmnet Organization (UNIDO)	2017
37	SAP Leonardo Digital manufacturing	J. Tulusan, P. Hidvegi	SAP Leonardo	2017
38	Unlocking Industry 4.0 Potential	E. Tidhar, S. Keynan, J. Siegman, D. Paikowsky	Deloitte	2018
39	Industry 4.0 as an evolution, not a revolution	N. Enose, S. Ramachandran	Infosys	2019
40	2019 Manufacturing Trends Report	Microsoft Team	Microsoft	2018

Appendix Table 1: Industry 4.0 reports information

ANNEX B - Interviews structure

In this section is presented the format used to conduct interviews. Considering that the technique used was the one of semi-structured interviews, the structure of the questions could variate in relation to the answers given by respondent.

i. **Company's Profile**
   - Which is your role inside the plant?
   - Do you have any Lean Manufacturing certification (i.e. Green Belt or Black Belt)?
   - How many people do you coordinate?
   - Have you ever heard about the term Lean 4.0?

ii. **Contextual Factors**
   - Which is the industry in which your plant works?
   - How many employees work in your plant?
   - Which is the age of your plant?

iii. **Production Strategy**
   - Do you produce customized products or standard products?
   - Do you have a repetitive production or a non-repetitive production?
   - Do you work with an inventory refill strategy or do you produce when an order arrives?

iv. **Lean Bundles Implementation**
   - For how many years have you implemented Lean Manufacturing?
   - Which are the reasons beyond the introduction of Lean Manufacturing practices in your plant?
   - In a scale from 0 (not implemented) to 5 (fully implemented) which is the level of implementation of the following Lean bundles?
     - Just in Time (JIT);
     - Total Quality Management (TQM);
     - Total Productive Maintenance (TPM);
     - Human Resource Management (HRM).

v. **Industry 4.0 Bundles Implementation**
   - Have you implemented Industry 4.0 tools after the introduction of Lean Manufacturing practices?

- Which are the reasons beyond the introduction of new digital technologies in your plant?
- For how many years have you implemented Industry 4.0?
- In a scale from 0 (not implemented) to 5 (fully implemented) which is the level of implementation of the following Industry 4.0 bundles?
    - Advanced Analytics
    - Internet of Things (IoT) and Cloud Computing;
    - Autonomous Vehicles;
    - Digital Manufacturing;
    - Robotics;
    - Virtual and Augmented Reality.

vi. Operational Performance

- Have you implemented Industry 4.0 tools in order to overcome to some Lean Manufacturing limitations? Or the implementation of Industry 4.0 was independent from Lean Manufacturing?
- Which are the performances that have been influenced by the combined implementation of Lean Manufacturing and Industry 4.0?
- Considering the impact of Industry 4.0 tools, applied to Lean Manufacturing processes, on performances, how much your performances are changed? (stable, increased from 1% to 20%, increased from 21% to 40%, increased more than 40%, decreased from 1% to 20%, decreased from 21% to 40%, decreased more than 40%)
    - Finished products first-pass quality;
    - Scrap and rework cost;
    - Productivity, defined as volume per year;
    - Per unit manufacturing cost excluding purchase material;
    - Customer Lead Time;
    - Manufacturing Cycle Time;
    - Total inventories monetary value;
    - Set-up time.

ANNEX C – Indexes building

In this section is displayed the methodology used to build Lean Manufacturing, Industry 4.0 and Lean 4.0 indexes.

As explained in *paragraph 4.4. Indexes Building*, according to the model developed by Soriano-Meier and Forrester (2002), Lean Manufacturing commitment level for each plant can be calculated with the following equation:

$$L_i = \frac{JIT_i + TQM_i + TPM_i + HRM_i}{4}$$

Where:

$$i = plant$$

Considering responses provided by Respondent N.1, his Lean Manufacturing commitment level is computed as:

$$L_1 = \frac{JIT_1 + TQM_1 + TPM_1 + HRM_1}{4} = \frac{1 + 1 + 1 + 3}{4} = 1{,}5$$

The same approach was used to compute the Industry 4.0 commitment level:

$$D_i = \frac{AA_i + IoT_i + AV_i + DM_i + R_i + VAR_i}{6}$$

Where:

$$i = plant$$

Considering responses provided by Respondent N.1, his Industry 4.0 commitment level is computed as:

$$D_1 = \frac{AA_1 + IoT_1 + AV_1 + DM_1 + R_1 + VAR_1}{6} = \frac{2 + 1 + 0 + 1 + 1 + 0}{6} = 0{,}83$$

Finally, according to the model developed by Soriano-Meier and Forrester (2002), Lean 4.0 level for each plant can be calculated with the following equation:

$$L4.0_i = \frac{L_i + D_i}{2}$$

Where:

$$i = plant$$

Considering our example, the Lean 4.0 level of Respondent N.1 is:

$$L4.0_1 = \frac{L_1 + D_1}{2} = \frac{1{,}5 + 0{,}83}{2} = 1{,}17$$

ANNEX D – Survey-based performance changes

This section presents descriptive representations of the survey-based answers about changes in performances due to the application of Industry 4.0 tools to Lean Manufacturing processes. The percentages in *appendix tables 2, 3, 4, 5, 6, 7, 8* and *9* were used to build *table 19* and *table 20* in *paragraph 5.1 Preliminary Survey Analysis*.

The first metric asked was "finished product first pass quality" in 65% of the cases was improved, in particular 34% increases the quality in range of 1-20%, 10% of companies from 20% to 40% and 20% of the sample more than 40%.

	Percentage
Decreased more than 40%	0%
Decreased 20 - 40%	0%
Decreased 1 - 20%	3%
Stayed the same	32%
Increased 1 - 20%	34%
Increased 21 - 40%	10%
Increased more than 40%	20%

Appendix Table 2:Finished products first-pass quality

The second metric analysed was "scrap and rework costs". 39% of plants saved costs in a range of 1-20 per-cent, while 16% of plants suffered from an increased in costs, respectively 14% increased costs up to 20% while 2% in a range of 21-40 per cent.

	Percentage
Decreased more than 40%	0%
Decreased 20 - 40%	6%
Decreased 1 - 20%	39%
Stayed the same	39%
Increased 1 - 20%	14%
Increased 21 - 40%	2%
Increased more than 40%	0%

Appendix Table 3: Scrap and rework costs

Considering "productivity" measure, only 4% of plant has registered a decreased in volume since the introduction of Lean 4.0. The majority of plants (i.e. 67%), instead, increased their volumes. A significant portion of the sample (i.e. 20%) benefits from an huge increase which means a change in performances higher than 20%.

	Percentage
Decreased more than 40%	0%
Decreased 20 - 40%	0%
Decreased 1 - 20%	4%
Stayed the same	30%
Increased 1 - 20%	47%
Increased 21 - 40%	18%
Increased more than 40%	2%

Appendix Table 4: Productivity, defined as volume per year

The fifth metric asked in the questionnaire was "per unit manufacturing cost" and most of the plants have registered no changes in their performances (i.e. 40%). The sample does not present a clear pattern of increase or decrease in the specific performance since 32% of plants decreased their costs, while on the opposite 28% of plants suffered from higher costs. This measure has to be further investigated, since in the second analysis through direct-interviews, some respondent highlight that the increase seen in manufacturing cost was due to the more reliable and punctual measure which, thanks to the introduction of Lean 4.0, evidence source of cost previously not considered.

	Percentage
Decreased more than 40%	0%
Decreased 20 - 40%	1%
Decreased 1 - 20%	31%
Stayed the same	40%
Increased 1 - 20%	26%
Increased 21 - 40%	2%
Increased more than 40%	0%

Appendix Table 5: Per unit manufacturing cost excluding purchase material

Regarding “customer lead time” 46% of plants have decrease their lead time (respectively 39% up to 20%, while 7% in a range of 21-40 per cent) while only 13% declared to have seen a increase in their lead time. In 41% of the cases, instead, customer lead time is not affected by Lean 4.0.

	Percentage
Decreased more than 40%	0%
Decreased 20 - 40%	7%
Decreased 1 - 20%	39%
Stayed the same	41%
Increased 1 - 20%	13%
Increased 21 - 40%	0%
Increased more than 40%	0%

Appendix Table 6: Customer Lead Time

A pattern of decrease is seen in “manufacturing cycle time” since no one of the respondents have seen an increase of time in that metric. 61% of the plants, in fact, have decrease their manufacturing cycle time up to 20%, while 5% of respondents declared to have seen a huge decrease in their manufacturing cycle time (i.e. 21-40 per cent).

	Percentage
Decreased more than 40%	0%
Decreased 21 - 40%	5%
Decreased 1 - 20%	61%
Stayed the same	34%
Increased 1 - 20%	0%
Increased 21 - 40%	0%
Increased more than 40%	0%

Appendix Table 7: Manufacturing Cycle Time

Lean 4.0, considering “inventories monetary value”, in almost half of the plants (i.e. 47%) does not have bring to any change. On one hand in 32%, plants have decreased their inventory value, on the other hand 22% of plants have increase the amount of money stuck as stock.

	Percentage
Decreased more than 40%	0%
Decreased 20 - 40%	3%
Decreased 1 - 20%	29%
Stayed the same	47%
Increased 1 - 20%	21%
Increased 21 - 40%	1%
Increased more than 40%	0%

Appendix Table 8: Total inventories monetary value

The last performance investigated was “set-up time”. This performance is one of the most affected by Lean 4.0 introduction since no plants have increased their set-up time and 60% of plants decreased it. In particular, 51% of plants decreased the set-up time up to 20%, 7% in a range 21-40% and 2% of respondents even more than 40%.

	Percentage
Decreased more than 40%	2%
Decreased 20 - 40%	7%
Decreased 1 - 20%	51%
Stayed the same	40%
Increased 1 - 20%	0%
Increased 21 - 40%	0%
Increased more than 40%	0%

Appendix Table 9: Set-up time

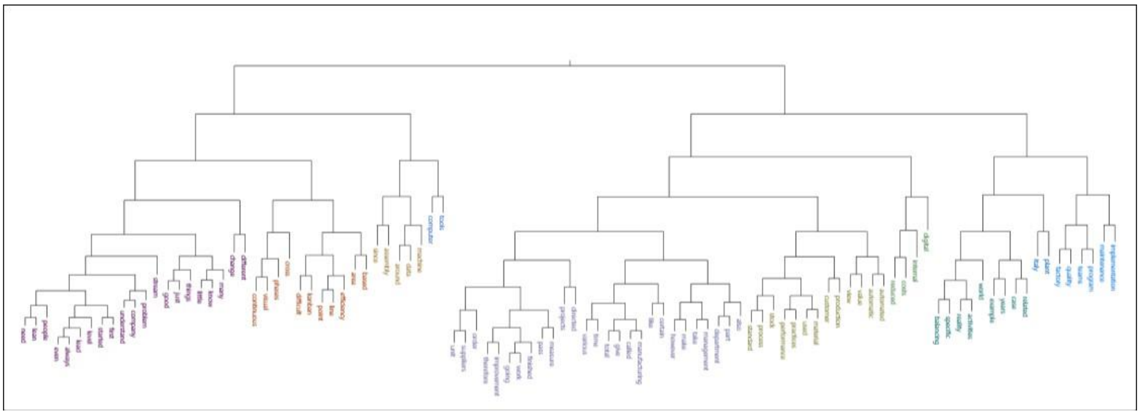
The qualitative analysis of the sample about the changes in performances described in the previous *appendix tables 2, 3, 4, 5, 6, 7, 8* and *9,* was used both to provide a descriptive analysis of the sample gathered and, in combination with the encoded value associated to each cluster (*table 16*), to compute the total value of each performance in *paragraph 5.1 Preliminary Survey Analysis*.

An illustrative example of how the total value of each performance (i.e. Y_i) was computed according to *equation 23,* is provided. For example, “finished products first-pass quality” total value was calculated as follow:

$$Y_1 = 0 \times (-3) + 0 \times (-2) + 0.03 \times (-1) + 0.32 \times 0 + 0.34 \times 1 + 0.10 \times 2 + 0.20 \times 3 = 1.12$$

ANNEX E – NVivo words' connection in interviews

In the following figure (*appendix figure 1*) is presented the analysis of words' connection performed with software NVivo:



Appendix Figure 1: Words' connection analysis