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Integrating Lean Manufacturing and Digital Technologies: A Survey of Norwegian Manufacturing Companies

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Preface

In the last semester of the Master of Science in Engineering Program at the Norwegian University of Science and Technology (NTNU), the students are required to write a master thesis. This master project was carried out in the spring semester of 2018 by stud.tech. William Wehler Knudtzon at the Department of Mechanical and Industrial Engineering as part of the 5-year master's degree program Engineering and ICT.

I would like to thank my teacher Jan Ola Strandhagen who gave me the possibility to write about this subject, and for giving informative and interesting lectures throughout my years at NTNU.

I would also like to thank my supervisor Sven-Vegard Buer. If not for his valuable help and feedback, I would not have been able to complete this thesis. He has gone out of his way to help me, I am really grateful.

Lastly, I'd like to thank my family for all the support, as well as Helene for being the best motivator during the times of writing this thesis.

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Summary

When it comes to Lean manufacturing and digital technologies, their link has been examined by several researchers. However, most of the literature are theoretical studies, and thus there is a lack of empirical studies on the subject. The main goal of this thesis was to map Norwegian manufacturers, and to measure the operational performance results of having implemented Lean manufacturing and digital technologies into the production processes. This thesis is motivated by the following research questions: 1) What is the current level of adaptation of Lean manufacturing and digital technologies among manufacturing plants in Norway? 2) How is operational performance associated with the level of Lean manufacturing implementation? 3) How is operational performance associated with the level of digital technology implementation? And 4) How is operational performance associated with the combined implementation level of both Lean manufacturing and digital technologies?

The findings from the research show that the current level of adaption of Lean manufacturing and operational performance in Norway is above average. The findings also state that both Lean manufacturing and digital technologies are positively correlated with operational performance. The findings were not conclusive on the combined implementation level of both Lean manufacturing and digital technologies.

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List of abbreviations

TPS	Toyota Production System
JIT	Just-In-Time
POM	Production and Operations Management
TPM	Total Productive Maintenance
SPC	Statistical Process Control
WIP	Work-In-Process
SMED	Single Minute Exchange of Dies
IoT	Internet of Things
CPS	Cyber-Physical Systems
MRP	Material Requirements Planning
ERP	Enterprise Resource Planning
ICT	Information and Communications Technology
DAOP	Dimensions Affecting Operational Performance
PCA	Principle Component Analysis

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1 Introduction

This chapter describes the background and the motivation behind this master thesis. The problem formulation explored, and the project scope will be determined. Then, the objectives and research questions will be presented, and finally, the structure of the thesis will be explained.

1.1 Background and motivation

Lean manufacturing principles have for a long time been hailed as a solution for improving efficiency and competitiveness in manufacturing firms (von Haartman et al., 2016). Originating from the Toyota Production System (Ohno, 1988), lean manufacturing was first introduced as a term to describe the manufacturing system used by Toyota by Krafcik (1988) after visiting more than fifty Japanese plants and finding them more efficient than their American counterparts. Shah and Ward (2007) defines Lean production as *"... an integrated socio-technical system whose main objective is to eliminate waste by concurrently reducing or minimizing supplier, customer, and internal variability."*

Traditionally, Lean manufacturing have often been viewed as independent from ICT, and sometimes ICT have been seen as a waste to be eliminated to achieve a full Lean transformation. Technology is seen as a waste, a non-value-adding activity, rather than a tool to help achieve and sustain positive change (Bell, 2006, Powell and Strandhagen, 2011). However, new digital technologies have emerged and barriers between the traditional IT and Lean manufacturing are starting to crumble. Cyber-physical systems, Internet of Things, and cloud computing are all "buzzwords" that have sprung out to light in the last decade, and researchers are finding new ways of using digital technologies to improve upon existing Lean manufacturing practices (Sanders et al., 2016).

Increased performance is arguably the main motivator behind adopting improvement programs such as Lean manufacturing and digital technology. The five basic performance objectives quality, speed, dependability, flexibility, and cost can all affect a production company's profitability and competitiveness in a market(Slack et al., 2010). Buer et al. (2018) present studies examining whether changes in the production system by integrating digital technologies affects different performance dimensions of the system. However, several of these studies only discuss and hypothesize on a conceptual level, and Buer et al. (2018) suggests that empirical studies on the performance implications of a Lean manufacturing and digital technology integration is needed. This forms the motivation behind this master project, which is to gather empirical data regarding the performance impacts of combining Lean manufacturing and digital technologies.

1.2 Problem formulation

Despite the popularity of both Lean manufacturing and digital technologies, the literature on the relationship between the two is still lacking, as illustrated by (Buer et al., 2018). The studies so far have mainly investigated this issue on a conceptual level, lacking empirical references. It is thus a need for empirical research in this area, to ensure relevancy of the findings. This master project will focus on conducting an empirical study on the performance impacts of combining Lean manufacturing and digital technologies. Using literature, hypotheses and a survey will be developed. The recipients of the survey will be Norwegian manufacturers. This will be the first large scale survey conducted in Norway regarding these issues. The survey data will be analyzed, and the results will be presented. This chapter will analyze tasks that will be performed during the master project.

Elaborate on the addressed problem and describe the scope of the project.

This relates to the start-up phase of a project and relates to issues typically treated in the pre-study report. The actual problem should be analyzed; research questions should be defined in order to get an overview of work to be performed. It is also essential to know when to perform the different tasks required to fulfill the project. Project planning is therefore also important in this phase.

Study relevant background literature and create hypotheses.

In order to develop an understanding of the main topics of the project, a literature study is required to obtain theoretical background. This could be either new information or different views on a particular topic. Using the gained information, hypotheses will be developed.

Develop and perform a survey to obtain relevant empirical data.

The obtained information will be used to develop a survey, to be sent out to Norwegian manufacturers. The point of the survey is to gain insight into the Norwegian manufacturing plants, concerning the main topics of the master project. The collected information should be logged in a proper manner, to be used in the later stages of the project.

Analyze and evaluate the data and discuss the results.

The data from the survey will be analyzed statistically and evaluated. The results will be discussed and used to check the validation of the hypotheses proposed earlier in the project.

Conclude the project with a final report.

The report will be written in parallel with the other tasks during the whole project. After all of the other tasks are completed, the report can be finalized and delivered.

1.3 Project scope

The main goal of this thesis is to map Norwegian manufacturers, and to measure the operational performance results of having implemented Lean manufacturing and digital technologies into the production processes.

1.3.1 Research Questions

Based on the main goal of the project, research questions can be defined. In every research process, well defined research questions are important. The research questions provide insight into the purpose of the study, as well as what questions the study will attempt to answer. For this project, the following research questions are proposed:

RQ1:

What is the current level of adaptation of Lean manufacturing and digital technologies among manufacturing plants in Norway?

As there is a lack of empirical data on integration of Lean manufacturing and digital technologies, the aim of this research question is to gain an overview of the status of adopted Lean manufacturing practices and digital technologies in Norwegian manufacturing companies.

RQ2:

A) How is operational performance associated with the level of Lean manufacturing implementation?

B) How is operational performance associated with the level of digital technology implementation?

C) How is operational performance associated with the combined implementation level of both Lean manufacturing and digital technologies?

There is a lot of research examining the relationship between Lean manufacturing and operational performance (Belekoukias et al., 2014, Chavez et al., 2013). However, as Buer et al. (2018) state there is a need for more empirical data regarding operational performance and digital technology, as well as combined benefits of Lean manufacturing and digital technologies.

1.4 Thesis structure

Chapter 1 Introduction	The introduction chapter presents the background and motivation of the thesis, the problem description, the thesis research questions and scope, and the structure of the thesis.
Chapter 2 Literature review	The literature review will present the relevant information regarding the thesis main topics, Lean manufacturing, digital technologies, and operational performance. Finally, the link between the three topics will be examined.
Chapter 3 Methodology	First, a general description of different research methods will be presented, followed by an argumentation for the selected research strategy this project will be applying. The next sub-chapters will describe the methods selected; literature review and data collection through a survey.
Chapter 4 Data analysis and findings	This chapter will present the data analysis and the results of the analysis. First, the sample characteristics gained from the survey will be presented. Then, the data will be examined, followed by the data analysis results. Finally, a discussion of the results will be presented.
Chapter 5 Conclusion	This chapter will conclude the master thesis, by examining the steps taken, and whether the research questions have been answered. This chapter will also include limitations of the master thesis and recommendations for further work.

2 Literature review

This chapter is a presentation of the theoretical background of the master projects topics, and will present the main theory behind Lean manufacturing, digital technologies, and operational performance. The Lean manufacturing section will include an elaboration on the six internal Lean manufacturing practices. Then, digital technology will be explained, followed by a section on operational performance. Finally, the last section will examine the link between Lean manufacturing, digital technology, and operational performance.

2.1 Lean manufacturing

Lean production principles have for a long time been hailed as a solution for improving efficiency and competitiveness in manufacturing firms (von Haartman et al., 2016). The principles originate from the Toyota Production System (TPS), where the primary goal is cost reduction and waste elimination. Waste in this context refers to overproduction, waiting time, inventory, defective goods, or any other factor the can disrupt the even flow of goods along the transformation process (Chavez et al., 2013). This can be achieved through quantity control, quality assurance, and respect for humanity (Ohno, 1988). Ohno recommends producing only the kinds of units needed, at the time needed, and in the quantities needed. The production method just-in-time (JIT) is a key component of TPS.

The term lean was coined by Krafcik (1988) to describe the manufacturing system used by Toyota. He called TPS Fordism with a Japanese flavor, a reference to Henry Ford and his assembly line. After visiting more than fifty plants, Krafcik (1988) found that on average, the Japanese plants were more efficient than their American cousins. Toyota had found a way to adapt Ford's constant-flow production philosophy, while also achieving the capability of flexibility producing a wide variety of products using continuous-flow principles.

Lean manufacturing is a term that has had many different definitions and approaches through the years. Bhamu and Singh Sangwan (2014) performed a literature review on lean manufacturing, reviewing 209 research papers and found a plethora of definitions. From their research, they found that lean may be a way, a process, a set of principles, a set of tools and techniques, an approach, a concept, a philosophy, a practice, a system, a program, a manufacturing paradigm, or a model.

Lean manufacturing is most frequently associated with elimination of waste commonly held by firms as excess inventory or excess capacity (machine or human) to better the effects of variability in supply, processing time, or demand (Shah and Ward, 2007). For this project, the definition from Shah and Ward (2007) will be used. Shah and Ward (2007) defines lean production as follows: *"Lean production is an integrated socio-technical system whose main objective is to eliminate waste by concurrently reducing or minimizing supplier, customer, and internal variability."* They argue that this definition show evidence of clarity, communicability, consistency, parsimony, differentiability, inclusivity, and exclusivity, as suggested by Wacker (2004). Shah and Ward (2007) also argue that their definition of lean production will *"…also help to bridge the gap between the differing philosophical and practice/tools perspectives witnessed in existing literature."*

When looking at the definition, it is worth noting the word socio-technical is being used. Lean production management have a big focus on both the machines and the people running them. To be able to eliminate excess capacity a flexible, dedicated, and engaged workforce is required

(Shah and Ward, 2007). The essence of lean thinking is that all business processes and functions integrate into a unified, coherent system with the purpose of using lean principles and tools to provide better value to customers through continuous improvement and elimination of waste (Fullerton et al., 2014). A practical implication is that operations personnel cannot operate in isolation. To gain the best results of lean manufacturing management, good communications and a strong working relationships must be developed to achieve their expected gains in efficiency and performance from lean initiatives (Fullerton et al., 2014). This is illustrated by Krafcik (1988); a Toyota executive was asked how many industrial engineers they had working and he answered: *"We have 2,100 team members working on the factory floor; therefore we have 2,100 industrial engineers."*. This view emphasizes the human beings as the bedrock of all organizations (Ringen et al., 2014).

Shah and Ward (2007) mapped and found that lean production consist of 10 factors, and these factors characterize 10 distinct dimensions of a lean system. These can be found in Figure 1. Shah and Ward (2007) argue that lean production is conceptually multifaceted, meaning that just implementing some of the concepts will not have the desired effect on production efficiency and waste elimination. This is because even if one type of waste has been eliminated, there will still be other types left as the implemented concept only "covers" one area of wastes.

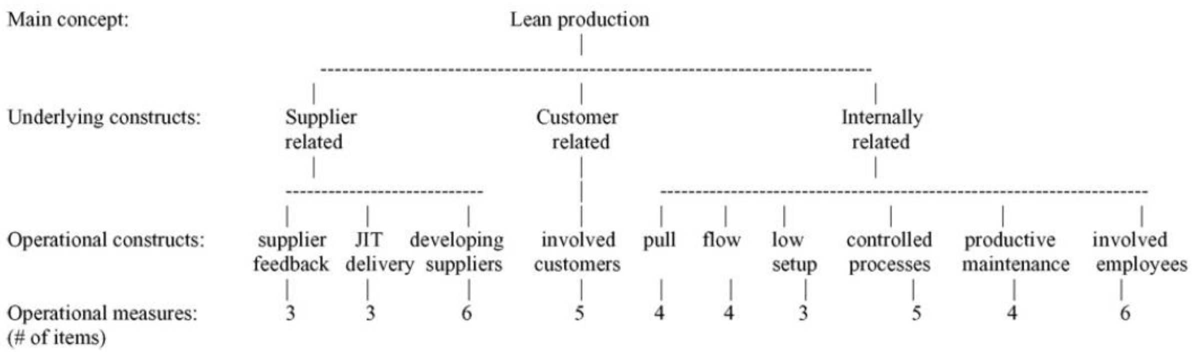

Figure 1: The factors of Lean Production (Shah and Ward, 2007)

Sanders et al. (2016) groups the 10 dimensions into four major factors, depending on the entities involved in each of the dimensions. These four factors are the supplier factor, customer factor, process factor, and control and human factor. The 10 dimensions belong to the different factors as shown in

Table 1 together with a short description of each.

Table 1: Grouped dimensions of lean manufacturing with descriptions (Sanders et al., 2016), (Shah and Ward, 2007)

Factors	Dimensions	Description
Supplier factors	Supplier feedback	Provide regular feedback to suppliers about their performance.
	Supplier development	Develop supplier so they can be more involved in the production process of local firm
	Just in time delivery by suppliers	Ensures suppliers deliver the right quantity at the right time in the right place
Customer factor	Customer involvement	Focus on a firm's customers and their needs
Process factors	Pull production	Facilitate JIT production including Kanban cards which serves as start/stop signal for production
	Continuous flow	Establish mechanisms that enable and ease the continuous flow of products
	Setup time reduction	Reduce process downtime between product changeovers.
Control and human factors	Total productive maintenance (TPM)	Address equipment downtime through total productive maintenance and thus achieve a high level of equipment availability
	Statistical process control (SPC)	Ensure each process will supply defect free units to subsequent process
	Employee involvement	Employee's role in problem solving, and their cross functional character

Li et al. (2005) describe internal lean practices as the practices of eliminating waste in a manufacturing system, characterized by reduced set-up times, small lot sizes, and pull-production. For this project, the focus will be on the six internal lean practices; pull production, continuous flow, setup time reduction, total productive maintenance (TPM), statistical process control (SPC), and employee involvement. The following sub-chapter will go more into depth of these practices.

2.1.1 Internal lean practices

2.1.1.1 Pull production

The pull system is a way of implementing JIT principles, with the finished product "pulled" through the system downstream at the actual demand rate (Siha, 1994). In pull systems, the release of orders tries to balance the desired throughput (service) level with the lowest work-in-process (WIP) level (González-R et al., 2012). The most well-known pull control system is a Kanban. In Kanban, production authorization cards, called Kanbans, are used to control and limit the release of parts into each production stage (Khojasteh and Sato, 2015).

In the later years, different pull production systems have been developed and presented. González-R et al. (2012) identified 18 different token-based pull production control systems. Tokens usually consist of cards that authorize certain production tasks to be performed. There is no single superior pull production system, different systems work well in different scenarios. In their analysis of three pull production systems; Kanban, CONWIP, and Base-stock, Khojasteh and Sato (2015) found that there is no general superiority amongst the analyzed pull production systems.

2.1.1.2 Continuous flow

One-piece flow (or continuous flow) is a concept of carrying one work piece at a time between two adjacent operations, which help the company to achieve true just-in-time manufacturing (Li et al., 2012). Benefits of one-piece flow include keeping WIP at the lowest level, encouraging work balance and better quality, eliminating waste, and making it easier to identify the source of problems quickly. The goal is to move single parts from operation to operation, without interruption, with focus on the product and the process rather than the transporting or storage of either (Gornicki, 2014). This ensures a continuous flow of products through the manufacturing processes.

Looking at a case company, Witt (2006) observed that when replacing the assembly line with cellular manufacturing the newfound flexibility accommodated spikes in the ordering process, inventories in the warehouse were reduced, and the company gained a quicker response to customers' needs. Continuous and uniform flow will bring minimum cycle time and work-in-process inventory levels, and maximum throughput of each product. Thus, developing and maintaining continuous and uniform flow of value-creating processes is the key to successfully achieving lean production (Storch and Lim, 1999).

2.1.1.3 Setup time reduction

In a production environment where many varieties of products are being manufactured, the workers must set up the different machines used in the production process. This part of operations is not creating value and is a contributor to delays and time lost, and is considered waste (Chavez et al., 2013). Thus, it is in a company's best interests to make sure the setup time of these machines is reduced as much as possible. Van Goubergen and Van Landeghem (2002) describes three different reasons for lowering the setup times; increased flexibility, removing bottle necks and minimizing cost. Increased flexibility is achieved by conducting more changeovers and reducing lot size, increased bottleneck-capacities can be done in order to maximize the line availability for production, while minimizing cost is important since production costs are related to equipment effectiveness (Sabadka et al., 2017).

Single Minute Exchange of Dies (SMED) is one of the lean tools that is utilized to reduce setup time and provide quick equipment changeover and rapid die exchange (Almomani et al., 2013). SMED suggests a simple approach to improve changeover operations significantly. Introduced by Shingō (1985), the core idea of SMED is to reduce the time wasted in changeover steps through performing many activities while the equipment is running, and to simplify and streamline the remaining steps making the production flow more smoothly.

2.1.1.4 Total productive maintenance

Total productive maintenance (TPM) is an innovative approach to maintenance techniques that optimize equipment effectiveness through continuous improvement involving both product and service processes (Agustiady and Cudney, 2018). The objective with TPM is to attain maximum efficiency, prevent losses and reach "zero accidents", "zero defects" and "zero breakdowns" in the manufacturing process (Rolfsen, 2014). According to Wireman (2004), TPM has five goals; improving equipment effectiveness, improving maintenance efficiency and effectiveness, early equipment management and maintenance prevention, training to improve the skills of all people involved, and involving operators in routine maintenance.

There are eight pillars in TPM; overall equipment effectiveness, autonomous maintenance, planned maintenance, training and education, early equipment management, quality maintenance, office TPM, and safety, health and environment (Piechnicki et al., 2015). Together, they mark the “total” in TPM, because all the pillars are important to gain the benefits of TPM. Agustiady and Cudney (2018) mention several benefits to TPM, including sharpening employee equipment-related knowledge and skills, establishing baseline equipment specifications, promoting easy auditing and diagnosis of equipment, controlling variation of equipment and reducing defects, and eliminating unplanned downtime.

2.1.1.5 Statistical process control

Statistical process control (SPC) is a technique for controlling processes in order to distinguish causes of variation and signal the need for corrective actions (Avakh Darestani and Nasiri, 2016). A process that is "in control" is one that produces statistically consistent variation. The key to successfully controlling a process is to minimize the degree of variation present among its elements. The results of a process are directly related to the variation of its elements (Cosper, 1999). SPC implies the following concepts: 1) Statistical, meaning data collected systematically, summarized, analyzed, and interpreted; 2) Process, meaning a series of actions or methods of operation; 3) Control, meaning to regulate or check, and measure performance (Morse, 1993).

Six Sigma is a philosophy for company-wide quality improvement. It is developed and promoted by Motorola and based on the insights of SPC and Design of Experiments (Mast et al., 2000). The Six Sigma process uses two defined methodologies, DMAIC and DMADV. DMAIC involves five steps: define, measure, analyze, improve, and control. It is used to improve an existing process. DMADV (define, measure, analyze, design, and verify), on the other hand, is used when a new process or service is needed (Carter, 2010). Application of SPC to a process that has been fully explored and understood using Six Sigma methods can be improved significantly (Walters and Anderson-Cook, 2005). Examples of tools and visual aids used throughout the Six Sigma process includes Pareto charts, cause-and effect diagrams (often called fish bone), scatter plots, and histograms (Carter, 2010).

2.1.1.6 Employee involvement

Employee involvement practices are intended to inject the information and knowledge of non-management employees into higher-level organizational decision-making processes (Yang and Konrad, 2011). Vidal (2007) distinguishes between two types of involvement; substantive and nominal empowerment. Substantive empowerment involves new responsibilities, including regular involvement in problem-solving and decision-making activities, along with formal authority and effective capacity. Nominal empowerment involves active seeking of input on the delegation of new responsibilities to workers, but without effective authority or regular engagement in decision-making and problem-solving. Croucher (2010) states that quality management requires increased levels of employee involvement, especially in three main elements of quality management; continuous improvement, team-working, and employee involvement.

Employee involvement programs should generate new ideas to improve organizational products and processes, which may have positive impacts on firm financial performance depending upon strategy, industry environment, and other external factors (Yang and Konrad, 2011). Amah and Ahiauzu (2013) found that employee involvement is positively related to profitability, productivity, and market share. During his research, Croucher (2010) found that employee involvement improved managers’ understandings of production processes and difficulties regarding machinery, equipment, and processes. Croucher (2010) also found that improving their employees' non-firm specific skills positively affected the quality of the production output.

2.2 Digital technologies

In the realm of manufacturing, the advances of science and technology continuously support the development of industrialization all around the world (Belvedere et al., 2012). Advancements viewed as significant are often referred to as the industrial revolutions (Kagermann et al., 2013). The first three industrial revolutions took around two centuries, and are the result of, respectively: 1) The introduction of water and steam-powered mechanical manufacturing facilities; 2) The application of electrically-powered mass production technologies through the division of labor; and 3) The use of electronics and information technology (IT) to support further automation of manufacturing (Liao et al., 2017). These days, there is an advanced digitalization within factories where the combination of Internet technologies and future-oriented technologies in the field of "smart" objects (machines and products) seems to result in a new fundamental paradigm shift in industrial production (Lasi et al., 2014). Terms like Internet of Things (IoT) and Cyber-Physical Systems (CPS) are associated with the advanced digitalization, indicating a change in manufacturing where the physical and digital world meets. This digitalization is now being referred to as the beginning of a fourth industrial revolution. (Christman, 2002, Liao et al., 2017, Lasi et al., 2014, Kagermann et al., 2013, Hermann et al., 2015).

From government plans perspectives, Liao et al. (2017) describes digitalization plans from the United States, Germany, France, the United Kingdom, South Korea, China, Japan, and Singapore, as well as from the European Commission. Liao et al. (2017) also mentions industrial plans perspectives from several big companies, such as Cisco, General Electric, and IBM, who are heavily investing in IoT and CPS related projects. Digital technologies are changing the approaches to operations management in many field such as automation and industrial manufacturing, supply chain management, agile manufacturing, lean production, total quality management, etc. (Agrifoglio et al., 2017). A term used to describe this fourth industrial revolution have been called Industry 4.0, the name coming from the German governmental strategic initiative "Industrie 4.0" (Kagermann et al., 2013). Lasi et al. (2014) stated that outside of the German-speaking area, the term is not common. However, only three years later, Liao et al. (2017) discovers that the term is spreading throughout Europe and to the rest of the world. This is an indicator that the term is catching on. Industry 4.0 have gained an extra type of interest as this is the first time an industrial revolution is predicted before happening, and companies and research institutes will have an opportunity to actively shape the future (Hermann et al., 2015). A substantially increased operational effectiveness and development of entirely new business models, services, and products are all part of Industry 4.0 (Kagermann et al., 2013). To be able to achieve Industry 4.0, digital technology is a major part of the transformation.

Digital technology used for manufacturing has been around for many years. Early examples are computer-aided design (CAD) and computer-aided engineering (CAE). Khanchanapong et al. (2014) mentions three groups (or components) of digital manufacturing technologies that are distinct but related to one another. The first component is design manufacturing technologies. These technologies include tools such as CAD and CAE, as well as computer-aided production planning (CAPP) that focus on product and process design issues. The second component is process manufacturing technologies, which enables efficient and flexible manufacturing processes. These technologies include automated manufacturing (AM), real-time process control systems, CNC (Computer Numerical Control) machines, and robots. The third and final component is administrative manufacturing technologies, which aid in internal and external communication, as well as planning of critical company resources. These technologies consist of material requirements planning (MRP), manufacturing resources planning (MRPII), and enterprise resource planning (ERP) systems.

Talking about digital manufacturing, Christman (2002) describes software support for functional areas such as: 1) Translation of design data to manufacturing; 2) Full process planning; 3) Production operations planning and machining process planning; 4) Assembly definition and sequencing; 5) Detailed line, cell, station and task design; 6) Quality measurement and reporting; and 7) Manufacturing documentation, shop floor instruction and collaboration. Chryssolouris et al. (2009) conclude that digital manufacturing incorporates technologies for the virtual representation of factories, buildings, resources, machine systems equipment, labor staff and their skills, as well as for the closer integration of product and process development through modelling and simulation. All these examples of software support have been developed and improved, and new factors in digital technology is CPS, IoT and cloud computing.

Cyber-Physical Systems, or CPS, are described as a system where physical and digital representations cannot be differentiated in a reasonable way (Lasi et al., 2014). Embedded computers and networks monitor and control the physical processes, usually with feedback loops where physical processes affect computations and vice versa (Lee, 2008). Examples of CPS are RFID tags, computer controllers in cars, and networked building control systems monitoring HVAC and energy consumption. Hermann et al. (2015) states that the development of CPS as characterized by three phases, with the third and newest being where sensors and actuators can store and analyze data. The use of CPS geared towards supporting collaborative business processes and associated business networks for all aspects of smart factories and smart product life cycles will connect people, objects, and systems to each other (Kagermann et al., 2013). The CPS mechanisms permit controlling and monitoring via algorithms directly integrated in the systems and users around them. This allows objects to communicate with their environment and reconfigure in real time in response to new needs (Moeuf et al., 2017).

Internet of things, or IoT, is a term used to describe the digital connections between devices. Ardolino et al. (2017) describes IoT as *"…a global network in which billions of devices can be heterogeneously interconnected to exchange data and interact to extend their functions beyond the physical world and reach common goals without direct human intervention"*. IoT have also been called the Industrial Internet and is enabled using tags, sensors, actuators, and connectivity devices. Through unique addressing schemes, these components interact with each other and cooperate with their neighboring "smart" objects to reach common goals (Giusto et al., 2010). Hermann et al. (2015) states that these "smart" objects can be understood as CPS, and thus that IoT can be defined as a network in which CPS operate with each other. Examples of IoT networks are smart factories, smart homes, and smart grids. Connected devices and the IoT promise to shift manufacturing from a reactive model to a more proactive and, in some cases, a predictive model (Van den Bossche et al., 2016).

Cloud computing is another type of digital technology that is proving effective and reasonably priced for companies. Cloud computing allows access to a shared pool of computing resources such as servers, storages, and operating systems that can be convenient, configured and provisioned on-demand, with minimal management effort (Ardolino et al., 2017). Communication and exchange of information can be expanded easily with the use of cloud computing technologies by providing easy means of network connectivity. With reaction time of a few milliseconds and large bandwidths, information sharing across multiple systems and networks in real time can now ensure that data and applications are available everywhere, all the time and from any terminal (Moeuf et al., 2017). With cloud computing, companies purchase services rather than products for their IT-organization. Infrastructure, software, and platform as a service, such as cloud-based ERP systems, are examples of services possible with cloud computing (Ardolino et al., 2017).

Despite the increased popularity of digital technologies, most industries are still in the beginning stages with regard to digital manufacturing (Van den Bossche et al., 2016). In a report, Eleftheriadis and Myklebust (2017) asked manufacturing companies in Østfold county in Norway and found that 30% had just a little bit of knowledge about Industry 4.0 and only 10% knew the concept of Industry 4.0 well, which means that the remaining 60% had no knowledge of Industry 4.0. This shows that even though Industry 4.0 and digital technologies are gaining traction in research, companies seem to be lagging in implementing the new digital technologies in their daily operations. However, this does not mean manufacturing companies are not using digital technologies at all. When looking for knowledge about terms related to digitalization and Industry 4.0, Eleftheriadis and Myklebust (2017) state that few of their surveyed companies have heard about CPS. It can be argued that this is because the term CPS is not a commonly used term in the manufacturing industries, and not because the companies are not utilizing digital technologies, such as CPS.

Digital technologies and digital manufacturing can be hard to implement for a manufacturing company. Shinohara et al. (2017) identifies 20 difficulties related to daily work considering digital manufacturing concepts and tools. The most prominent being that the data network does not meet the minimum requirements. This can be explained as there is a large amount of data received and sent by users, and there is a need for a viable speed for data transfer. Put in other words, the IoT cannot function properly when there are internet connectivity issues. Shinohara et al. (2017) also presents 27 critical success factors for digital manufacturing implementation. These are divided into five categories; technical, organizational, project, management, and external. Most of the difficulties come from poorly implemented critical success factors. The organizational factors are particularly important, as lack of specialized training, communication of project scope, and workload management to enable innovation activities affects productivity.

All in all, digital technologies, with CPS, IoT, and cloud computing, are the future of manufacturing. It could be the fourth industrial revolution, with the main themes involving a merge of the physical and technical, and connectivity from end-to-end of the digital manufacturing process. Even though the Industry 4.0 terms are not well known in the manufacturing industries, there is evidence that many manufacturing companies have started to implement digital technologies (Ardolino et al., 2017, Kagermann et al., 2013, Lee, 2008). The question is whether the implementation of digital technologies affect the performance of the manufacturing companies.

2.3 Operational performance

Operations management can have a very significant impact on a business' performance, both financially and productionally. Slack et al. (2010) describes how operations management can reduce costs, risk, and the need for investment, while increasing revenue and enhancing innovation. Manufacturing companies are under immense pressure to pursue operational excellence and improve their performance in order to reduce their costs and provide products of higher quality in shorter lead times (Belekoukias et al., 2014). Performing worse than the market competition can result in decreased sales and, worst case, bankruptcy. Slack et al. (2010) describes the five basic performance objectives; quality, speed, dependability, flexibility, and cost. The performance objectives are not meant to be separate objectives. Often, the performance objectives are intertwined, and one performance objective may affect other objectives. These performance objectives apply to all kinds of operations, and this chapter will describe what the five performance objectives mean for manufacturing operations.

Improving the quality of products and processes leading to creation of these products is a primary goal of integrated quality management (Jayaram and Ahire, 1998). Reeves and Bednar (1994) presents four "roots" of what quality is: 1) Excellence; 2) Value; 3) Conformance to specifications; and 4) Meeting and/or exceeding customers' expectations. Quality is the most visible part of what an operation does, and it is something a customer can find relatively easy to judge about the operation. Thus, quality is a major influence on customer satisfaction and dissatisfaction (Slack et al., 2010).. Reduced cost can be the result of high quality. If there are few mistakes made in the production process of a product, less time will be needed to correct mistakes and more time can be used for production. (Jayaram and Ahire, 1998, Slack et al., 2010)

In operations management, the speed performance objective refers to the elapsed time between customers requesting products or services and receiving them (Slack et al., 2010). In production, this is commonly known as lead time. A short lead time can result in a more flexible production, as the manufacturing company will be able to respond quickly to changes in customer demand (de Treville et al., 2004). This means reduced risk, as forecasting events a week ahead is far less of a risk than forecasting months or years ahead (Slack et al., 2010). Speed can also reduce inventories. Because of increased reduced lead time (speed), you need less inventories to meet the demand.

Dependability is referring to the time for customers to receive their ordered product when the product is needed, or when it was promised to be delivered. (Slack et al., 2010). If a product is always late, the customers perception of a product or company can decrease in the long run. In a production environment, the inventory for finished products is the "customer". If there is a machine breakdown, the product will take longer to finish, as the machine will need repairing before the production process can continue. In this case, dependability can also be called reliability. When an operation is perfectly dependable, a level of trust will be built up between the different parts of the operation. Then, each part of the operation can focus on improving their own areas of responsibility (Slack et al., 2010).

Manufacturing flexibility is the capacity to deploy or redeploy production resources efficiently as required by changes in the environment (Camisón and Villar López, 2010). Slack et al. (2010) describes four types of flexibility, shown in Table 2. Flexible manufacturing companies can see the benefits in their ability to produce a high variety of products, including specific customer requests, at high volumes. This is called mass customization. Other advantages include speeding up response, saving time due to quick changeovers, and maintaining dependability, as flexibility helps keeping the operation on schedule even if unexpected event should arise.

Table 2: The four types of flexibility (Slack et al., 2010)

Flexibility type	**Description**
Product/service flexibility	The operation's ability to introduce new or modified products and services
Mix flexibility	The operation's ability to produce a wide range or mix of products and services
Volume flexibility	The operation's ability to change its level of output or activity to produce different quantities or volumes of products and services over time
Delivery flexibility	The operation's ability to change the timing of the delivery of its services or products.

For every company, manufacturing or other types, low cost is a universally attractive objective (Slack et al., 2010). When costs are reduced, profits are increased. All operations have an interest in keeping their costs as low as is compatible with the levels of quality, speed, dependability, and flexibility that their customers require. Cost is the performance objective which is affected by all the other performance objectives. If a manufacturing company have a high level of performance, the costs will be lowered, as the production will run smoothly without mistakes. On the other hand, if the performance levels of a manufacturing company are low, the costs might increase due to time lost to repairs of equipment, damaged products, and high inventory levels. Figure 2 shows how the five performance objectives are related, as well as the external and internal effects of the performance objectives (Slack et al., 2010).

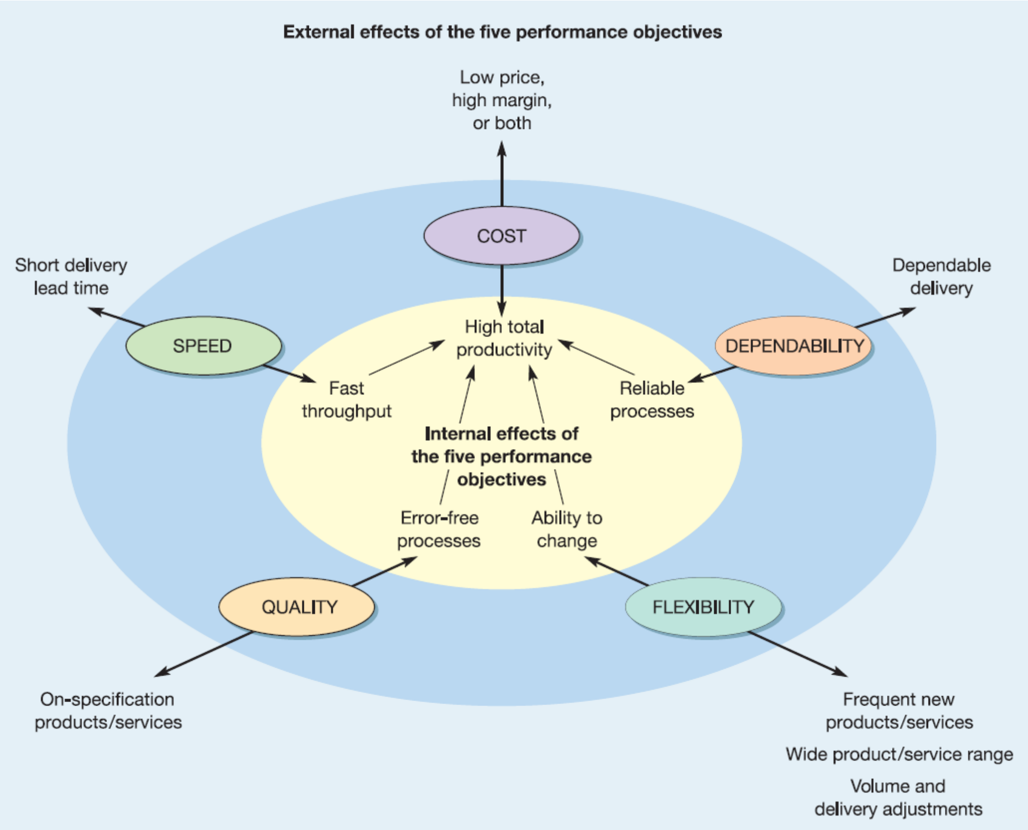

Figure 2: Performance objectives with external and internal effects (Slack et al., 2010)

2.4 Linking Lean manufacturing, digital technology, and operational performance

Traditionally, Lean manufacturing have often been viewed as independent from ICT, and sometimes ICT have been seen as a waste to be eliminated to achieve a full Lean transformation. Technology is seen as a waste, a non-value-adding activity, rather than a tool to help achieve and sustain positive change (Bell, 2006, Powell and Strandhagen, 2011). In an example, Bell (2006) mentions a manufacturing plant that has started a Lean transformation, and in the process eliminated a poorly functioning MRP (Material Requirements Planning) system. Encouraged by the increase in performance and lowered inventory levels, they were hesitant to consider a new ERP (Enterprise Resource Planning) system proposed by central management. However, the manufacturing plant still wanted an ATP (Available to Promise) function in the customer order entry system *"to help the salespeople manage customer expectations and delivery schedules so that we can maintain level production and avoid stockouts."* This would require some form of production planning and scheduling system, e. g. an ERP system.

Powell and Strandhagen (2011) describes how a common argument between Lean production and ERP systems is how Lean production is a "pull" system while ERP systems usually are "push" systems. As mentioned in section 2.1.1.1, in Lean manufacturing products are "pulled" through the production system, while a "push" system uses global and centralized information stored within the central ERP system in order to drive all production stages (Powell and Strandhagen, 2011). Another argument is that Lean manufacturing strives for decentralized control of production through empowered workers, while ERP use a centralized planning and control database. Powell and Strandhagen (2011) argues that the main disconnect between Lean production and ERP systems is that Lean methods are used to control production activity over the short-term horizon, while ERP is focused over the medium- and long-term. Other contrasting attributes of Lean and traditional ICT are presented by Bell (2006) and shown in Table 3.

Table 3: Contrasting attributes of Lean and traditional ICT (Bell, 2006)

Attribute	Lean	Traditional ICT
Change management	Organic, incremental and continuous	Engineered and planned large events
Organization	Cross-functional teams	Central command and control
Measures	Top-down and bottom-up performance measures linking improvement initiatives to strategic goals	Cost containment and uptime
Knowledge management	Generalization	Specialization
Education	Process focus	Task focus
Definition of Success	Speed and Agility	Stability

However, with the emergence and upgrades of the Internet, and other maturing information technologies, many opportunities for rapid innovation has been created. Bell (2006) states that Lean ICT can be a powerful tool to aid the continuous improvement of any enterprise in any industry, and Powell and Strandhagen (2011) argues that Lean thinking should be applied to ERP systems and other support processes of manufacturing. Bell (2006) states that *"For lasting Lean transformation, one must focus on the whole enterprise, understanding the synergistic flows of value and information across the entire value stream"*. This means that when the ICT support tools, such as an ERP system, is set up with Lean thinking in mind, only the usable information is sent through the system. With the emerging digital communication technologies, such as IoT and cloud computing, the information can be accessed in real time and from anywhere. This solves the arguments highlighted by Powell and Strandhagen (2011), as the ERP system can be decentralized and utilized by the empowered workers, as well as be used for short term planning. Powell and Strandhagen (2011) also mentions an example of a hybrid between Lean and ERP, called ERP-Kanban, where the Lean control principle is a major influence on the ERP system. Thus, the ERP system can be used for "pull" production and the last argument is solved, and it can be argued that there is a connection between Lean manufacturing and digital technologies.

When looking at Lean manufacturing, digital technologies, and operational performance, there are four different links between them: 1) The link between Lean manufacturing and digital technologies, as mentioned above; 2) The link between Lean manufacturing and operational performance; 3) The link between digital technologies and operational performance; and 4) The link between all three. This is illustrated in Figure 3. Buer et al. (2018) performed a literature review, mapping the current research on the link between digital technologies and Lean manufacturing. Among other areas, they suggest that there is a research gap on empirical studies on the performance implications of a digital technology and Lean manufacturing integration.

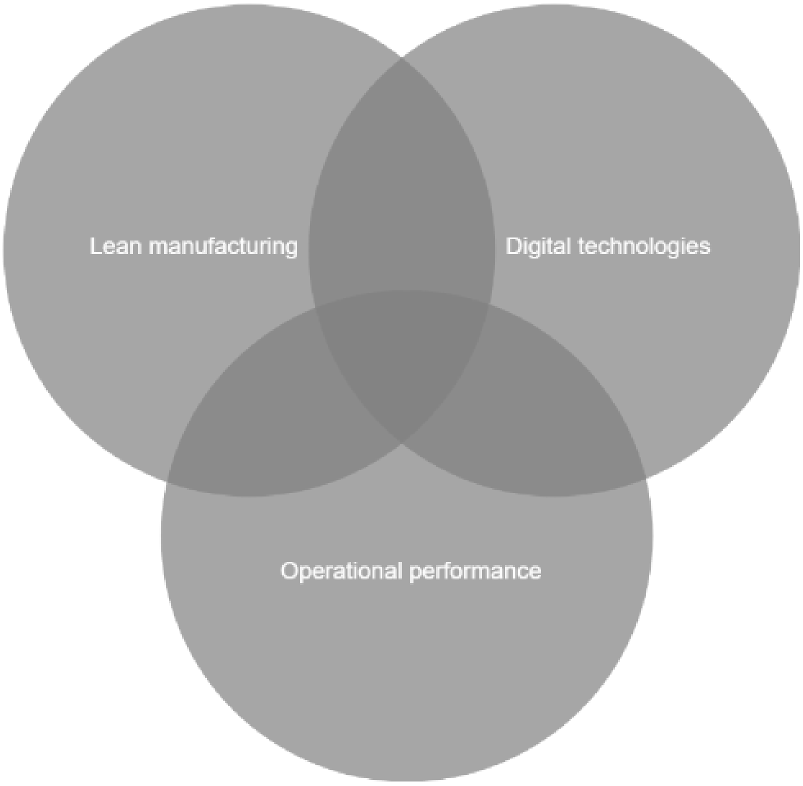

Figure 3: The links between Lean manufacturing, digital technologies, and operational performance

A study based on data from the European Manufacturing Survey (EMS) found an indication that Lean practices may be a prerequisite for digital technologies used in production (von Haartman et al., 2016). Their analysis showed that the use of digital technologies is highly correlated with Lean practices, companies that are more advanced in applying Lean practices do also use digital technologies to a larger extent. von Haartman et al. (2016) conclude that Lean practices provide a basis for implementation of digital technologies.

Identifying three use cases where digital technologies can build on the Lean manufacturing foundation, Mrugalska and Wyrwicka (2017) showed how a well-functioning Lean manufacturing system can be a good foundation for digital technologies. If the system foundation is solid and well documented, implementation costs of digital technology components can be reduced drastically. On the assumption that the company culture is one where change is continuously driven, workforce adaption of new technologies would be rapid, and operational performance will be improved.

Tortorella and Fettermann (2017) examined the relationship between Lean manufacturing and the implementation of digital technologies in Brazilian manufacturing companies. Their findings suggest that companies that are widely implementing Lean manufacturing are more likely to adopt digital technologies, and that their operational performance appears to be positively impacted by such association. The results of Tortorella and Fettermann (2017) also shows that the size of a manufacturing company may not be a barrier to the positive impacts of a Lean manufacturing and digital technologies implementation.

Davies et al. (2017) states that through embarking on a lean improvement project, beyond the core focus of delivering customer value and enabling cost reduction, several benefits become apparent which may appear less tangible but will be seen as enablers to adopting digital technologies. Lean manufacturing is a socio-technical system, as mentioned in section 2.1, and organizational culture is an important aspect. To ensure continuous improvement, both the management and the workforce must actively drive change. There is likely to be a problem-solving structure embedded, and the production and service system within a Lean manufacturing environment is likely to be stable, productive and efficient with minimal production delays, defects, and rejections. Thus, the Lean manufacturing environment is an enabler to implementing digital technologies as a change in operational performance within a company.

In a study of complementary effects of digital technologies and Lean manufacturing practices on manufacturing operational performance, Khanchanapong et al. (2014) found that both digital technologies and Lean manufacturing are associated with operational performance, suggesting that both are valuable resources for achieving operational advantage. Their findings also demonstrate that when digital technologies and Lean manufacturing are combined, the synergistic effects are significantly higher than the combination of their unique effects. Thus, Khanchanapong et al. (2014) suggest that companies should invest in both resources simultaneously, rather than choosing one over the other.

Looking at the three studies above (Davies et al., 2017, Khanchanapong et al., 2014, Tortorella and Fettermann, 2017), a trend can be observed in all of them. They all argue that a combined integration of Lean manufacturing and digital technologies can positively affect operational performance. This project has set out to check whether this claim also holds true among Norwegian manufactures.

3 Methodology

This master thesis is conducted as a research-based project with defined project objectives and research questions. The project should have clear plan to meet the objectives and answer the research questions. Choosing a methodology that fits this purpose is important and this chapter explains the research methods utilized in this project. First, a general description of different research methods will be presented, followed by an argumentation for the selected research strategy this project will be applying. The next sub-chapters will describe the methods selected; literature review and data collection through a survey.

3.1 Research methods and strategy

The term method refers to the technique of data collection and analysis rather than the interpretation of empirical findings (Croom, 2008). The methods help collect samples, data, and find a solution to a problem (Rajasekar et al., 2006). By using proper methods, the result of a thesis, study or project can be retested, with the same results found. However, simply being aware of the methods used is not sufficient to be able to retest the result of previous research. The procedure of how the methods were performed to get the results must also be known.

Research methodology is a systematic way to solve a problem (Rajasekar et al., 2006). Researchers should describe the procedures of which they go about their work. Using the resulting recipe will make another researcher able to perform the same research and obtain the same results as the original researcher. The main aim of the research methodology is to give the work plan of research. There are two main methods used when conducting research; quantitative and qualitative methods. Their characteristics are presented in

Table 4. While quantitative and qualitative methods are distinctive, they can still be used in the same research methodology. For example, case research often involves both quantitative and qualitative methods (Croom, 2008).

Quantitative research adopts a deductive research, testing hypotheses in order to build upon an existing body of knowledge. The quantitative methods use variables which are observable, tangible, and clearly defined (Croom, 2008). Statistics is the most widely used branch of mathematics in quantitative research (Rajasekar et al., 2006). As the results of quantitative methods often are presented as a number, or a set of numbers, statistical analysis is a common method to analyze the results. The ability to replicate, and thus verify, quantitative research is seen as a critical indicator of the validity of the research (Croom, 2008). Examples of quantitative methods are surveys, modelling, and simulations.

Qualitative methods variously recognize and attempt to account for the significance of interpretation, perception and interaction in the process of defining, collecting and analyzing research evidence (Croom, 2008). More than finding quantifiable numbers, qualitative research is more concerned with identifying patterns or processes that cannot be measured. However, numbers can also be ascribed to subjective and qualitative variables (Croom, 2008). Qualitative methods can be used to understand the meaning of numbers obtained by quantitative methods (Rajasekar et al., 2006). Examples of qualitative methods are case research, action research, and interviews.

Table 4: The characteristics of quantitative and qualitative methods (Adopted from Rajasekar et al. (2006), (Buer, 2014))

Quantitative methods	Qualitative methods
Numerical	Non-numerical
Non-descriptive	Descriptive
Applies statistics or mathematics and uses numbers.	Applies reasoning and uses words.
Iterative process whereby evidence is evaluated	Aim is to get the meaning, feeling, and describe the situation
Results often presented in tables or graphs	Cannot be graphed
Conclusive	Exploratory
Investigates the what, where and when of decision making	Investigates the why and how of decision making

The main goal of this project is to map Norwegian manufacturers, and to measure the operational performance results of having implemented Lean manufacturing and digital technologies into the production processes. This can be defined as confirmatory research, also called theory-testing (Forza, 2002). The research strategy for this project will use two main research methods; literature review and survey. A general understanding of main topics is needed to perform research. A literature review is a good method of gaining knowledge and understanding of topics, and thus a logical first step in the research process. This project aims to map manufacturing plants in Norway and there are several methods available to do this. Some methods considered for mapping the manufacturing plants are case studies, interviews, and performing a survey.

Case studies can give a good insight into selected companies. However, there is a limited amount of existing case studies of Norwegian manufacturing plants and many of these might be outdated. An option could be to perform new case studies but given the time limitations of this project this option would not be possible to complete in time. Interviews can be excluded for the same reason; the results will only consist of a select few companies and thus not be representable for all manufacturing plants in Norway. A survey can cover many companies in a short amount of time which makes the method a logical choice considering the project aim.

Figure 4 illustrates the main steps of this project, with the corresponding sections in parenthesis. The following sections of this chapter will explain how the methods will be performed.

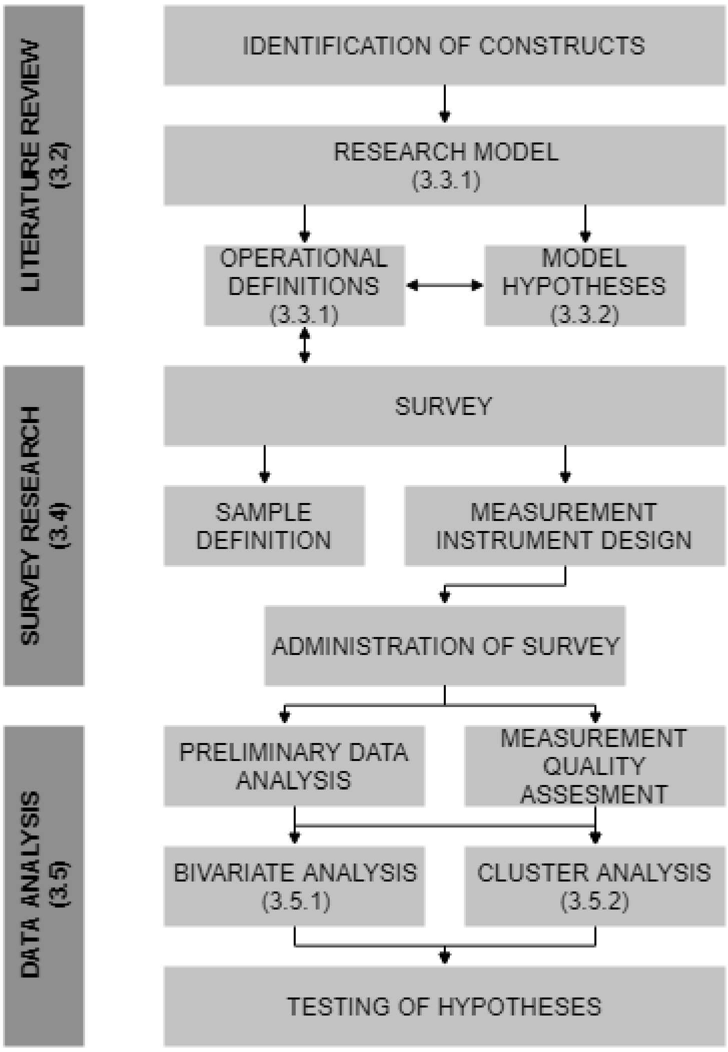

Figure 4: The main steps of the research process

3.2 Literature review

A fundamental part of any academic research is to review the existing academic literature in the field of interest. Croom (2008) states that the literature review contributes to the research process and development of the researcher in four areas: 1) Helping to inform the researcher's understanding of the existing state of knowledge on the topic of interest; 2) The review guides the development of constructs, hypotheses, and questions employed in the study of the topic; 3) It generates a justification for the choice of research methodology; and 4) The literature review helps to develop and refine important research skills. To be able to perform theory-testing, relevant theoretical constructs must be developed from the existing literature (Croom, 2008, Forza, 2002, Malhotra and Grover, 1998).

The goal of the literature review is to gain an understanding of the master project's three main topics; Lean manufacturing, digital technologies, and operational performance. The literature review is also used to observe the most common methods used to measure operational performance in manufacturing companies.

For the literature search, no specific scientific journal has been prioritized, as the subjects discussed in this project cover a broad field and limiting the literature search could result in missed information. The main databases used for literature search were Oria, Scopus, Science

Direct, Springer, and Google Scholar. To determine relevant articles, the abstract and the keywords were read. Another method of finding literature utilized was the snowball sampling method. New articles were found by examining the reference lists of previously found, and accepted, articles. The tool used to manage references is EndNote X8.

3.3 Model development

To be able to identify factors affecting the operational performance objectives of manufacturing companies, as well as how and how much, it is important to gain knowledge about the relationship between the factors and the operational performance objectives. In this chapter, the model development process will be presented. Then, the choice of variables will be identified and justified. The last section will describe the hypotheses of the research model.

Researchers wanting to explain phenomena often depict their theoretical framework through a schematic diagram, or model, as this may be useful to facilitate communication (Forza, 2002). Conceptual modeling involves capturing various aspects of the real world, that can then be translated into a relational or some other logical model (Storey et al., 2015).

Wacker (1998) presents a general procedure for theory-building and the empirical support for theory. This procedure is shown in Figure 5. Each of the stages are required for a theory to be considered a "good" theory and unless a proposed theory has all the stages, it does not meet the criteria of the formal definition of theory. The first column shows the components of theory and the second states why these components are necessary. The third column give the common question each stage addresses, while the last column gives the most relevant virtues for that stage to ensure that any theory developed is a "good" theory.

	Purpose of this step	Common question	'Good' theory virtues emphasized
Definitions of variables	Defines who and what are included and what is specifically excluded in the definition.	Who? What?	Uniqueness, conservation
Limiting the domain	Observes and limits the conditions by when (antecedent event) and where the subsequent event are expected to occur.	When? Where?	Generalizability
Relationship (model) building	Logically assembles the reasoning for each relationship for internal consistency.	Why? How?	Parsimony, fecundity, internal consistency, abstractness
Theory predictions and empirical support	Gives specific predictions. Important for setting conditions where a theory predicts. Tests model by criteria to give empirical verification for the theory. The riskiness of the test is an important consideration.	Could the event occur? Should the event occur? Would the event occur?	Empirical tests refutability

Figure 5: The general procedure for theory-building and empirical support for theory (Wacker, 1998)

3.3.1 Research model and operationalization

Inspired by the research methods of Khanchanapong et al. (2014) and Tortorella and Fettermann (2017), a starting point for the development of the model was determined. Both look at the how implementation of Lean manufacturing and digital technologies affect operational performance. Khanchanapong et al. (2014) starts by examining the unique effects of Lean manufacturing and digital technologies on operational performance, before looking at the synergetic effect of both Lean manufacturing and digital technologies on operational performance. As the research questions of this thesis in section 1.3.1 state, this project will attempt to use a similar approach as Khanchanapong et al. (2014), though related to Norwegian manufacturing plants.

This thesis will use the six internal Lean practices, described in section 2.1.1, and two dimensions of digital technology, adapted from PwC (2018). The two dimensions are: 1) Value chains, processes, and IT architecture; and 2) Organization and culture. For the operational performance, this project uses the five operational performance objectives presented in section 2.3. The final research model is illustrated in Figure 6. It consists of eight independent variables, the dimensions affecting operational performance (DAOP), and five dependent variables, the five operational performance objectives. The DAOP are separated into two main categories; internal Lean practices and digital technologies. As stated above, first the effect of the internal Lean practices (x_1-x_6) on the different operational performance objectives (y_1-y_5) will be tested. Second, the effects of the two digital technologies dimensions (x_7-x_8) on the performance objectives will be tested. Finally, the combined effect of internal Lean practices and digital technologies on operational performance will be tested.

In order to provide a measure of a concept, it is necessary to have an indicator, often called an operational definition, that will stand for the concept (Bryman, 2016). After the theoretical model have been developed, the next step is to transform the theoretical concepts into observable and measurable elements. If the theoretical concept is multidimensional, then all of its dimensions have to find corresponding elements in the operational definition (Forza, 2002). Before the selection of variables and their operationalization is explained, the process for representing one variable through several items must be explained.

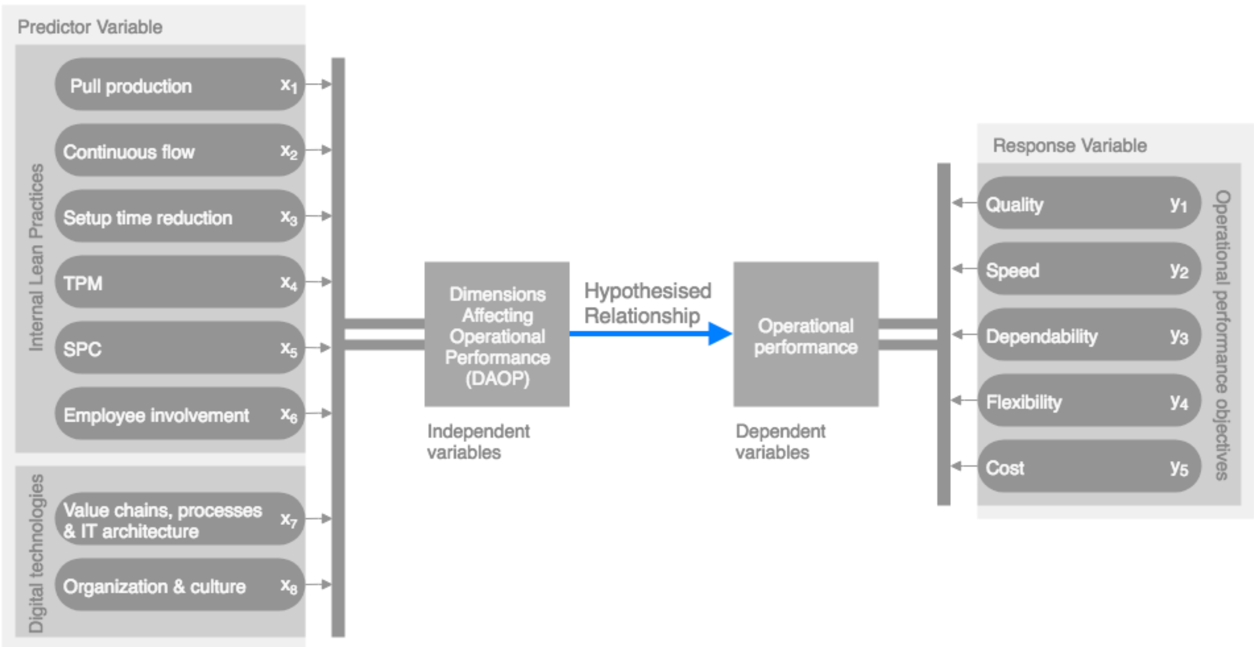

Figure 6: Research model with eight independent variables, hypothesized to affect five different dependent variables.

3.3.1.1 Summated scales

Summated scales are formed by combining several individual variables into a single composite measure, where the total or average score is used in the analysis. The objective is to avoid the use of only a single variable to represent a concept and to instead use several variables as indicators, representing different facets of the concept to obtain a more well-rounded perspective (Hair et al., 2010). Hair et al. (2010) describes two specific benefits to summated scales: 1) It provides a way to reduce measurement error, by reducing the reliance on a single response. Using the average response to a set of related variables, the measurement error that might occur in a single question will be reduced; and 2) It has the ability to represent multiple aspects of a concept in a single measure.

Measurement validity is the extent to which a scale or set of measures accurately represents the concept of interest (Bryman, 2016, Hair et al., 2010). It is important that a measurement instrument measures what it is intended to measure and not something else. Measurement reliability, on the other hand, refers to the consistency of a measure of a concept, that is, the degree of consistency between multiple measurements of a variable (Bryman, 2016, Hair et al., 2010). Summated scales need to be tested for reliability, both external and internal. External reliability, or stability, can be examined using the test-retest method. This test checks for consistency over time. Internal reliability tests whether the indicators in the summated scale are consistent, meaning if scores on one indicator are related to the scores of the other indicators(Bryman, 2016, Hair et al., 2010). A common method of assessing internal reliability is by measuring the Cronbach's alpha. Finally, an underlying assumption and essential requirement for creating a summated scale is that the items are unidimensional, meaning they are strongly associated with each other and represent a single concept (Hair et al., 2010). The test of unidimensionality is that each summated scale consists of items highly loaded on a single factor and can be empirically assessed using factor analysis.

For this master project, in order to ensure the quality of the measurements, tests that were able to be performed in the limited time window of the project were conducted. Measurement validity was ensured by using established measurements found in literature and by consulting the supervisors. Internal reliability was tested by calculating the Cronbach's alpha and through factor analysis. Due to the limited time frame, a test for external reliability was not conducted, and the author is aware of the possible measurement errors that may occur.

3.3.1.2 Operational performance objectives ($y_{1\text{-}5}$)

The operational performance objectives are the dependent variables of this project and are explained in detail in section 2.3. They are quality, speed, dependability, flexibility, and cost. There are different methods of measuring the operational performance objectives. Khanchanapong et al. (2014) measures the operational performance of a company by asking respondents to rate their company's performance against its primary competitor on the industry on a five-point Likert scale from "much worse" to "much better". Tortorella and Fettermann (2017), on the other hand, assessed the observed operational performance change during the last three years, also using a five-point Likert scale. Other studies have also measured operational performance change, Ghobakhloo and Hong (2014) and Shah and Ward (2003) both used the change during a five year period.

For this master project, the five operational performance objectives were measured by asking respondents about the change in the last five years. This choice was made because it is more likely that a company know their own change better than how their performance measures rate compared to their primary competitors.

3.3.1.3 Internal Lean practices ($x_{1\text{-}6}$)

The first dimension of the independent variables are the internal Lean practices, which are explained in detail in section 2.1.1. This master project will use an adapted version of the operational measure of Lean production developed by Shah and Ward (2007). Their operational measure includes both external and internal Lean practices, but since this master project is only looking at the internal Lean practices, the utilized part of the operational measure will only include the part containing the internal Lean practices. The measures used are further explained in section 3.4.4.

3.3.1.4 Digital technologies (x_{7-8})

The second dimension of independent variables are digital technologies. Digital technologies are described in section 2.2. There are different ways of measuring a company's implementation of digital technologies. Khanchanapong et al. (2014) uses three major dimensions; design, process, and administrative technologies. Tortorella and Fettermann (2017) use a questionnaire with ten questions to determine the level of adaptation of digital technologies. Both studies utilized a five-point Likert scale. This master project uses an adapted measurement from the Industry 4.0 Digital Operations Self-Assessment by PwC (2018) to measure two dimensions of digital technologies; value chains, processes, and IT architecture, and organization and culture. The measures of the two dimensions are further explained in section 3.4.4.

3.3.2 Research model hypotheses

A hypothesis is a logically conjured relationship between two or more variables (measures) expressed in the form of testable statements (Forza, 2002). Once the operational constructs have been articulated, the propositions that specify the relationships among the constructs have to be translated into hypotheses, relating empirical indicators (Forza, 2002). These hypotheses are called alternative hypotheses and they are denoted by $H_{1...n}$. There is also a need to define a hypothesis that is logically opposite of the alternative hypotheses. This is called the null hypothesis and is denoted by H_0 (Field, 2009). The null hypothesis is formulated so that it can be tested for possible rejection, and if the null hypothesis is rejected, then all alternative hypotheses related to the tested relationship could be supported (Forza, 2002).

For this master project, the null hypothesis H_0 is:

There is no relationship between the dimensions affecting operational performance (DAOP) and the operational performance objectives.

Table 5 presents the hypotheses for this master project, which were based on the findings of the literature review and discussions with the supervisor.

Table 5: The developed hypotheses for this master project thesis

Index	Hypothesis
H_0	There is no relationship between the dimensions affecting operational performance (DAOP) and the operational performance objectives.
H_1	Internal Lean practices are positively associated with quality performance
H_2	Internal Lean practices are positively associated with speed performance
H_3	Internal Lean practices are positively associated with dependability performance
H_4	Internal Lean practices are positively associated with flexibility performance
H_5	Internal Lean practices are positively associated with cost reduction
H_6	Digital technologies are positively associated with quality performance
H_7	Digital technologies are positively associated with speed performance
H_8	Digital technologies are positively associated with dependability performance
H_9	Digital technologies are positively associated with flexibility performance
H_{10}	Digital technologies are positively associated with cost reduction
H_{11}	There is a synergistic relationship between internal Lean practices and digital technologies in predicting quality performance
H_{12}	There is a synergistic relationship between internal Lean practices and digital technologies in predicting speed performance
H_{13}	There is a synergistic relationship between internal Lean practices and digital technologies in predicting dependability performance
H_{14}	There is a synergistic relationship between internal Lean practices and digital technologies in predicting flexibility performance
H_{15}	There is a synergistic relationship between internal Lean practices and digital technologies in predicting cost performance

3.4 Survey research

Survey research is prominent as a methodology that has been used to study unstructured organizational problems in the production and operations management (POM) area (Malhotra and Grover, 1998). A survey involves the collection of information from a large group of people or a population. According to Malhotra and Grover (1998), survey research has three distinct characteristics. First, it involves collection of information by asking people for information in some structured format. Second, survey research is usually a quantitative method that requires standardized information in order to define or describe variables, or to study relationships between variables. Third, information is gathered via a sample, which is a fraction of the population. For this project the survey will be quantitative, with the exception of an optional comment box for recipients to express their subjective thoughts.

Forza (2002) presents three types of survey research; exploratory, confirmatory, and descriptive. Exploratory survey research takes place during the early stages of research into a phenomenon, when the objective is to gain preliminary insight on a topic. Confirmatory or theory testing survey research aim to test theorized hypotheses of well-defined concepts. Descriptive survey research is aimed at understanding the relevance of a certain phenomenon and describing the distribution of a phenomenon in a population. As mentioned in section 3.1, this project will be using confirmatory or theory-testing survey research. The steps involved can be found in the theory-testing survey research process from Forza (2002), which can be found in Figure 7.

The first step is to develop the operational definitions. This will be done using the main theory found during the literature review, by transforming the theoretical concepts into observable and measurable elements. Then, hypotheses are developed, followed by the design of the survey. The survey is pilot tested and adjusted based on the insights gained form the pilot. After this is complete, the data collection is performed. This is followed by the analysis of the data, and finally, the hypotheses are tested, and the results are interpreted.

When conducting a survey, there are several errors that can interfere with the results of the survey and skew the conclusions. Malhotra and Grover (1998) identifies four error components that can affect the results of a survey research. The four error components are shown in Table 6.

Table 6: The four types of error in survey research. Adapted from Malhotra and Grover (1998), Forza (2002)

Error	Description
Sampling error	A sample with no capability of representing the population, caused by inadequate sample selection or because of auto-selection effects. Excludes the possibility of generalizing results beyond original sample.
Measurement error	Data derived from the use of measures which do not match the theoretical dimensions, or are not reliable, make any test meaningless.
Statistical conclusion error	When performing statistical tests there is a probability of accepting a conclusion that the investigated relationship (or other effect) does not exist, even when it does exist.
Internal validity error	When the explanation given of what has been observed is less plausible than rival ones, then the conclusions can be considered erroneous.

Major decisions about data collection and time horizon must always be made prior to designing and selecting a sample, and constructing the questionnaire and the other material (Forza, 2002). Given the time constraints of this project, the survey will be a web-based self-administered survey sent out by email to make certain a significant amount of data from several respondents will be obtained.

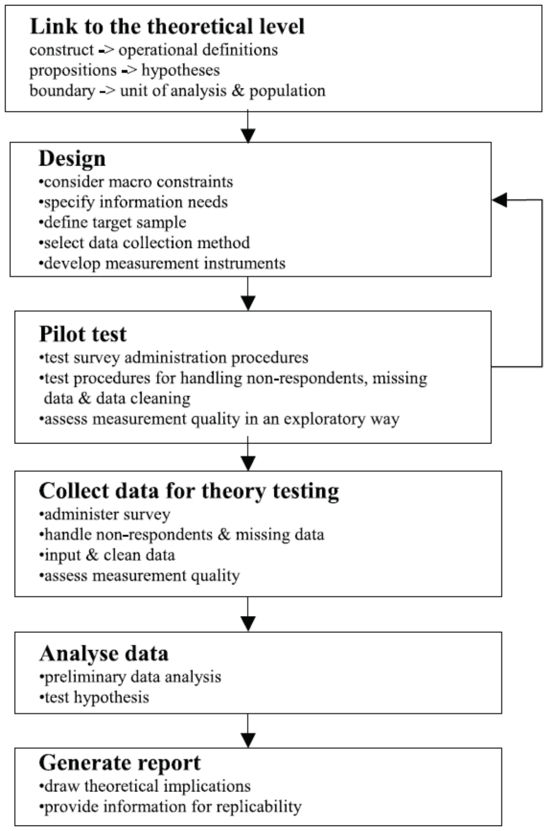

Figure 7: The theory-testing survey research process (Forza, 2002)

3.4.1 The sample

In order to generalize the findings of this project, a representative sample of manufacturing companies need to be selected out of the population. The population refers to the entire group of people, firms, plants, or things that a researcher wishes to investigate (Forza, 2002). The sample is a subset of the population, comprising of members selected from the population. Sampling is the process of selecting a sufficient number of elements from the population so that studying of the sample allows for a generalization of the properties or characteristics of the population elements. Sampling overcomes the difficulties of collecting data from the entire population (Forza, 2002).

When performing sampling, it important to reduce the sampling error as much as possible. A sampling error may occur if there is a difference between the sample and the population it is meant to represent. This can be caused by the sample being biased. Bryman (2016) describes three sources of bias. First, if a non-probability or non-random sampling method is being used, there is a possibility that human judgement will affect the selection process. An example of such a method is convenience sampling, where the purpose is to obtain quick information, even if the method might be unreliable (Forza, 2002). The bias of a non-probability method can be eliminated through a probability sampling, such as simple random sampling. The second source of bias is and inadequate sampling frame, where if the sampling frame is not comprehensive or inaccurate, it cannot represent the population even if a probability sampling method is employed. The third source of bias is called non-response bias. This occurs when some members of the sample do not respond to the questionnaire being sent out. Malhotra and Grover (1998) states that response rates of under 20% is *"…extremely undesirable"*. Non-response bias can be combated by trying to increase the response rate such that the non-response bias is minimized as much as possible.

For this master project the population frame is all manufacturing companies in Norway and two types of sampling methods were used. First the non-probabilistic method convenience sampling was used because of the given time frame of the master project created a need for quick information. This was done by identifying manufacturing companies through existing contacts of the university. To decrease the non-probability sampling method bias, a second sampling method was also utilized: The probabilistic method called single random sampling. This was performed by searching the Norwegian company database developed by Proff AS and randomly select manufacturing companies. After performing the sampling methods, the final sample contained 200 Norwegian manufacturing companies.

As a non-probabilistic method was used, the population frame lacks detail, and the sample was prone to occurrences of non-response bias, the sample was expected to include all three types of bias. Efforts were made to reduce the bias, such as also using a probabilistic sampling method and attempts to increase the response rate.

3.4.2 Sample size

Sample size is a complex issue which is linked to the significance level and the statistical power of the test, as well as the size of the researched relationship (Forza, 2002). The level of statistical significance is the level of risk a researcher is prepared to take in stating that a relationship between two variables exist in the sample, when in fact the relationship does not exist in the population. The statistical significance is usually denoted by the Greek letter α (Bryman, 2016).

There are two statistical inference errors a researcher can make; the Type I error, rejecting the null hypothesis H_0 when it is true, and the Type II error, H_0 is not rejected when the alternative hypothesis H_a is true (Forza, 2002). The probability of making a Type I error is the significance level (α). Typical for operations management, $\alpha = 0{,}05$. The null hypothesis is rejected if the observed significance level (p-value) is less than the chosen value of α (Forza, 2002). However, as decreasing of the chosen α is reducing the risk of a Type I error, the probability of making a Type II error increases. This is because the researcher is more likely to confirm the null hypothesis when the significance level α is lower (Bryman, 2016). The probability of a Type II error is β, and the statistical power is equal to $1-\beta$.

A high statistical power is required to reduce the probability of failing to detect an effect when it is present. Balance between the two types of errors is needed because reducing one type of error raises the likelihood of increasing the probability of the other type of error (Forza, 2002). A low statistical power leads to a study which is not able to detect large size effects, while a high statistical power leads to committing unnecessary resources only in order to be able to detect trivial effects. Forza (2002) states that there is a general agreement in which a statistical power of about 0,8 represents a reasonable and realistic value for research.

Table 7 shows the relationship between the effect size, statistical power and sample size. To gain an increased statistical power at a low significance level while still detecting small effects, the sample size need to increase (Forza, 2002).

Table 7: Effect size, statistical power and sample size (Forza, 2002)

	Stat. power = 0.6		Stat. power = 0.8	
	α = 0.05	α = 0.01	α = 0.05	α = 0.01
Large effect (e.g. strong association)	12	18	17	24
Medium effect (e.g. medium association)	30	45	44	62
Small effect (e.g. small association)	179	274	271	385

Another aspect to consider is the generalizability attained through the sample size. With many potential external factors affecting the results, it is important to have a sample large enough to still be generalizable (Bryman, 2016, Hair et al., 2010). Hair et al. (2010) recommends a minimum ratio of 5:1, meaning five observations for one independent variable. With a sample size of 200 and a total number of eight independent variables, the response rate should be at least 20%, equaling 40 respondents. This response rate was determined to be the minimum goal of this master project.

3.4.3 Collection method within survey research

There are many ways of collecting data when performing research. In survey research, the two main methods used to collect data are interviews and questionnaires (Forza, 2002). As explained in section 3.1, the limited time frame of this master project will make it difficult to perform several interviews, thus a questionnaire was selected as the data collection method of this project. Questionnaires, also called surveys or forms, can be administered personally, by telephone, or mailed to the respondents. This project used a web-based self-administered survey.

Bryman (2016) describes the advantages and disadvantaged of using this type of survey. Advantages include easy processing of answers, comparability of answers, the meaning of the question may be clarified, and the survey is easy to complete. Disadvantages include a loss of spontaneity in respondents’ answers, difficulty in making forced-choice answers mutually exclusive and exhaustive, variation among respondent in interpretation of answers, and the questions may be irritating to respondents whom are unable to find a category they feel applies to them.

The tool used for setting up an electronic survey was SelectSurvey, a tool accessible to members of NTNU. This tool was chosen because it offers a professional interface, offers plenty of options for data analysis and export, and offers a high level of security and privacy for the respondents and the collected data.

The survey was sent out via email to the sample. In order to increase the response rate, a reminder was sent out after two weeks.

3.4.4 The measurement instrument

One of the main characteristics of a survey is that it relies on structured instruments to collect information (Forza, 2002). The design of the survey includes tasks such as wording of questions, scales on which answers are placed, as well as a clear presentation of the questions and survey in general (Bryman, 2016, Forza, 2002).

When formulating the questions, the researcher should ensure that the language of the questionnaire is consistent with the respondent’s level of understanding. There is also a choice in creating open-ended or closed questions. Open-ended questions allow respondents to answer in any way they choose. Closed questions limit respondents to a choice among alternatives given by the researcher and facilitate quick decisions and easy information coding. However, the researcher has to ensure the alternatives are mutually exclusive and collectively exhaustive (Forza, 2002). For the survey of this master project, the questions were written in both English and Norwegian, and the respondents had the opportunity to answer the questions in their preferred language. Open-ended questions were only used to ask for the company name and the respondents position in the company. Otherwise, closed questions were created.

The second task in developing the measurement instrument concerns the scale to be used to measure the answers. The scale choice depends on the ease of which both respondent can answer and the subsequent analyses will be done. Forza (2002) describes four basic types of scale; nominal, ordinal, interval, and ratio. These are further described in Table 8. For data analysis, there are two main kinds of data, metric and non-metric. Metric data is quantitative data and often use interval or ratio scales. Non-metric data is qualitative data and often use nominal and ordinal scales (Forza, 2002). For this master project, the two scaling types used are nominal and interval, using multiple choice items for some introductory questions and a five-point Likert scale for the rest of the questions.

Table 8: The different scale type and the corresponding scale techniques (Forza, 2002)

Basic scale type	**Highlights**	**Scaling technique**
Nominal	Difference	Multiple choice items, adjective checklist, staple scale
Ordinal	Difference, order	Formed ranking scale, paired comparison scale
Interval	Difference, order, distance	Likert scale, verbal frequency scale, comparative scale, semantic differential scale
Ratio	Difference, order, distance with 0 as a meaningful natural origin	Fixed sum scale

Some basic rules of curtesy, presentability, and readability are key for a successful data collection. It is important for a self-completing questionnaire that the layout is easy on the eye, and that it facilitates the answering of all questions that are relevant to the respondent (Bryman, 2016, Forza, 2002). This was ensured by using the questionnaire tool SelectSurvey. The survey was split into 4 parts: 1) Introduction of respondent’s company; 2) Lean implementation; 3) Digitalization and 4) Operational performance.

The introduction covered the respondent’s company name and type of industry, as well as the position in the company of the respondent. The introduction also asked for the firm size, in terms of number of employees (<50, 50-250, >250) and the company’s annual turnover (<€10M, €10M-€50M, >€50M). The introduction also asked about the type of production environment of the company.

The Lean implementation part asked about the number of years since starting a Lean implementation in the company. Then the adapted version of the operational measure of Lean production developed by Shah and Ward (2007) was used and can be seen in Table 9. These were all measured using a five-point Likert scale, from no implementation (1) to complete implementation (5).

Table 9: Internal Lean practices measures. Adapted from (Shah and Ward, 2007)

Internal Lean practice	Item label
Pull production	Production is “pulled” by the shipment of finished goods
	Production at stations is “pulled” by the current demand of the next station
	We use a “pull” production system
	We use Kanban, squares, or containers of signals for production control
Continuous flow	Products are classified into groups with similar processing requirements
	Products are classified into groups with similar routing requirements
	Equipment is grouped to produce a continuous flow of families of products
	Families of products determine our factory layout
Setup time reduction	Our employees practice setups to reduce the time required
	We are working to lower setup times in our plant
	We have low set up times of equipment in our plant
SPC	Large number of equipment/processes on shop floor are currently under SPC
	Extensive use of statistical techniques to reduce process variance
	Charts showing defect rates are used as tools on the shop floor
	We use fishbone diagrams to identify causes of quality problems
	We conduct process capability studies before product launch
TPM	We dedicate a portion of everyday to planned equipment maintenance related activities
	We maintain all our equipment regularly
	We maintain excellent records of all equipment maintenance related activities
	We post equipment maintenance records on shop floor for active sharing with employees
Employee involvement	Shop floor employees are key to problem solving teams
	Shop floor employees drive suggestion programs
	Shop floor employees lead product/process improvement efforts
	Shop floor employees undergo cross functional training

The digitalization part of the survey used measures of digitalization implementation adapted from the Industry 4.0 Digital Operations Self-Assessment by PwC (2018) to measure two dimensions of digital technologies; value chains, processes, and IT architecture, and organization and culture. These can be seen in

Table 10 and are measured on a five-point Likert scale, from no degree of digitalization (1) to full implementation (5). In the final survey, the respondents got some extra information and examples when rating their digitalization, to make it easier for the respondent to answer.

Table 10: Digitalization implementation measures. Adapted from (PwC, 2018)

Dimension	**Item label**
Value chains, processes & IT architecture	How would you rate the degree of digitization of your vertical value chain (from product development to production)?
	To which extent do you have a real-time view on your production and can dynamically react on changes in demand?
	To which degree do you have an end-to-end IT enabled planning and control process from sales forecasting, over production to warehouse planning and logistics?
	How advanced is the digitization of your production equipment (sensors, IoT connection, digital monitoring, control, optimization and automation)?
	How would you rate the degree of digitization of your horizontal value chain (from customer order over supplier, production and logistic to service)?
	To which extent does your IT architecture (hardware) address the overall requirements from digitization and Industry 4.0?
	To which extent do you use a manufacturing execution system (MES) or similar to control your manufacturing process?
	How advanced is your IT integration with customers, suppliers and fulfillment partners?
Organization and culture	How would you rate your capability to create value from data?
	How are your capabilities and resources related to Industry 4.0 (e.g. data analytics, IoT, CPS, HMI, production security, digital PLM etc.) in your organization?
	What level of involvement, support and expertise do executive and senior management have in your organization with regards to Industry 4.0?
	To which extent is your IT organization able to fulfill business requirements in the requested time, quality and cost?
	To which extent does your organization institutionalize collaboration on Industry 4.0 topics along with external partners such as academia, industry, suppliers or customers?

Finally, the operational performance was measured as mentioned in section 3.3.1.2, by asking respondents about the change in the last five years of the five operational performance objectives; quality, speed, dependability, flexibility, and cost, operationalized by product quality, lead time, process reliability, process flexibility and production cost per unit. These were all rated on a five-point Likert scale, form much worse (1), through neutral (3), and to much better (5).

3.4.5 Pilot testing

Forza (2002) states that the researcher must examine the measurement properties of the survey questionnaires and examine the viability of the administration of these surveys. The survey was tested by study colleagues and employees at the Mechanical and Industrial Engineering department at NTNU to increase the measurement validity and to verify that the questions are clear and understandable. The questions have been adjusted and pre-tested several times before the final version was sent to the sample of the population.

3.4.6 Approval of data protection official for research

The anonymity and privacy of those who participate in the research process should be respected, and personal information concerning research participants should be kept confidential (Bryman, 2016). A research project at NTNU have to be notified to the Norwegian Centre for Research Data (NSD) if it collects, registers, and processes data about individuals. Even if the personal data is not published, a notification is still required (NSD, 2018).

As this survey could potentially identify respondents due to questions regarding company name and job position, a notification was sent to NSD. The approval to conduct the survey was received a couple of weeks after application was sent. The approval of NSD is included in Appendix A.

3.4.7 Cleaning of received data

The received data was manually examined in order to identify potential mistakes or missing data. Incomplete responses were removed, and large amounts of missing data was handled by contacting the respondent to obtain the missing data. As the respondents had the opportunity to select their preferred language, the data from both languages had to be combined. The data was carefully examined to make to combination of the two languages valid.

3.5 Data analysis

When the data have been collected, it has to be analyzed. This section describes in in detail how the data analysis will be performed. This is followed by the process of examining data. Finally, description of the interpretation of the results will be presented.

3.5.1 Bivariate analysis

Bivariate analysis is concerned with the analysis of two variables at a time on order to uncover whether or not the two variables are related (Bryman, 2016). Thus, bivariate analysis is a good method of testing the first ten hypotheses (H_1-H_{10}). A variety of techniques can be used to examine relationships, but their use depends on the nature of the two variables being analyzed. All the variables of this project, independent and dependent, are interval variables. Bryman (2016) states that the method of performing a bivariate analysis using two interval variables is by calculating the Pearson's *r*.

The key features of Pearson's *r* are as follows: 1) The coefficient will almost certainly lie between 0 (no relationship) and 1 (perfect relationship), indicating the strength of the relationship; 2) The closer the coefficient is to 1, the stronger the relationship; and 3) The coefficient will be either positive or negative, indicating the direction of the relationship (Bryman, 2016). Bryman (2016) also states the importance of plotting a scatter diagram of the two variables in order to determine that the nature of the relationship does not violate the assumptions being made when this method of correlation is employed.

When calculating the Pearson's *r*, there has to be made a choice of a one-tailed or two-tailed test. A statistical model that tests a directional hypothesis is called a one-tailed test, whereas one testing a non-directional hypothesis is known as a two-tailed test (Field, 2009). The first ten hypotheses of this project are directional hypotheses, as they all hypothesize a positive relationship between the independent and dependent variable. Thus, for this project, the Pearson's *r* will be calculated with a one-tailed significance test.

3.5.2 Cluster analysis

To determine if the final five hypotheses (H_{11}-H_{15}) hold true, a cluster analysis will be performed. The primary goal of cluster analysis is to partition a set of objects into two or more groups based on the similarity of the objects for a set of specified characteristics (Hair et al., 2010). Applying a similar clustering method as Tortorella and Fettermann (2017), the TwoStep cluster method was used to identify the proper number (*k*) of clusters, followed by the k-means clustering method to rearrange observations into *k* clusters. Three types of sets of clusters were created; one set for internal Lean practices, one set for digital technologies, and finally, one set for each of the five operational performance objectives. An ANOVA (Analysis of Variance) were performed to verify differences in means of clustering variables calculated using data from each cluster.

For this project, results of the data analysis would show that the data describing the five operational performance objectives did not follow a normal distribution. However, since the operational performance objectives were divided into clusters, these variables could be considered categorical and thus, nominal variables. Bryman (2016) states that the relationship between nominal and interval variables can be described using a chi-square test, together with a contingency table and Cramér's V.

3.5.3 Examination of data

Both Forza (2002) and Hair et al. (2010) state the importance of performing some preliminary data analysis to acquire knowledge of the characteristics and properties of the collected data, and thus, a better interpretation of the results can be gained. Before testing hypotheses, it is useful to check the assumptions underlying the tests. Preliminary data analysis is performed by checking central tendencies, dispersions, frequency distributions, and correlations. Forza (2002) states that it is good practice to calculate: 1) The frequency distribution of the demographic variables; 2) The mean, standard deviation, range and variance of the other dependent and independent variables; and 3) An inter-correlation matrix of the variables. The following steps were taking to prepare the data for analysis as presented by (Hair et al., 2010): 1) Graphical examination; 2) Detection and handling of outliers; 3) Testing the assumptions; and 4) Testing unidimensionality and reliability of summated scales.

For the graphical examination, histograms of every variable which shows the distribution of the collected data points was analyzed. Then, as described above, the relationships between the variables would provide a good overview of the characteristics of the data.

Outliers are extreme values at either end of the distribution. Both the mean and the standard deviation are affected by outliers (Bryman, 2016), and thus, detection and handling of outliers is an important part of the examination of data. An outlier is still a valid and correct observation and may still be a representative of the population as a whole. In such cases, the researcher can leave the outlier in the data set. For this project, boxplots were created for each variable to identify outliers in the collected data.

Multivariate techniques and the univariate counterparts are all based on a fundamental set of assumptions representing the requirements of the underlying statistical theory (Hair et al., 2010). Four of these assumptions potentially affect every univariate and multivariate statistical technique: 1) Normality; 2) Homoscedasticity; 3) Linearity; and 4) Absence of correlated errors. Before the analysis, normality was tested using Q-Q plots, as well as the Shapiro-Wilks test and a modification of the Kolmogorov-Smirnov test. Linearity was graphically assessed with scatterplots of the variables to identify any non-linear patterns in the data. Homoscedasticity and absence of correlated errors can be performed by using the resulting residuals of a multiple regression (Hair et al., 2010).

In section 3.3.1.1, it was stated that an underlying assumption and essential requirement for creating a summated scale is that the items are unidimensional. This will be tested through a principle components analysis, a factor analysis that explains the interrelationships among variables, by showing in which amount a variable measures the same concept and how many concepts are measured (Hair et al., 2010). To determine the suitability of factor analysis for this master project, the Bartlett test for sphericity and the Kaiser-Meyer-Olkin (KMO) test were assessed. The Bartlett test for sphericity requires a significant value less than 0,05 and the KOM requires a result of more than 0,5 to continue the factor analysis. It was also stated in section 3.3.1.1 that internal reliability was to be tested by calculating the Cronbach's alpha. Forza (2002) states that new developed measures can be accepted with $\alpha \geq 0{,}6$, otherwise $\alpha \geq 0{,}7$ should be the threshold. When $\alpha \geq 0{,}8$, the measure is very reliable.

3.5.4 Interpretation of the results

When interpreting the results of statistical testing, the researcher moves from the empirical to the theoretical domain. This process implies considerations of inference and generalization (Forza, 2002). In making an inference on relations between variables, the researcher could incur a statistical error, as explained in section 3.4.2, or an internal validity error, as explained in section 3.4. Even when data analysis results are consistent with the theory at the sample level, the researcher should take care in inferring that the same consistency holds at the population level (Forza, 2002). The ideal data set for this master project would be a high correlation between the dependent variables and the independent variables, and a low correlation between the independent variables. However, this is not often the case, as independent variables often relate on some level. Steps have to been taken to assess the degree of multicollinearity, to determine its impact and to apply countermeasures (Hair et al., 2010).

4 Data analysis and findings

4.1 Sample characteristics

In this section, the characteristics of the sample is presented in order to understand the external validity of the results. The topics presented are response rate, company size and annual, position of respondents, and the production environment of the companies of the sample. The section is finished with an evaluation of the sample.

4.1.1 Response rate

From the 200 companies contacted, 44 responses were received. This gives a response rate of 22%, which is above the minimum goal for this project of 20%. Even though this response rate is within the expected range when surveying operations management (according to Malhotra and Grover (1998)), the response rate can have been influenced by several factors. The companies receiving the survey might not want to participate or share information about their company, or they were unable to understand the questions. Another factor may be that the contact emails used to distribute the survey were outdated and not in use, such that the company never received the survey at all. Another factor may be language barriers; however, the chance of this factor was reduced as the survey had the option of both English and Norwegian. Still, the risk of non-response bias is something to consider when performing the data analysis. Most of the respondents filled out the whole survey, though some missed a few questions. When there were multiple data points missing, the company was contacted in order to fill the missing data points.

4.1.2 Company size and annual turnover

There are different sized companies that have responded to the survey, as shown in Table 11. One can observe that most Norwegian manufacturing companies in the sample are big companies.

Table 11: Company size among respondents

Number of employees	Respondents	% of total sample
< 50	6	13,6 %
50-250	20	45,5 %
> 250	18	40,9 %
Total	44	100 %

The annual turnover of the companies is presented in Table 12. Of the sample, 88,6 % of the companies have an annual turnover of more than €10M, and more than half have an annual turnover of more than €50M.

Table 12: Company annual turnover

Annual turnover	Respondents	% of total sample
< €10M	5	11,4 %
€10M-€50M	15	34,1 %
> €50M	24	54,5 %
Total	44	100 %

4.1.3 Position of respondents

In order to determine whether the respondent could actually answer for the company, the position of the respondent at the company was asked. The findings are presented in Table 13. The results show that there is a diversity in the positions of the respondents, however, most of the respondent have key responsibilities at their respective companies and is regarded of having sufficient knowledge on the topics of the survey.

Table 13: Positions of respondents at their individual company

Position	Respondents	% of total sample
Managing director	9	20,5%
Plant manager	9	20,5%
Project manager	4	9,1%
Lean manager	3	6,8%
Technical manager	3	6,8%
Quality manager	2	4,5%
Supply Chain Manager	2	4,5%
Analysis and improvement manager	1	2,3%
Bid Manager	1	2,3%
Department manager	1	2,3%
Director Research and Technology	1	2,3%
Executive Vice President	1	2,3%
Group Director Operations Standards	1	2,3%
Head of Digital Business Intelligence	1	2,3%
Logistics manager	1	2,3%
Manager Production Development & Projects	1	2,3%
Manufacturing engineer	1	2,3%
Purchase Part Inventory Control Manager	1	2,3%
SVP Equipment & Solutions	1	2,3%
Total	44	100,0%

4.1.4 Production environment

The respondent's company's production environment asked about, as it would be interesting to see if the results of the sample can be generalized across all production environments, or whether the sample only contains responses from companies with certain production environments. The production environments the respondents could choose from where; 1) Complex customer order production; 2) Configure-to-order products; 3) Batch production of standardized products; and 4) Repetitive mass production (as described by (Jonsson and Mattsson, 2003)). The results can be seen in Table 14 and shows a broad mix between the four available production environment categories. This can suggest that the data from the sample might be generalizable across all production environments.

Table 14: Production environments among respondents

Production environment	Respondents	% of total sample
Complex customer order production	13	29,5%
Configure-to-order products	13	29,5%
Batch production of standardized products	10	22,7%
Repetitive mass production	8	18,2%
Total	44	100,0%

4.1.5 Evaluation of the sample

With a response rate of 22% and a number of 44 respondents, the analysis as prone to non-response bias. The distribution of company size shows that there are more big companies than small, and as such, the results of the analysis might be more representative of larger companies. However, the distribution over the different production environments suggest that the analysis might be generalizable regardless of production environment. Still, with such a small response rate, the results of the analysis should be interpreted with care.

4.2 Examination of the data

This section will present the preliminary analysis of the responses in order to assess possible factors increasing measurement error of every variable. The constructs of the two main dimensions (internal Lean factors and digital technologies) are also presented. Finally, a bivariate analysis of the variables, detection and handling of outliers, as well as a testing of the assumptions is described.

4.2.1 Internal Lean practices

To be able to construct the internal Lean practices domain, the measures for the six internal Lean practices had to be tested for scale and reliability, and for unidimensionality. In order to assess reliability for the scales, the Cronbach's alpha was calculated and the unidimensionality was tested using principle component analysis (PCA). Pull production, continuous flow, total productive maintenance, and employee involvement were all constructed using four measures. Setup time reduction and statistical process control were constructed using three and five measures, respectively. The Cronbach's alphas for the six variables, as well as the loading factor for each item in the scale can be seen in

Table 15. The results for the KMO and Bartlett tests can be seen in Appendix B, figures B.1-B.6. The Cronbach's alphas of pull production, continuous flow, setup time reduction, and SPC are all over 0,8, meaning that they are very reliable. TPM is just above the threshold of 0,7, while employee involvement is just below the threshold. However, Forza (2002) states that $\alpha \geq 0{,}6$ can be accepted, and since the Cronbach's alpha of employee involvement is closer to 0,7 than 0,6, this can be accepted as well. Thus, all the six variables are reliable. The KMO and Bartlett tests of all the variables are accepted, and it can be argued that the summated scales for the internal Lean practices can be created.

Table 15: Scale validity and reliability of internal Lean practices

Scales	Items	Loading factors	Cronbach's alpha
Pull production	Production is "pulled" by the shipment of finished goods	0.862	0.810
	Production at stations is "pulled" by the current demand of the next station	0.887	
	We use a "pull" production system	0.875	
	We use Kanban, squares, or containers of signals for production control	0.568	
Continuous flow	Products are classified into groups with similar processing requirements	0.832	0.803
	Products are classified into groups with similar routing requirements	0.829	
	Equipment is grouped to produce a continuous flow of families of products	0.802	
	Families of products determine our factory layout	0.705	
Setup time reduction	Our employees practice setups to reduce the time required	0.931	0.808
	We are working to lower setup times in our plant	0.890	
	We have low set up times of equipment in our plant	0.731	
SPC	Large number of equipment/processes on shop floor are currently under SPC	0.843	0.848
	Extensive use of statistical techniques to reduce process variance	0.926	
	Charts showing defect rates are used as tools on the shop floor	0.798	
	We use fishbone diagrams to identify causes of quality problems	0.706	
	We conduct process capability studies before product launch	0.678	
TPM	We dedicate a portion of everyday to planned equipment maintenance related activities	0.716	0.731
	We maintain all our equipment regularly	0.646	
	We maintain excellent records of all equipment maintenance related activities	0.816	
	We post equipment maintenance records on shop floor for active sharing with employees	0.787	
Employee involvement	Shop floor employees are key to problem solving teams	0.574	0.688
	Shop floor employees drive suggestion programs	0.828	
	Shop floor employees lead product/process improvement efforts	0.832	
	Shop floor employees undergo cross functional training	0.604	

The histograms of the six internal Lean practices can be seen in Figure 8-Figure 13.

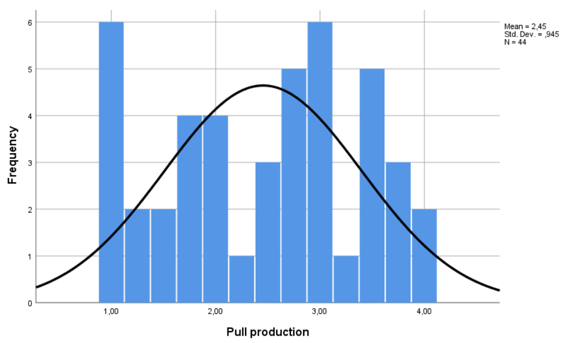

Figure 8: Pull production histogram

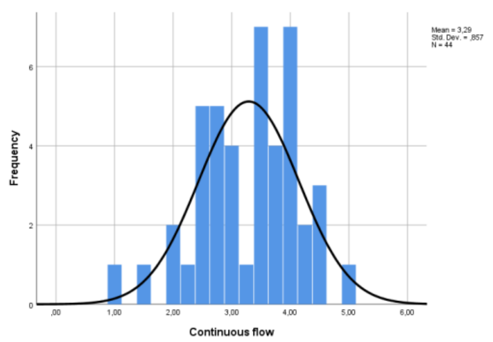

Figure 9: Continuous flow histogram

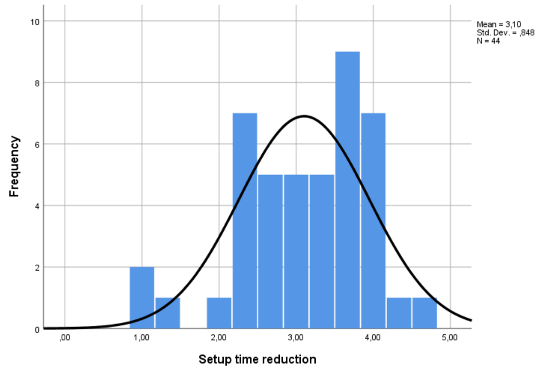

Figure 10: Setup time reduction histogram

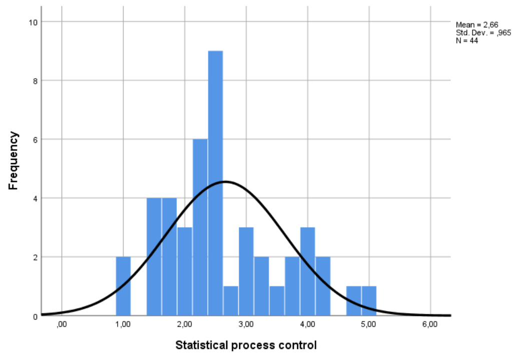

Figure 11: SPC histogram

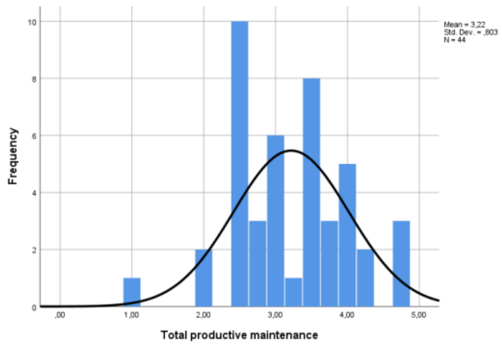

Figure 12: Total productive maintenance histogram

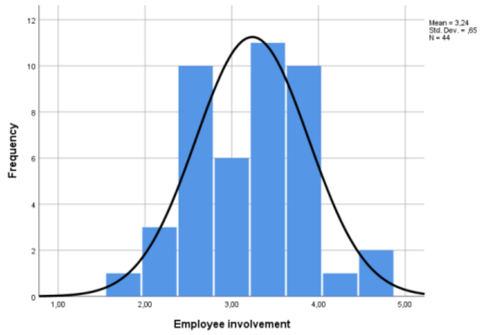

Figure 13: Employee involvement histogram

4.2.1.1 Construction of the internal Lean practices dimension

The internal Lean practices dimension can be constructed, now that the six internal Lean practices scales are confirmed. Thus, another summated scale is to be created. The Cronbach's alpha using the six scales are calculated to be 0,710, and the KMO and Bartlett tests give 0,648 and 0,000, thus multicollinearity is not a problem. The histogram of the summated scale can be seen in Figure 14.

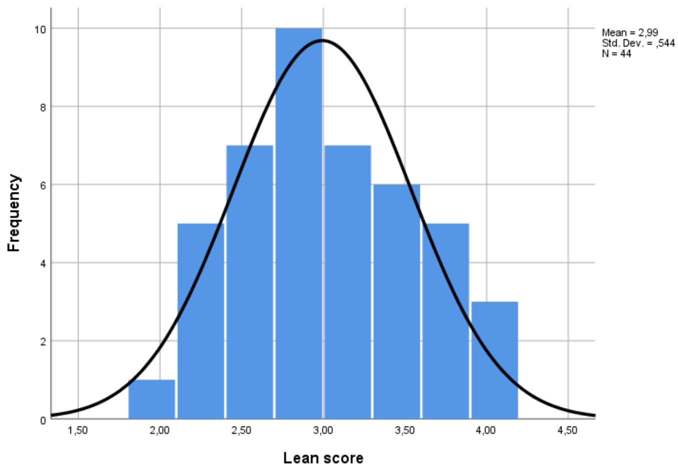

Figure 14: Internal Lean practice dimension histogram

4.2.2 Digital technologies

As with the internal Lean practices domain, to be able to construct the digital technologies domain, the measures for the two digital technology variables had to be tested for scale and reliability, and for unidimensionality. The result can be seen in Table 16, and the results show that summated scales can be made for both the digital technology dimensions. The corresponding histograms can be found in Figure 15 and Figure 16.

Table 16: Scale validity and reliability of digital technologies

Scale	Cronbach's alpha	KMO	Bartlett
Value chains, processes & IT architecture	0.749	0.667	0.000
Organization and culture	0.760	0.783	0.000

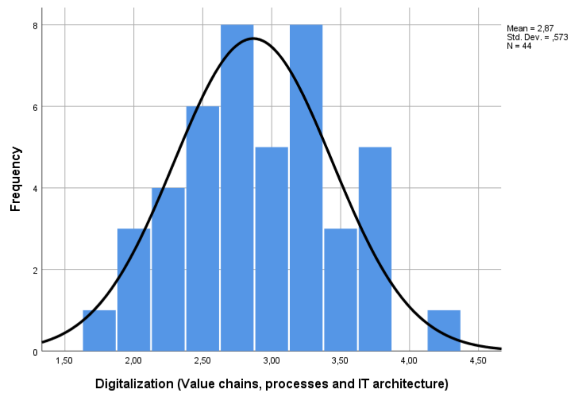

Figure 15: Value chains, processes & IT architecture histogram

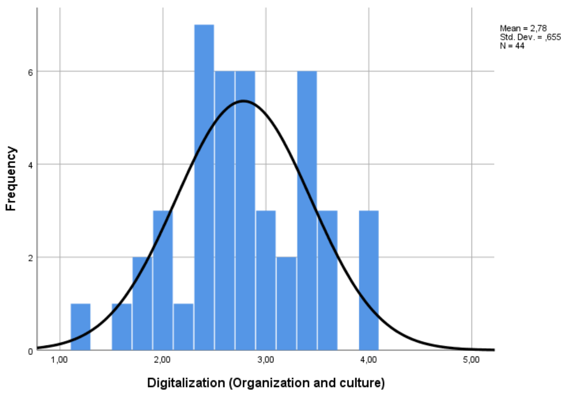

Figure 16: Organization and culture histogram

4.2.2.1 Construction of the digital technologies variable

The digital technologies dimension can be constructed, as the two digital technology scales are confirmed. Thus, another summated scale is to be created. The Cronbach's alpha using the two scales are calculated to be 0,643, and the KMO and Bartlett tests give 0,500 and 0,001, respectively. A Cronbach's alpha below 0,6 is not accepted. In this case, when $\alpha = 0{,}643$, we can accept the correlation, especially since there are only two variables. As α increases when the number of variables increase, a Cronbach's alpha of 0,643 is acceptable. KMO = 0,500, which is just on the lower limit of acceptable. Bartlett's test gives a significance of 0,001, and this is still significant. The summated scale can therefore be created. The histogram of the summated scale can be seen in Figure 17.

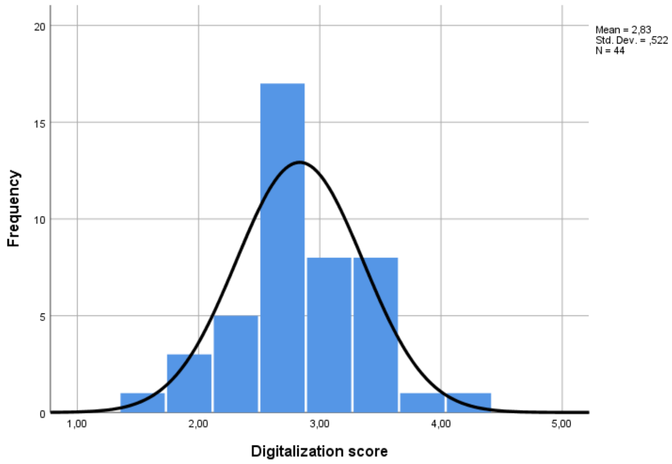

Figure 17: Digital technologies dimension histogram

4.2.3 Operational performance

As the five operational performance objectives measures only consist of one variable, summated scales cannot be created. The following section will examine the respondents measures of the different operational performance objectives.

4.2.3.1 Quality performance

The frequency table describing the change in quality performance can be seen in Table 17. The Likert scale of this measure, as well as the other measures of operational performance, is going from 1-5 where 1 equals "much worse" and 5 equals "much better". Looking at the frequency table, one can observe that the majority of the respondents report better quality performance during the last five years. Only one respondent has had a negative change during the last five years, while nine respondents have not changed. Two respondents also report a much better change.

Table 17: Frequencies of the quality measure

Rating	**Respondents**	**# of total sample**
Worse	1	2,3%
Same level	9	20,5%
Better	32	72,7%
Much better	2	4,5%
Total	44	100,0%

4.2.3.2 Speed performance

The frequency chart of the speed performance measure can be seen in Table 18. Looking at the frequency table, one can observe that the majority of the respondents report better speed performance during the last five years. However, for this measure three respondents have had a negative change during the last five years, while seven respondents have not changed. Four respondents also report a much better change.

Table 18: Frequencies of the speed measure

Rating	Respondents	# of total sample
Worse	3	6,8%
Same level	7	15,9%
Better	30	68,2%
Much better	4	9,1%
Total	44	100,0%

4.2.3.3 Dependability performance

The frequency chart of the dependability performance measure can be seen in Table 19. For this table, one can observe that there are many respondents whom are reporting no change in dependability. Still, the majority of respondents have had a positive change during the last five years. Only one respondent has had a negative change, while two respondents a much better change.

Table 19: Frequencies of the dependability measure

Rating	Respondents	# of total sample
Worse	1	2,3%
Same level	16	36,4%
Better	25	56,8%
Much better	2	4,5%
Total	44	100,0%

4.2.3.4 Flexibility performance

The frequency chart of the flexibility performance measure can be seen in Table 20.The first notable observation in this frequency chart is that no respondent reports a negative change in flexibility during the last five years. Over 75 % reports a positive change, while only 10 respondents have had no change during the last five years.

Table 20: The frequencies of the flexibility measure

Rating	Respondents	# of total sample
Same level	10	22,7%
Better	32	72,7%
Much better	2	4,5%
Total	44	100,0%

4.2.3.5 Cost performance

The frequency chart of the cost performance measure can be seen in Table 21. Looking at the frequency table, one can observe that the majority of the respondents report better quality performance during the last five years. However, for this measure three respondents have had a negative change during the last five years, while seven respondents have not changed. Four respondents also report a much better change.

Table 21: The frequencies of the cost measure

Rating	**Respondents**	**# of total sample**
Worse	5	11,4%
Same level	9	20,5%
Better	29	65,9%
Much better	1	2,3%
Total	44	100,0%

4.2.4 Bivariate analysis

As mentioned in section 3.5.1, this project will use a bivariate analysis to determine the relationship between the dependent and independent variables, and thus, test the ten first hypotheses given in section 3.3.2. As both the dependent and the independent variables are scaled on intervals (using a Likert scale), the bivariate analysis method used will be the Pearson's *r*. Because the hypotheses to be tested (H_1-H_{10}) are directional, the significant test utilized will be the one-tailed test of significance. The correlation matrix between the variables is presented in Table 22.

Table 22: Correlation matrix for the variables

Correlations

		Quality	Speed	Depend.	Flexibility	Cost	Lean	Digital.
Quality	Pearson's *r*	1						
	Sig. (1-tailed)							
Speed	Pearson's *r*	,369**	1					
	Sig. (1-tailed)	,007						
Dependability	Pearson's *r*	,187	,201	1				
	Sig. (1-tailed)	,112	,095					
Flexibility	Pearson's *r*	,201	,225	,313*	1			
	Sig. (1-tailed)	,096	,071	,019				
Cost	Pearson's *r*	,424**	,517**	,494**	,177	1		
	Sig. (1-tailed)	,002	,000	,000	,126			
Lean	Pearson's *r*	,288*	,257*	,014	,044	,327*	1	
	Sig. (1-tailed)	,029	,046	,464	,388	,015		
Digitalization	Pearson's *r*	,412**	,232	,092	-,036	,355**	,503**	1
	Sig. (1-tailed)	,003	,065	,277	,407	,009	,000	

**. Correlation is significant at the 0.01 level (1-tailed).

*. Correlation is significant at the 0.05 level (1-tailed).

Looking at the correlation matrix, there are several significant relationships between the variables. Both internal Lean practices and digital technologies are significantly related to several operational performance objectives, and thus, the null hypothesis H_0 can be rejected.

Internal Lean practices are statistically correlated with quality, speed, and cost, at the $p < 0,05$ level, thus supporting hypotheses H_1, H_2, and H_5. However, Internal Lean practices does not correlate with dependability and flexibility, leading to a rejection of H_3 and H_4. When it comes to digital technologies, there are two performance objectives that correlate significantly; quality and cost, both significant at the $p < 0,01$ level. This observation supports hypotheses H_6 and H_{10}. It is also shown that digital technologies are significantly correlated with speed performance, but this is only significant at the $p < 0,1$ level. As mentioned in section 3.4.2, the typical α-value in operations management is equal to 0,05, thus H_7 must be rejected, together with H_8 and H_9.

There are other interesting observations in the correlation matrix as well. First, the dependent variable cost performance is significantly related to the other dependent variables, besides flexibility, at a $p < 0.01$ level. This is logical as Slack et al. (2010) states that cost is the performance objective which is affected by all the other performance objectives, as mentioned in section 2.3. A second interesting observation is that the independent variables, internal Lean practices and digital technologies, are significantly correlated at a $p < 0,01$ level. This indicates that companies with a higher level of lean implementation, also tend to have implemented digital technologies to a large degree and may support a synergistic relationship between internal Lean practices and digital technologies.

4.2.5 Detection and handling of outliers

As mentioned in section 3.5.3, boxplots were created to identify outliers in the measured variables. The boxplots can be seen in Figure 18, and show several outliers in the variables quality performance, speed performance, and flexibility performance, and one outlier in the digitalization score variable. Outliers must be viewed within the context of the analysis and should be evaluated by the type of information they may provide (Hair et al., 2010). Following the guidelines proposed by Hair et al. (2010), outliers were assessed for data entry error or a mistake in coding, but no procedural error was found. The digitalization score outlier is most likely an observation that have occurred due to an extraordinary event. After examining the data of respondent 39, no discrepancies were found, and the outlier can be seen as a natural part of the population. The outliers in the three dependent variables are most likely due to the fact that the variables were created by a single measure on a short interval. The data will be kept for the analysis, but the author is aware that the result may be affected.

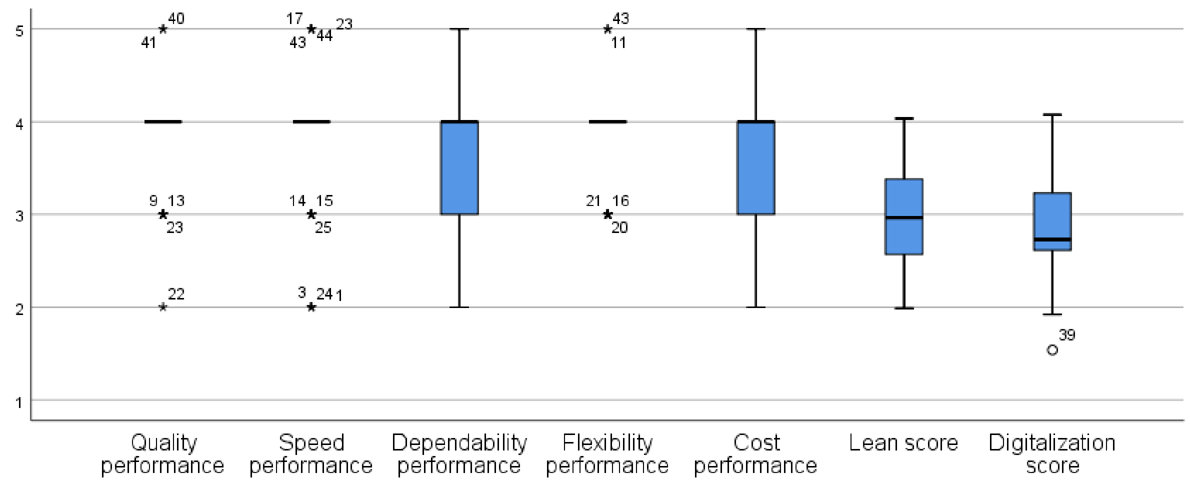

Figure 18: Boxplots describing the different variables

4.2.6 Testing the assumptions

Before performing any multiple variable analysis, the variables must be tested for normality and linearity, as stated in section 3.5.3. The normality was tested using Q-Q plots, as well as the Shapiro-Wilks test and a modification of the Kolmogorov-Smirnov test. Linearity was graphically assessed with scatterplots of the variables to identify any non-linear patterns in the data. The scatterplots can be found in appendix B, figures B.7-B.11. Linear patterns were found regarding quality, speed, cost, and the independent variables. No other major non-linearities were observed. The normality was tested using Shapiro-Wilks test and the Kolmogorov - Smirnov test. The results can be seen in Table 23. The tests show that none of the five operational performance measures are normally distributed. The normal Q-Q plots of the internal Lean practices and digital technologies are shown in Figure 19.

Table 23: Tests of normality

	Kolmogorov-Smirnova			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Quality performance	,417	44	,000	,689	44	,000
Speed performance	,387	44	,000	,745	44	,000
Dependability performance	,337	44	,000	,778	44	,000
Flexibility performance	,416	44	,000	,663	44	,000
Cost performance	,395	44	,000	,712	44	,000
Lean score	,077	44	,200*	,975	44	,439
Digitalization score	,117	44	,146	,983	44	,737

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

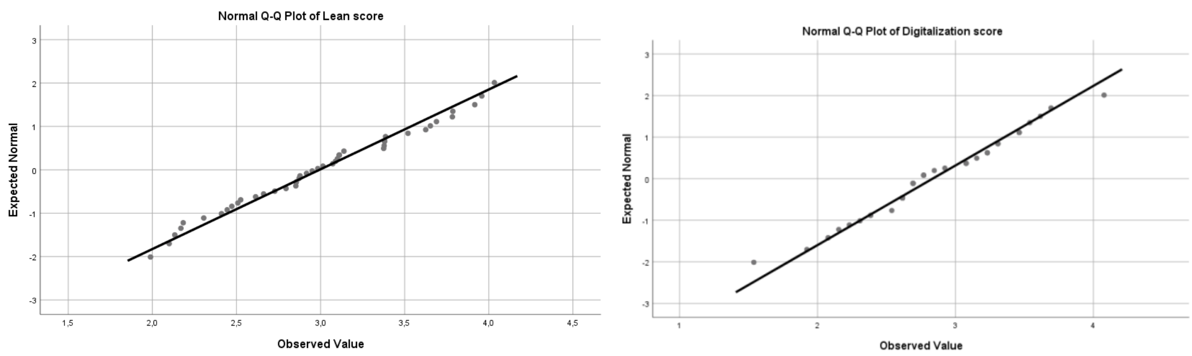

Figure 19: Normal Q-Q Plot of internal Lean manufacturing and digital technologies

4.3 Analysis results

In the previous sections, the collected data was first analyzed for sample characteristics, then the independent variables were constructed using summated scales. The bivariate analysis was performed, and ten hypotheses were tested, with a rejection of the null hypothesis. After the handling of outliers, the data was tested for assumptions and the five operational performance objectives were found not be normally distributed. Following, the results of the cluster analysis are presented and interpreted.

4.3.1 Cluster analysis

As mentioned in section 3.5.2, the primary goal of cluster analysis is to partition a set of objects into two or more groups based on the similarity of the objects for a set of specified characteristics. The TwoStep cluster method was used to identify the proper number (*k*) of clusters, followed by the k-means clustering method to rearrange observations into *k* clusters. For all the variables, the value *k* was found to be 2. Three types of sets of clusters were created; one set for internal Lean practices, one set for digital technologies, and finally, one set for each of the five operational performance objectives. The internal Lean variables were clustered as low and high implementation of internal Lean practices (LLP and HLP). The digital technologies were clustered as low and high implementation of digital technologies (LDT and HDT). The five operational performance objectives were clustered as low performance and high performance, respectively for quality (LQL, HQL), speed (LSP, HSP), dependability (LDP, HDP), flexibility (LFX, HFX), and cost (LCO, HCO). The Chi-square test among the levels of digital technologies and internal Lean practices according to the operational performance objectives can be seen in Table 24. Even though the some of the data seem to correlate, there were no significant values found, and thus, the hypotheses H_{11}-H_{15} must be rejected.

Table 24: Chi-square test among levels of digital technologies and internal Lean practices, according to the operational performance objectives

		LLP		HLP		
Quality performance	Digital technologies	Frequency	Adjusted residual	Frequency	Adjusted residual	Total frequency
LQL	LDT	10	1.7	6	-1.7	16
	HDT	6	-1.7	12	1.7	18
	Total frequency	16		18		34
HQL	LDT	7	2.1	3	-2.1	10
	HDT	.	-2.1	.	2.1	
	Total frequency	7		3		10

		LLP		HLP		
Speed performance	Digital technologies	Frequency	Adjusted residual	Frequency	Adjusted residual	Total frequency
LSP	LDT	10	1.4	8	-1.4	18
	HDT	5	-1.4	11	1.4	16
	Total frequency	15		19		34
HSP	LDT	7	1.2	1	-1.2	8
	HDT	1	-1.2	1	1.2	2
	Total frequency	8		2		10

		LLP		HLP		
Dependability performance	Digital technologies	Frequency	Adjusted residual	Frequency	Adjusted residual	Total frequency
LDP	LDT	8	1.4	6	-1.4	14
	HDT	4	-1.4	9	1.4	13
	Total frequency	12		15		27
HDP	LDT	9	1.4	3	-1.4	12
	HDT	2	-1.4	6	1.4	5
	Total frequency	11		9		17

		LLP		HLP		
Flexibility performance	Digital technologies	Frequency	Adjusted residual	Frequency	Adjusted residual	Total frequency
LFX	LDT	12	1.4	8	-1.4	20
	HDT	5	-1.4	9	1.4	14
	Total frequency	17		17		34
HFX	LDT	5	1.8	1	-1.8	6
	HDT	1	-1.8	3	1.8	4
	Total frequency	6		4		10

		LLP		HLP		
Cost performance	Digital technologies	Frequency	Adjusted residual	Frequency	Adjusted residual	Total frequency
LCO	LDT	9	1.5	5	-1.5	14
	HDT	6	-1.5	10	1.5	16
	Total frequency	15		15		30
HCO	LDT	8	1.8	4	-1.8	12
	HDT	0	-1.8	2	1.8	2
	Total frequency	8		6		14

4.4 Discussion of results

This master project set out to: 1) Map the current level of adaption of Lean manufacturing and digital technologies among Norwegian manufacturing plants; 2) Find out how operational performance is associated with the level of Lean manufacturing and digital technologies implementation; and 3) Find out how operational performance is associated with the combined implementation of both Lean manufacturing and digital technologies.

The first question can be answered by looking at the data collected from the survey on internal Lean practices and digital technologies found in Table 25. From the table, one can see that the average of both are close to three. As they both were measured on a five-point Likert scale, it can be argued that the current level of adaptation is a little over average. The minimum value of internal Lean practices is almost half a point more than the minimum value of digital technologies, which can be expected as Lean manufacturing have been around for a longer time than digital technologies. However, the mean being as high as it is, might reflect on how efficient and digital Norwegian manufacturers are. As the response rate of the survey could have been higher, the results of the survey are expected to not clearly show the full picture but can still give an indication of the current level of adaption of Lean manufacturing and digital technologies in Norway.

Table 25: Statistics on internal Lean practices and digital technologies

	Internal Lean practices	Digital technologies
Mean	2,9932	2,8339
Median	2,9667	2,7308
Std. Deviation	,54378	,52223
Range	2,04	2,54
Minimum	1,99	1,54
Maximum	4,03	4,08

The other research questions can be answered by looking at the research model hypotheses in

Table 26. Five hypotheses were accepted, showing that there is a correlation individually between internal Lean practices and some operational performance objectives, and that there is a correlation between digital technologies and some operational performance objectives.

Table 26: Summary of hypotheses accepted/rejected

Index	Hypothesis	Accepted/rejected
H_0	There is no relationship between the dimensions affecting operational performance (DAOP) and the operational performance objectives.	Rejected
H_1	Internal Lean practices are positively associated with quality performance	Accepted
H_2	Internal Lean practices are positively associated with speed performance	Accepted
H_3	Internal Lean practices are positively associated with dependability performance	Rejected
H_4	Internal Lean practices are positively associated with flexibility performance	Rejected
H_5	Internal Lean practices are positively associated with cost reduction	Accepted
H_6	Digital technologies are positively associated with quality performance	Accepted
H_7	Digital technologies are positively associated with speed performance	Rejected
H_8	Digital technologies are positively associated with dependability performance	Rejected
H_9	Digital technologies are positively associated with flexibility performance	Rejected
H_{10}	Digital technologies are positively associated with cost reduction	Accepted
H_{11}	There is a synergistic relationship between internal Lean practices and digital technologies in predicting quality performance	Rejected
H_{12}	There is a synergistic relationship between internal Lean practices and digital technologies in predicting speed performance	Rejected
H_{13}	There is a synergistic relationship between internal Lean practices and digital technologies in predicting dependability performance	Rejected
H_{14}	There is a synergistic relationship between internal Lean practices and digital technologies in predicting flexibility performance	Rejected
H_{15}	There is a synergistic relationship between internal Lean practices and digital technologies in predicting cost performance	Rejected

This result does not mean that the rejected relationships does not exist, merely that they were not found. The single measures of operational performance objectives might have biased the data, as the measured data was not a normal distribution. Another factor to consider was the number of respondents, as the 22% response rate is only 2% above the required minimum. A bigger sample of data might prove more significant.

4.4.1 Summarizing the implications

This master project shows that there is an adaptation of internal Lean practices and digital technologies among Norwegian manufacturers. As the data was only collected in Norway, the generalizations can only describe Norwegian manufacturers, though similarities to manufacturing companies in countries similar to Norway might be possible to find.

There is a positive correlation between Lean manufacturing and operational performance, and a positive correlation between digital technologies and operational performance. And also important, there is a positive correlation between Lean manufacturing and digital technologies.

5 Conclusion

This chapter concludes the thesis work and describes the steps taken in the attempt to answer the research questions and evaluates whether the objectives were met. The findings are summarized and the implications for theory and practice are further described. Finally, the research limitations are elaborated and recommendations for further work is given.

The main goal of this thesis was to map Norwegian manufacturers, and to measure the operational performance results of having implemented Lean manufacturing and digital technologies into the production processes. To be able to do this, a survey had to be developed in order to answer the research questions. Through a literature review, knowledge about the three main topics, Lean manufacturing, digital technologies, and operational performance was obtained. The literature review also examined the links between the three main research topics. Using the literature, a research process framework (Figure 4) was made and a research model illustrating the relationship between independent variables affecting operational performance was created (Figure 6). The research model was hypothesized, and the variables operationalized to translate theory into the practical domain.

In order to test the model and hypotheses, data was gathered from Norwegian manufacturers through survey research. A questionnaire was designed and sent out to 200 manufacturing companies in Norway, with a resulting response rate of 22% (44 respondents). The data was cleaned, and missing data was handled. This response rate was quite good, but it was discovered that the measures of the operational performance objectives were lacking, and thus, interfering with the results. The respondents were well distributed among the four different production environments, making the data received more generalizable.

The relationship between the different variables was examined using a bivariate analysis, and in doing so, the null hypotheses could be rejected, and five hypotheses could be accepted. The five accepted hypotheses were:

- H_1 Internal Lean practices are positively associated with quality performance
- H_2 Internal Lean practices are positively associated with speed performance
- H_5 Internal Lean practices are positively associated with cost reduction
- H_6 Digital technologies are positively associated with quality performance
- H_{10} Digital technologies are positively associated with cost reduction

The other hypotheses were attempted to be confirmed using a cluster analysis, but the attempt was not successful, and no significant correlations were found. The lack of measures in data regarding operational performance may have affected the results of the statistical analysis, as the data was found to not be normal distributed.

As for contributions to theory, besides the accepted hypotheses, a research model and a survey framework was created in order to be able to assess the proposed hypotheses. This can possibly be used again in order to assess the Norwegian manufacturing companies.

5.1 Limitations

Time

This project was conducted during the spring semester at NTNU, with a delivery deadline at June 11, 2018. The official start of the project was January 15, 2018, and the project time frame was 21 weeks. Given the limited amount of time available to carry out the project, the survey result may have been affected. This is due to how long one can wait for replies from the recipients of the survey. A shorter answer deadline for the recipients of the survey might lead to a lower response rate, which may in turn negatively influence the results from the survey.

Literature

There were two main limitations when it came to literature. Firstly, even if the literature study was comprehensive, the possibility of leaving out some of the relevant literature is significant. The literature that was used was limited to that of NTNU's library, both physical copies and online databases. As this project included a theoretical background of three main subjects, the total amount of available literature was too large to process. This may have resulted in relevant literature being missed or excluded. Another limitation was the language barrier. This project was only using literature written in English or Norwegian, thus relevant information written in other languages was not included in the thesis.

Survey

The results of the survey may not be representative of the full reality, as there are many variables to consider when conducting a survey. These variables include the grade of clear and concise questions, the understanding of definitions of concepts and terminology and subjective answers. How relevant the questions were to the specific recipient may have also limited the results of the survey, as the survey was intended to be sent out to a broad number of manufacturing plants. Another limitation was the response rate, because of the timeframe as discussed above, as well as other uncontrollable factors. To counter non-answer bias, the survey was designed carefully, and reminders was sent out. The survey was, however, intended to constitute a representative sample. Lastly, even though the survey would give an indication on the relationship of variables, it could not answer why the relationships existed.

5.2 Recommendations for further work

Several opportunities for further work could be identified through the study. The questionnaire developed could be improved and used to measure the Norwegian manufacturing companies over several years, in order to gain more reliable data.

The data gathered for this project can be used further for both qualitative and quantitative analysis. The data gathered can always be examined more, using other statistical analysis methods than used in this thesis.

Another different approach that could be interesting to examine is how different production environments would be affected by the results of this project. The results might be applicable for all, or only for some production environments.

Appendix A

Sven-Vegard Buer

7491 TRONDHEIM

Vår dato: 15.03.2018 | Vår ref: 59623 / 3 / STM | Deres dato: | Deres ref:

Forenklet vurdering fra NSD Personvernombudet for forskning

Vi viser til melding om behandling av personopplysninger, mottatt 05.03.2018.
Meldingen gjelder prosjektet:

59623	*Lean og digitalisering – muligheter og utfordringer*
Behandlingsansvarlig	*NTNU, ved institusjonens øverste leder*
Daglig ansvarlig	*Sven-Vegard Buer*
Student	*William Knudtzon*

Vurdering

Etter gjennomgang av opplysningene i meldeskjemaet med vedlegg, vurderer vi at prosjektet er omfattet av personopplysningsloven § 31. Personopplysningene som blir samlet inn er ikke sensitive, prosjektet er samtykkebasert og har lav personvernulempe. Prosjektet har derfor fått en forenklet vurdering. Du kan gå i gang med prosjektet. Du har selvstendig ansvar for å følge vilkårene under og sette deg inn i veiledningen i dette brevet.

Vilkår for vår vurdering

Vår anbefaling forutsetter at du gjennomfører prosjektet i tråd med:

- opplysningene gitt i meldeskjemaet
- krav til informert samtykke
- at du ikke innhenter sensitive opplysninger
- veiledning i dette brevet
- NTNU sine retningslinjer for datasikkerhet

Veiledning

Krav til informert samtykke

Utvalget skal få skriftlig og/eller muntlig informasjon om prosjektet og samtykke til deltakelse.
Informasjon må minst omfatte:

- at NTNU er behandlingsansvarlig institusjon for prosjektet
- daglig ansvarlig (eventuelt student og veileders) sine kontaktopplysninger
- prosjektets formål og hva opplysningene skal brukes til
- hvilke opplysninger som skal innhentes og hvordan opplysningene innhentes

Dokumentet er elektronisk produsert og godkjent ved NSDs rutiner for elektronisk godkjenning.

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NSD – Norwegian Centre for Research Data NO-5007 Bergen, NORWAY Faks: +47-55 58 96 50 www.nsd.no

Appendix B – Data examination

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,776
Bartlett's Test of Sphericity	Approx. Chi-Square	69,217
	df	6
	Sig.	,000

Figure B.1: KMO and Bartlett test for x1

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,636
Bartlett's Test of Sphericity	Approx. Chi-Square	72,406
	df	6
	Sig.	,000

Figure B.2: KMO and Bartlett test for x2

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,610
Bartlett's Test of Sphericity	Approx. Chi-Square	56,477
	df	3
	Sig.	,000

Figure B.3: KMO and Bartlett test for x3

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,681
Bartlett's Test of Sphericity	Approx. Chi-Square	125,344
	df	10
	Sig.	,000

Figure B.2: KMO and Bartlett test for x4

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,595
Bartlett's Test of Sphericity	Approx. Chi-Square	39,604
	df	6
	Sig.	,000

Figure B.5: KMO and Bartlett test for x5

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,663
Bartlett's Test of Sphericity	Approx. Chi-Square	31,289
	df	6
	Sig.	,000

Figure B.6: KMO and Bartlett test for x6

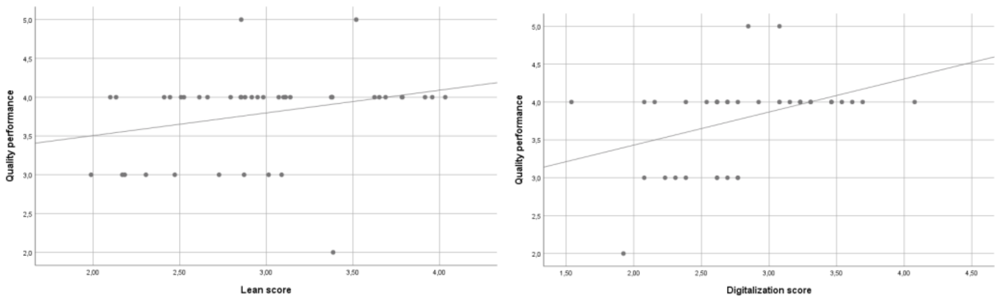

Figure B.7: Scatterplots of the independent variables related to quality performance

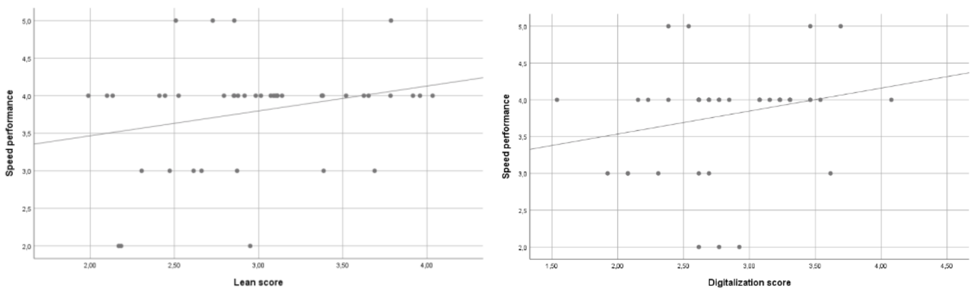

Figure B.8: Scatterplots of the independent variables related to speed performance

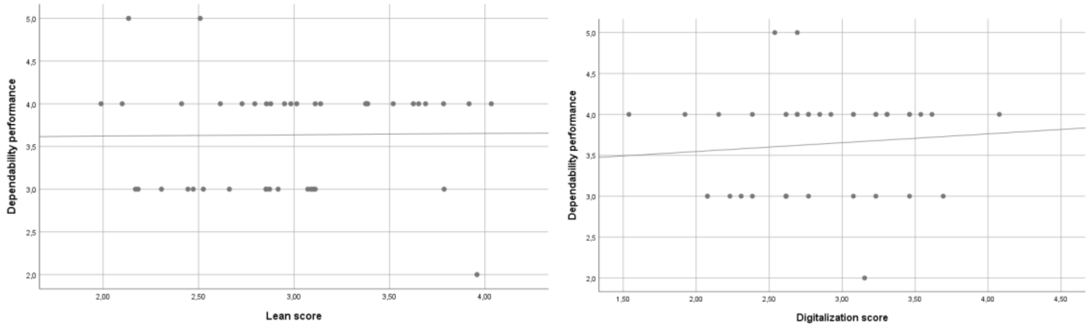

Figure B.9: Scatterplots of the independent variables related to dependability performance

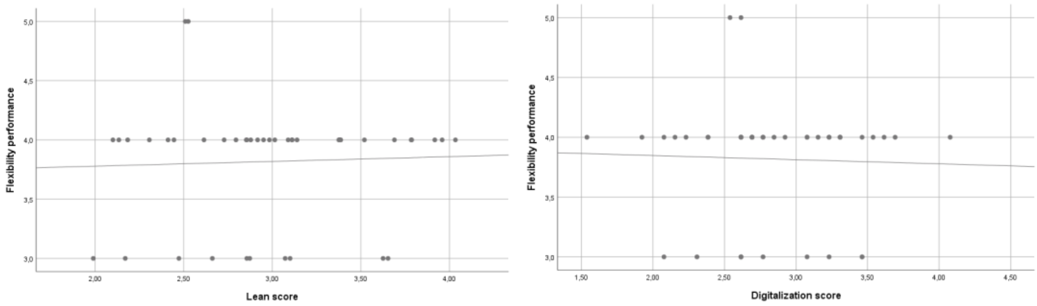

Figure B.10: Scatterplots of the independent variables related to flexibility performance

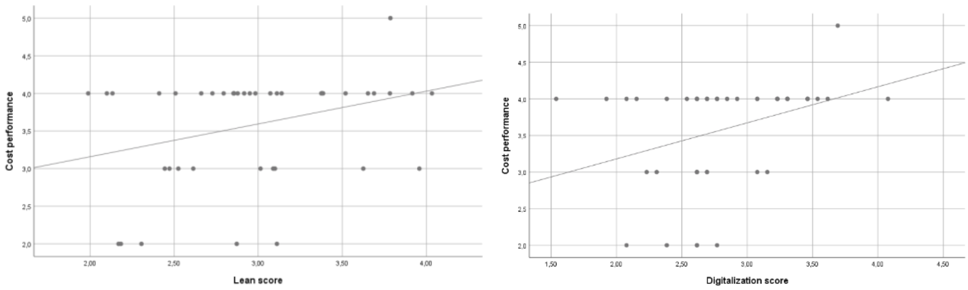

Figure B.11: Scatterplots of the independent variables related to flexibility performance

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