VILNIUS UNIVERSITY
FACULTY OF ECONOMICS AND BUSINESS ADMINISTRATION

BUSINESS PROCESS MANAGEMENT

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MASTER THESIS

DARBUOTOJŲ SKAITMENINIŲ KOMPETENCIJŲ POVEIKIS KOKYBEI, ŠVAISTYMUI IR KAŠTAMS GAMYBOS PROCESE MEDIJUOJANT SKAITMENIZAVIMO LYGIUI	THE EFFECT OF EMPLOYEE DIGITAL COMPETENCIES ON QUALITY, WASTE AND COST IN THE MANUFACTURING PRODUCTION PROCESS: THE MEDIATING ROLE OF DIGITALISATION

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Vilnius, 2025

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INTRODUCTION

Topic relevance

Relevance of different kind of technologies play an important role in our world today. Companies nowadays are looking for a competitive advantage that allows them to have a stronger presence in the market. Digital competencies of employees with the release of new gadgets and technological breakthroughs are pivotal to achieve needed results. Digital tools are being released each year, which in turn gives industries a lot of choices regarding systems and tools (Valamede and Akkari, 2020). Only with the effective use of tools, digitalisation can help different industries to enhance their current processes which in turn will boost customer satisfaction and retention (Valenduc and Vendramin, 2017). Digital tools and innovations are needed in the Manufacturing industry, because currently this industry revolves on humans and machines working together in the production process to achieve needed results and company goals. It is important to note that Digital Competencies are essential for successful implementation, because technological savviness allows employees to use the tools effectively. Recent studies suggest that digitalisation in the manufacturing industry is important as it can affect the existing production process of the company (Shahbazi, 2015). For any technology implementation to be successful, the company needs to be ready to make necessary adjustments that will allow their company to differentiate from others and attract high paying customers (Fremont, 2021). This is extremely important as in the ever-changing industry like manufacturing, focus on the customers is key. It is worth noting that for digitalisation to be effective it is important that the workers using technologies have digital competencies that would allow them to use the tools effectively (Huu, 2023). For this reason, it is necessary to research the strength of the effect employee digital competencies have on improving the manufacturing production process with the help of digitalisation. This information would serve as a theoretical guideline on the importance of technological savviness on the Production Process and can be used for further theoretical and practical analysis.

Research gap and exploration level

Existing sources regarding digitalisation in manufacturing industry focused on theoretical frameworks and broad research of the whole industry or Production Process, not going in depth into the most important metrics – Quality, Waste and Cost (Fremont, 2021; Isaksson *et al.,* 2018; Stucke, & Ezrachi, 2020). In these broad papers authors investigated the overall impact Digitalisation has on the manufacturing industry without looking at how digital technologies affect the specific metrics of the Production Process which is one of the main objectives of this thesis.

When it comes to Employee Digital Competencies, previous research investigated in what way digital competencies affect digital autonomy of the workers and their innovative work behaviours. It has focused on looking into technological savviness of the employees generally and its effects which is helpful for the thesis, however there is a need to look into how it can affect a specific industry of manufacturing and also specifically the Production Process through Digitalisation. The study has identified the lack of findings due to small sample size and primarily qualitative research being conducted (Huu, 2023). Due to that, quantitative research about the strength of the effect the digital competencies of people working in the manufacturing industry have on Quality, Cost and Waste with the help of Digitalisation would be an ideal way to fill these research gaps.

As the Employee Digital Competencies were researched in previous studies, the relationship between Digitalisation and digital proficiency was investigated to determine whether Digital Competencies are needed in a digital transformation scenario and it was found that digital competencies are needed in order to use the digital tools effectively, however it was research made on a broader scale not looking into the nuances of specific industries (Blanka, Krumay, & Rueckel, 2022). Moreover, this study lacked quantitative analysis which could add more depth to this research.

Regarding the research gaps, there is a need for empirical research in which we need to look at effects Employee Digital Competencies have on the Production Process of companies in the manufacturing industry with the help of Digitalisation. Also, it is important to highlight not only the benefits or drawbacks of the new technologies but also the importance of digital competencies the workers need to have in order to use them effectively and in turn enhance the current company business processes.

Research novelty / contribution to science

The research novelty of this paper consists of the in-depth analysis of the strength of the effect Employee Digital Competencies have on the Production Process in Manufacturing industry, specifically on Quality, Waste and Cost. Since Digitalisation is already widely and successfully used abroad in a plethora of different industries, the scientific value of this paper would consist of clear answer whether Digital Competencies influence Quality, Waste and Cost in the Production Process of Manufacturing companies with the implementation of Digitalisation and to what extent. This would help companies in the field to determine, is it worthwhile and profitable to consider the use or change of their current systems and whether only the implementation of new technologies is needed or also significant up-front investments regarding developing Employee Digital Competencies. This paper will help companies to determine whether bigger focus on the skills and the proficiency of their employees will be an important solution to their problems, be it as a necessary change in only one department or the whole organization. For the researchers it would serve as a guideline and an incentive to investigate other important metrics and have further research in the manufacturing industry as this thesis focuses on three main metrics: Quality, Waste and Cost.

Research problem

Due to research gaps, there is uncertainty around the strength of the effect employee Digital Competencies have on Quality, Waste and Cost in the Manufacturing production Process with the implementation of Digitalisation.

Research question

What is the strength of the effect Employee Digital Competencies have on Quality, Waste and Cost in the Manufacturing Production Process, where Digitalisation level plays a mediating role?

Research aim

Assess and evaluate the effect Employee Digital Competencies have on Quality, Waste and Cost in the Manufacturing Production Process where Digitalisation level plays a mediating role.

Research objectives

1. To define the effect of Employee Digital Competencies on the Quality, Cost and Waste in the Manufacturing Production Process
2. To evaluate the strength of the effect Employee Digital Competencies have on success of implementation of Digitalisation
3. To define and discuss Key indicators of Quality, Cost and Waste in the Production Process
4. To evaluate the relationship between Employee Digital Competencies on Quality, Cost and Waste in the Manufacturing Production Process with the implementation of Digitalisation

The methods deployed by the Master thesis

1. Scientific literature analysis
2. Quantitative Online Questionnaire
3. Quantitative Data Analysis

The structure of the Master thesis:

The Master thesis consists of 4 chapters, each covering different aspects of the topic. In the first section, the introduction, the context, and the importance of the topic is revealed, to show why the topic chosen is important and relevant to the researchers and the stakeholders. The main problem, aim and objectives of the research are also found here to highlight the main topics that need to be studied and the main question which needs to be answered within this thesis. It is an important part that shows the basis of the whole thesis and serves as a guideline on how it will be written.

The second section is the analysis of scientific literature that serves a purpose of gathering theoretical knowledge base that is needed to later carry on the practical research. This chapter consists of thorough analysis of the scientific articles, seminal works, and other thesis to get important insights on the theoretical aspects of the chosen topic. In this section each independent and dependent variable is studied to get detrimental information and critically assess the previous studies in this field. It is important to have a deeper understanding of the topic and be able to spot patterns, analyse the information provided and evaluate the sources. With the written chapter the first research objective will be achieved.

The third section is empirical research methodology, which is the practical part of the thesis. It consists of the practical research methodology with the research methods chosen, data gathering and the analysis of the results. This is the section in which practical evidence is gathered to confirm or refute the hypotheses. The research is carried out to answer the main question of the thesis and with the help of research methodology, data analysis and result analysis, the second and third research objectives are achieved.

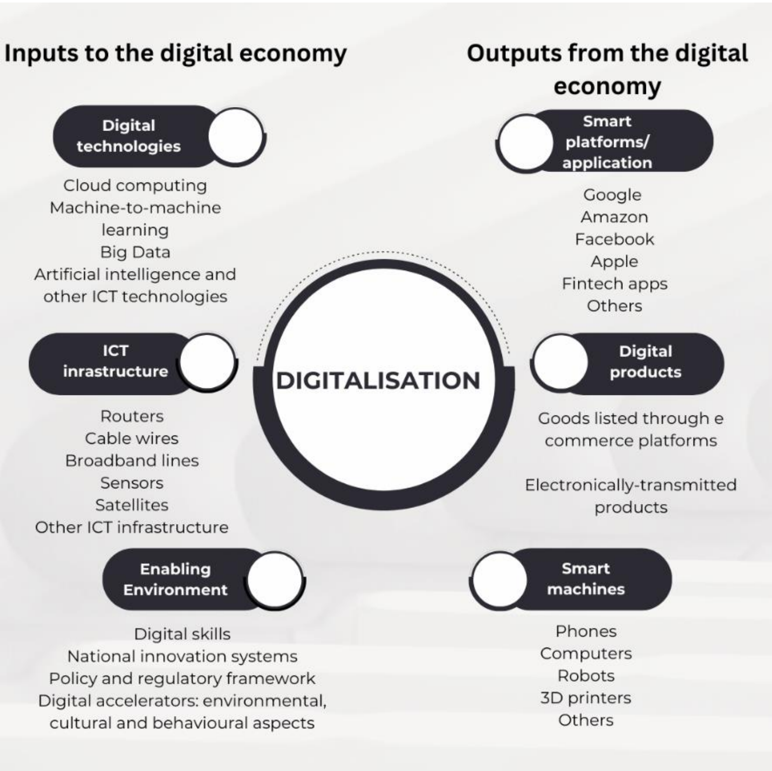
In the last section, conclusions and recommendations, the main results are summarised and written in accordance with the research objectives. It is an important chapter to outline the findings and propose necessary recommendations for the companies, that are willing to prioritize developing digital competencies through digitalisation to improve their Production Processes.

1. THEORETICAL ASPECTS OF EMPLOYEE DIGITAL COMPETENCIES AND IT'S EFFECT ON QUALITY, WASTE AND COST IN THE MANUFACTURING PRODUCTION PROCESS WITH THE IMPLEMENTATION OF DIGITALISATION

1.1. Theoretical concept of Digitalisation in Manufacturing

In the ever-changing world of innovation every year new and updated technologies are developed which makes the processes of different companies easier and more efficient. (Banga and te Velde, 2018). According to Banga and te Velde (2018), digitalisation can be described as follows: "digital transformation of the economy, achieved through an interaction of digital technologies". This description shows that digitalisation is linked to transforming current processes with the help of digital technologies, which is an accurate description of this phenomenon. It is especially important in the Manufacturing Industry, in which use of new technology is a must to achieve the needed results. With so many innovations being developed every year the industry needs to be on top of any news regarding digitalisation. As it is a complex term, *Figure 1* shows the variety of technologies Digitalisation encompasses.

Figure 1. *Aspects of Digitalisation*



Source: based on Banga & te Velde (2018)

It is evident that not only digital technologies, but also the infrastructure, the environment, digital product, platforms, applications and smart machines are a part of this phenomenon. Digitalisation encompasses a wide range of different aspects due to the nature of this process as the main goal of it is to transform the environment to a smart or digitally competent (Banga and Te Velde, 2018). This ensures a gradual and steady transition from the current manual labour to more sophisticated industrial process. The term „factory digitalisation“ was used in another study (Buer, Semini, Strandhagen & Sgarbossa, F. (2021) with a slightly different meaning, having the improvement of Production Process in mind with use of different digital solutions. This description is much more relevant to the manufacturing industry, therefore throughout this paper, the term digitalisation will refer to the process of using different innovative technological solutions in the context of the Production Process in a Manufacturing setting.

Another important term in the context of Digitalisation in the space of Manufacturing is “Industry 4.0”, which can be defined as a complex technological framework which main purpose is to digitalize the processes and transform the work of companies from manual to technological and autonomous mainly in the manufacturing field (Pereira, Alves & Arezes, 2023). It is important to highlight this phenomenon as well, because Digitalisation as a process is a tool with which industry 4.0 can be achieved. Industry 4.0 is a new term, which encompasses the motivation of companies to achieve strategic advantage with the use of technologies in their processes (Pereira *et al.,* 2023). However, it is worth noting that these improvements are possible only when employees develop and already possess the necessary digital competencies, as effective digital transformation relies heavily on employees and their skills (Dillinger, Bernhard & Reinhart, 2022). This shows that even though digital tools are important they should be looked at as an enabler or mediator, through which Employee Digital Competencies can impact the Production Process. Skilled employees have a big advantage as they are able and to ready to leverage these innovations and in-turn improve the production outcomes (Dillinger *et al.,* 2022). For this reason, it is important to note, that the use of these technologies and the future of Manufacturing which is linked strongly with Industry 4.0 is linked not only to technologies itself, but primarily to the ability of people to use them effectively in their line of work (Pereira *et al.,* 2023).

The Manufacturing Industry is an industry where a lot of technologies are used on a daily basis, especially when it comes to different types of manufacturing and the specific tools needed to produce a product. Augmented Reality is a relatively new technology, which can be defined as a tool that allows to overlay and show digital information in the real word with the use of a different type of technological gadgets (Pereira, Alves & Arezes, 2023). Augmented Reality as a technology is flexible and can be incorporated into a wide range of tools that are being used by manufacturers today, hence why companies seek out new digital solutions and use the newest innovations to boost their processes as in the case of Boeing and their use of AR in employee training (Frigo and Da Silva, 2016). With the use of Augmented Reality, the study found that the use of this technology in their training process have positively impacted the primary quality and reduced the number of usual mistakes made without the use of AR software. Even though this technology is new and relatively unknown it has helped a big company in training, which in turn helped them to spend less time and effort to train new staff. This is not the only practical use of this technology in the aerospace manufacturing as in the same study (Frigo & Da Silva, 2016) a new example was presented in which another huge company in the aerospace industry, Airbus, is using Augmented Reality application called "MiRA" that allows the workers to find errors after scanning different parts and in turn reduce the time of this point of the Production Process (Frigo & Da Silva, 2016). With the implementation of AR these companies have experienced major benefits to their Production Process even though this technology is not widely used in the Manufacturing industry. These examples show the power of selecting the right tools for the Production Process to ensure that benefits of the innovation outweigh the drawbacks, which are usually an investment of time and cost of technology implementation.

Digitalisation is an important step for every company to improve their current processes as it can provide a digital solution to a real-life problem that companies are facing every day. In an analysis of digitalisation in different markets, (Stucke, & Ezrachi, 2020) have managed to analyse the importance of digitalisation, as they have found that in some markets, digitalisation has had a huge impact and a revolutionary effect. If there are markets that benefit this much from this phenomenon it is worth looking into how it can affect the companies in the Manufacturing industry which rely on technologies and different tools to produce their products. In another study (Isaksson, Hallstedt, & Rönnbäck, 2018) examined the reason why digitalisation is important for the manufacturing industry specifically. They have found that the industry is highly competitive as it was mentioned that "competitiveness of manufacturers lie within their ability to adapt and develop efficient and effective practices to develop the needed solutions" (Isaksson *et al.,* 2018). It is important to note that achieve and develop the needed solutions faster and cheaper innovative solutions are essential, because they can provide the companies with the tools needed to differentiate from the market. The study also touches upon a question of whether currently used mechanical and technological tools are enough to satisfy the needs of the customers. Manufacturing industry is evolving with the use of different digital tools, and it is important to understand that the companies and employees that are unwilling to change and improve will unfortunately be left behind. Skilled and competent employees are able to use digital tools successfully and effectively, allowing the Production Process to be more efficient and innovative (Hernandez-de-Menendez, Morales-Menendez, Escobar, & McGovern, 2020). Overall, based on previous research in this section, it is worth noting that it seems that digitalisation itself relies on proficiency and technological savviness of the workers that operate these technologies to become an important part of the manufacturing industry.

Digitalisation is an important phenomenon, effects of which on entire markets and industries were studied in previous research. For example, Fernández-Macías (2018) has reported that the main advantage of digitalisation lays in lower costs and better efficiency regarding storing, using and processing digital information. It was also reported that digitalisation of the process is needed, because it means more effective control and understanding of it. These important benefits highlight the positive effect related to cost, which is due to use of new technologies. In another study Fremont (2021) draws our attention to digitalisation and its effect on growing in new markets. The author mentions the positive effect of digitalisation in this regard as the technologies used make significant improvements and add value to existing and new markets. It shows that digitalisation when used right opens new opportunities for businesses in new markets and strengthens the position in the current ones (Fremont, 2021). The author suggests that one of the most important effects of digitalisation is value creation, as digital solutions provide value for both the companies and the customers. Based on the author, in regard to processes of the company, introduction of innovations results in the following: "improved ways of working, the re-thinking of processes, the elimination of main regard to production processes, improved accuracy of tasks with better data" (Fremont, 2021). In a recent study Fu (2022) has identified some negative sides of Digitalisation in regard to the manufacturing in China. First, he identified that the fast adaptation of new technologies in China has commenced differently in regions of the country, which has resulted in a uneven level of digital proficiency throughout the country. This means that the companies aim to attract workers from specific cities where the digital proficiency is higher in order to get better results. It shows that companies understand the importance of skilled employees which play a pivotal part in digital transformation implementation (Potemkin & Rasskazova, 2020). This is why more companies are willing to invest in training nowadays to ensure that their workers are competent and able to tackle new challenges. Competent employees are then able to use the training and developed competencies to make informed decisions and impact the Production Process with their knowledge and ability (Potemkin & Rasskazova, 2020). It is evident that there are a lot of use cases for different technologies and innovative solutions can positively impact and improve companies in the manufacturing industry, however it is worth mentioning that Production Process does also face drawbacks in regard to digitalisation. Digitalisation albeit being a major phenomenon contributing positively to a variety of different industries, can have drawbacks when used in the Manufacturing industry specifically. Due to digital technologies being a costly investment another problem is the expanding gap between large enterprise and smaller and mid-sized businesses due to different budgets allocated in regard to digitalisation and developing digital competencies (Fu, 2022). This is the biggest problem, because different budget means different level of digitalisation implementation and a different degree of digital competencies of the employees. This discrepancy could result in digitalisation and digital competencies being a privilege which not many companies could afford.

In summary, Digitalisation as any other phenomenon has positive and negative sides, understanding of which is needed for any company wanting to improve their Production Process by implementing digital technologies into their line of work. It is looked as a process in which different innovative solutions are implemented to improve existing company processes. With correct implementation of various digital solutions, as the evidence shows, Digitalisation results in many benefits for the Production Process, however it is worth noting that there is a need to look into specific metrics which can be affected by these digital technologies.

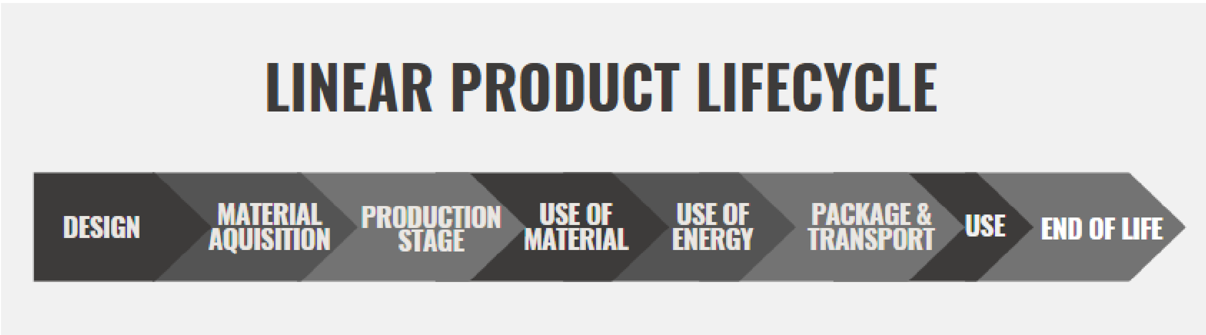
1.2. Theoretical concept of Production Process & Process result measures in Manufacturing

1.2.1. Theoretical concept of the Production Process

In any company in the Manufacturing industry Production Process is the most important part of the organization, as it has direct impact on the success or failure of the company. While a variety of definitions of the term have been suggested, this paper will use the definition found in the same study, in which it was mentioned that it is a concept in which resources are used to provide the end-goal for customer in a way of service or finished production. It was also mentioned that currently this process and the industry is evolving from a concept to more tools based and methodical approach. To produce a product from scratch it is essential to have a clear and efficient Production Process in place to avoid unnecessary delays and ensure customer satisfaction. It is also important to highlight the necessity to distinguish that process innovation is different to product innovation, both of which are an important part of the Production Process (Tidd and Dessant, 2018). In the case of the innovations of the product, the emphasis is on the product itself and involves the development of new, unique products or items. In the case of the innovations of the process however, the importance is towards they production methods and how they can be improved. In the context of the Production Process and improving with the help of Digitalization, it is important to highlight that the innovations are primarily used to enhance the process innovation and only after improving the processes, enhancement of the product innovation is possible (Tidd and Dessant, 2018). In the study it is noted that the technologies need to be agile, as in the current ever-changing market, it is extremely to be flexible and agile in order to make fast changes and lower the response time. The tools needed to get better quality in the Production Process can be described as quality control mechanisms, allowing the production process to be more efficient, accurate and productive. In order to run properly, the Production Process needs to address quality in order to minimize defects and maintain higher standards (Tidd and Dessant, 2018).

In the *Figure 2* it is evident that the linear product lifecycle consists of many steps which all need to be done on a high level in the Production Process. It shows the necessity to acquire resources, material used to produce the product, take into account not only the production stages itself but also designing the product first, after completion packaging and transporting it to customers in order for them to use said items. The materials are also identified in three different types: productive material, process material and residual material, each containing other aspects of the Production Process (Shahbazi, 2015). It shows that each product has a lifecycle in which the process of production plays a key role, as without effective Production Process in place the quality of the produced items is much lower. As mentioned previously higher quality standards are essential to improve quality, therefore it is worth looking into a proper way of establishing these standards (Tidd and Dessant, 2018). This ensures that the Production Process can be improved regarding Quality. In turn higher quality means that the Production Process is more effective.

Figure 2. *Linear product lifecycle*



Source: based on Shahbazi (2015)

Due to this the quality and efficiency of the Production Process are interchangeable, as both are needed for a fast and reliable rate of production. Any error in the Production Process not addressed on time results in costly mistakes, delays and more importantly disruption of the whole Production Process, that can negatively impact other line of products (Shahbazi, 2015). This is why manufacturing companies tend to emphasize the importance of the quality department, which ensures that everything is running smoothly. Moreover, the Production Process consists of various steps that serve different functions, all of which are essential and contribute to the final result – the product. However, without appropriate tools and innovations the Production Process cannot evolve in needed rate, so that is why important metrics show the output of the Production Process. (Esmaeilian *et al.,* 2016). As in any process there are several important indicators and metrics that contribute to its effectiveness to ensure the process runs smoothly.

In a recent study, written by Shahbazi (2015) the material efficiency was studied in regard to manufacturing in food industry which looked into various metrics in the Production Process like overall equipment effectiveness, cycle time, lead time and various others. However, during the study significance of three metrics were discussed: quality, waste and cost. The study has emphasized the importance of quality control as a necessity for the Production Process, as it was found that this change results in better quality standards and improvements for the final product (Shahbazi, 2015). This is the first metric which the author mentioned as an important one in the Production Process. It is also important to highlight the importance of innovation in the Production Process as it allows the reduce human error and boost the efficiency with the help of several new technologies. It is worth mentioning that the use of said technologies and innovations minimizes the environmental impact, which is one of the key strategic points for companies valuing sustainability (Tidd and Dessant, 2018). Cost was also discussed in this paper as in important metric, as it strongly correlates with the efficiency, as the cost can be lowered if the efficiency is improved (Shahbazi, 2015). While there are many proposed ways of how to lower the cost in the Production Process the most important finding of his in this regard was about the cost savings linked to initial investment in technology. It was found that even though digitalisation is a costly improvement in the short-term, long-term it can result in long-term savings due to a more efficient Production Process (Esmaeilian *et al.,* 2016). These finding suggest that any improvement be it a digital one or a standard change has a possibility to reduce cost by raising the efficiency. As with any change to the production process there can be barriers which make the implementation of the innovations difficult such as: employees not ready for change, poor management of resources, technological problems of implementation into the existing network and tools. However, it is important to highlight that if these barriers are tackled and the production process aligns with the company's strategic view on innovation, there is a big likelihood of improvement and success possible (Tidd and Dessant, 2018).

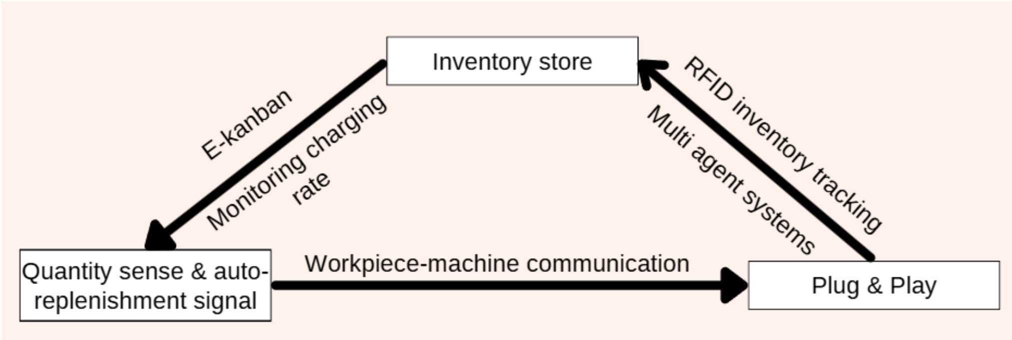
All these metrics are very prevalent in Lean Manufacturing and therefore are of big significance in the context of both the manufacturing industry and quality management. (Shahbazi, 2015). Each of the metrics have their own measures that track the performance and the result and allow to identify any potential faults in the process. For Quality these measures consist of defect rates, process efficiency and product traceability (Bankar and Nandurkar, 2023). For Waste there are several measures all of which are linked to the term "muda" including transportation, inventory, motion, waiting, over-processing, overproduction and defects (Leksic, Stefanic & Veza, 2020). For Cost the measures are the following: Cost of Quality, Cost of Inventory, Cost of Waste, Cost of Labor, Cost of Equipment (Durakovic, Demir, Abat & Emek, 2018).

In summary, Production Process can be defined as a concept in which value for the customer is provided with producing a product. The Production Process is the most important business process in manufacturing, which needs to be efficient, reliable and flexible to meet the customer demands. Even though there are countless Production Process results measures, one of the most important ones are: Waste, Cost and Quality. To ensure that the importance of the metrics is highlighted in this study, a theoretical analysis is needed to highlight the importance of each of these three metrics.

1.2.2. Theoretical concept of Quality in the Production Process

Quality is an important metric in any industry, but especially in manufacturing. It is important to define quality to have a deeper understanding of the concept of this metric to ensure that appropriate measures are implemented to achieve needed results. There are various definitions of quality, however, for this study other definition of Quality will be used, which was defined as a metric which is used in Production Process to ensure that the item is produced within predefined standards or specifications (Bankar and Nandurkar, 2023). This is an accurate definition which successfully defines this metric. This industry depends heavily on the production of high-level goods in order to satisfy the needs of the customer. Previous study has reported that faults in the quality of goods can have a serious negative impact on the satisfaction of customers and lead to higher costs due to need to fix the issues (Blanco-Encomienda, Rosillo-Díaz, & Muñoz-Rosas, 2021). This would result not only in customer dissatisfaction and the reduction of said clients, but also transitions to other metrics analysed in this thesis – waste and cost. It is important to note that quality is very important not only for the internal processes but also external customers, their needs and satisfaction (Carnerud and Bäckström, 2021). This combination of great quality and satisfying customer needs ensures that the Production Process goes smoothly and does not disrupt any other processes in the company. If the customer needs are not focused on, even though the quality of the products is high, the end result will be not acceptable for the client. Before implementing any innovation, customer needs and expectations need to be prioritized first (Tidd & Dessant, 2018) It is extremely important to have a customer centric approach and to tailor the Production Process to the needs of the client and make any necessary changes, to ensure that their preferences are being met (Carnerud and Bäckström, 2021). For this reason, technologies used can results in a much better improvement of Quality as evident in *Figure 3*. It is evident that real time monitoring and inventory tracking can significantly improve Quality in the Production Process, based on previous research (Sanders, Elangeswaran,& Wulfsberg, 2016).

Figure 3. *Effect of technologies on the Production Process*



Source: based on Sanders, Elangeswaran,& Wulfsberg (2016)

In a recent study, it was found that real-time monitoring of the work could provide a significant improvement to current levels of quality as each step of the Production Process is monitored in real time and any mistakes are found immediately (Clancy, Ahern, O'Sullivan, & Bruton, 2020). This could be possible with the help of IoT, as this technology allows to significantly improve quality with real-time monitoring, based on previous research findings (Bankar and Nandurkar, 2023). One of the main benefits of the use of this technology is that it used continuously, which means that the Quality is measured as long as the process is outgoing. This allows companies to decrease the defect rate, improve the process efficiency and enable product traceability (Bankar and Nandurkar, 2023). Moreover, the research showed that a lot of data is gathered in the process, which results in the ability to spot patterns and predict future mistakes regarding quality. To ensure that the quality of the Production Process as a whole is high, it is important to highlight the need track quality in each production stage, as this allows to check every single step and get large amounts of data which can be then gathered and processed with the help of new technologies (Carnerud and Bäckström, 2021). However, it is worth considering, that these innovations need to be implemented by humans and technological competencies need to be built first. Implementing any quality system or new technology is a rather difficult process due to resistance of the worker to change, lack of competencies needed to operate new systems and current systems not being flexible to add the necessary adjustments (Sanders *et al.,* 2016). Therefore, it is extremely important that the management proposes the change gradually in order for the employees to make necessary adjustments and in-turn have less resistance to change and more motivation (Carnerud and Bäckström, 2021). It is also worth mentioning that training is an essential part of successful implementation due to it having a large impact on the building of employee competencies. With proper training and adequate support, the current employees could improve the Quality of the Production Process significantly, positively impacting the Waste and Cost as well through digital tools and solutions. It is worth noting that in order to successfully implement any quality systems or innovations, the IT department needs to make sure that it is implemented in phases and supervised in order to have an effective and accurate implementation (Carnerud and Bäckström, 2021).

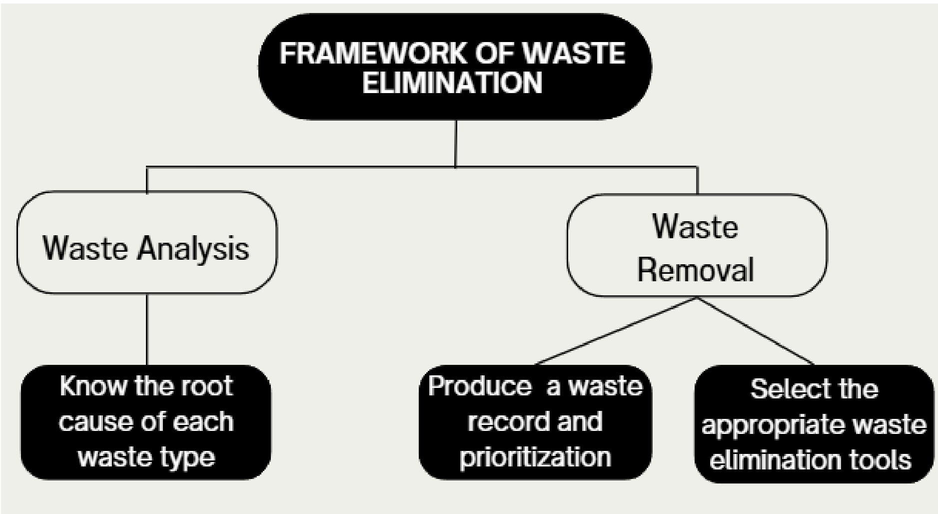
It has been suggested that quality is one of the most important metrics for the customer when choosing the provider, so this prompted companies to prioritize quality in order to attract more clients. (Blanco-Encomienda *et al.,* 2021). One study examined the effect machine learning and deep learning has on predictive quality in manufacturing, in which it was found that data analysis is a crucial step to find patterns and trends of issues in quality and digital solutions can aid in helping to fix them (Tercan and Meisen, 2022). During the research it was found that both machine learning and deep learning approaches show great results when it comes to quality control. The result of this study shows a potential trend of the use of digital solutions, towards which more manufacturing companies can drift in order to improve their current Production Process. The trends in the study show the future rise of digital solutions in quality control which are tied to Industry 4.0, digital quality control systems, artificial intelligence and integration of big data analytics to existing quality control processes (Carnerud and Bäckström, 2021). These tools provide a lot of different benefits and makes quality a predictive measure, as any potential defects, problems and bottlenecks can be spotted ahead of time due to patterns and collected analysed data. The need to use these technologies stems from the finding of the scientific article, in which it is specified that the current quality control tools may not be enough in the context of globalization, constant changes in expectations by the stakeholders and flexibility needed to fulfil the needs of the customer (Fundin, Bergquist, Eriksson & Gremyr, 2018). Therefore, even though digitalisation is closely linked to a better quality control system, without making necessary adjustments it is rather unlikely that these tools will succeed. However, with the correct implementation, businesses will see a tremendous improvement in the quality of their products.

In summary, Quality is an important metric, in regards not only to customer satisfaction but overall efficiency of the Production Process. Digital tools are used to improve quality control and introduce predictive measures to enhance the current workflow. It shows the need to have digital solutions that can improve Quality control, as well as competent employees that can leverage these technologies. Especially IoT, machine learning and deep learning were identified as innovations that aid in improvement of Quality. Although quality is an important metric it is worth analysing another metric, waste, that is closely related to the manufacturing industry specifically.

1.2.3. Theoretical concept of Waste in the Production Process

In simple terms waste can be defined as an activity that occurs in a process which increases the cost and time without adding value to the product or service (Mostafa and Dumrak, 2015). It is important to also note, that it is a metric in manufacturing as well as a resource that drives continuous improvement. In the paper it was specified that even though the activities in manufacturing can be classified into value adding, non-value adding and necessary, but not value adding, this classification is not enough to eliminate waste (Mostafa and Dumrak, 2015). A more thorough classification is needed to ensure that reducing or eliminating waste entirely will be possible in the Production Process. That is why a more comprehensive classification was proposed, that originated from Toyota Production System (TPS) and was first introduced by Ohno, which consisted of 7 Muda wastes: "1.) overproduction, 2.) waiting, 3.) unnecessary transport, 4.) incorrect processing, 5.) excess inventory, 6.) unnecessary movement, and 7.) defects" (Mostafa and Dumrak, 2015). This is the classification that will be used throughout this paper to ensure that the interpretation of waste is correct. It is also worth noting, that having a Production Process in place can significantly help to minimize waste, because there is a clear work structure in which problems are solved one after another, just like in lean activities (Leksic, Stefanic & Veza, 2020). That is why it important to ensure that a strong process is in place improving which will result in significant improvements. One particular study looked at waste elimination from another perspective, using digital solution to solve this practical problem. In the said study, it was reported that growing interest in industry 4.0 and its application automates and positively influences many manufacturing processes (Alieva and Haartman, 2020). It was a study that focused on use of digital technologies together with Lean Manufacturing to eliminate waste and proposed an innovative approach when compared to current practices. Previous studies have shown that there are a lot of different solutions involving lean activities or other methods that can improve waste management. In *Figure 4* a framework of waste elimination can be found with every necessary step. It is a process which is carried out in three phases, each of which have aspects which need to be addressed first. All of these steps are needed to successfully remove waste from current Production Process (Mostafa and Dumrak, 2015). Waste detection without any digital tools and solutions can be a timely and costly process, that is why this plan ensures that with Digitalisation in place, technologically competent employees will be able to detect and eliminate waste themselves even with the faults in technological detection. It is important to note that below process of waste elimination can be achieved only with the use of technologies, as it significantly shortens the time of identifying and eliminating waste (Mostafa and Dumrak, 2015). This is a process which needs to be done thoroughly in order to achieve needed results and investigate every single step. With the use of digital technologies, spotting and eliminating waste is easier and the whole process is more effective (Wagner, Herrmann, & Thiede, 2017). It is possible due to advanced methods of data collection, automation of tasks and monitoring the Production Process and each of its stages in real time. Even though a lot of different technologies can have a positive impact on Waste elimination, specifically IoT sensors allow to detect any pattern changes in the Production Process and can spot defects, that usually lead to Waste. This allows the company to solve the issues beforehand and therefore eliminate Waste in regard to the waiting and response times (Wagner *et al.,* 2017). Automation is another key concept which allows companies to minimize human error with the help of machines and robotics. This poses a risk of employment for people not willing to change and develop needed competencies to operate these new machines or robots but on the other hand it allows companies to cut costs and maintain less people with a higher production output (Wagner *et al.,* 2017). It also helps with overproduction, as the machines or robots can be programmed and set-up to produce only the needed amount, based on the orders received. However, automation involves some risks, mainly due to need to have an accurate and effective Production Process with Lean principles in mind, as automating the process of production without having clear system in place will result in unnecessary complexity, which in turn leads to more Waste (Wagner *et al.,* 2017). Also, it is important to note that new technologies require constant updates to work, which is both costly and time consuming (Leksic *et al.,* 2020). This is a thin line which companies need to have in mind before proceeding with these changes. With the successful implementation of technologies and developing Employee Digital competencies, companies can lower costs with the use of different innovative solutions (Mostafa and Dumrak, 2015).

Figure 4. Framework of Waste elimination



Source: based on Mostafa and Dumrak (2015)

To determine the effects of digitalisation in industry 4.0, Alieva and Haartman (2020) compared two European manufacturing companies both of which are big companies that see the importance of tracking, collecting and analysing important data with digital tools. During the study three digital wastes were identified in regards to data: not collecting data entirely, collecting but not using the data for feedback and improvement and not achieving the needed result. Both companies identified the need of data collection, interpretation and transformation and recognised the need to replace paper documents with digital tools integrated to their current ERP system. As these companies are successful and both employ over 30 000 employees their perspective on data and analytical tools shows a trend of manufacturing sector pivoting to a more digital approach in the near future (Alieva and Haartman, 2020). With the key waste elements relying heavily on technological assistance it is important to look into digitalisation as a tool for companies to pick the correct technology, that can track and eliminate waste efficiently but mainly developing digital competencies of the employees, as they will be responsible in operating the tools needed for success (Wagner *et al.,* 2017). For any successful business to reach needed results, waste and its reduction is one of the main tracked metrics to ensure profitability. On the other hand, companies struggle with lack of resources and funding, which undeniably slows the implementation of technologies and in turn slows down the process of waste removal (Leksic *et al.,* 2020). It is important to recognize where significant costs lay in the Production Process and how digitalisation can help to fix these issues.

In summary, waste can be defined as an activity that does not generate value and could be further classified as one of seven types of waste. Digital solutions help to eliminate waste and in turn improve the Production Process in this way. Especially IoT, robotics and automation are innovations which allow competent employees to leverage these technologies correctly and ensure that they are implemented correctly. As Quality, Waste and Cost are interchangeable in the Production Process, it is worth looking into all of them to determine the correct way of the innovation implementation.

1.2.4. Theoretical concept of Cost in the Production Process

Cost is a well-known term which is defined by monetary value of a product, material or process, however throughout this study a slightly different definition will be used, regarding cost as total expenses needed to produce a product, including cost of labor, materials and overhead (Al-Hattami *et al.,* 2020). When it comes to profitability, companies tend to reduce costs, when possible, simultaneously trying to keep their efficiency. In a recent study it was noted that pricing of products works on cost-plus approach, in other words having a profit margin which is priced on top of the cost of materials and preparation. Price is very important for the customer and due to this companies are looking into ways how they can reduce costs to ensure that they have a competitive price of their products in the market. This in turn results in more sales and larger profitability for the company. This shows the importance of lowering costs in the Production Process to propose the best-selling price of the product. Lower costs are also one of the primary goals of Lean, as this methodology focuses on eliminating waste or “muda” and as a result decrease cost in the Production Process (Durakovic, Demir, Abat & Emek, 2018). However, it is worth noting that both Waste and Cost are clearly separated but interrelated aspects of production (Ohno, 2019). In another study it was found that implementation of new technologies results in lower production costs, which can be seen as a positive and a negative, depending on the perspective (Banga and te Velde, 2018). From the company perspective implementation of technologies result directly in lower costs and higher efficiency but for the employee it can result in changes which are not always received positively. It is worth noting that reduced costs allow companies to hire more employees, however one of the main criteria of hire would be the technological competence, as the employee will need to operate and use these tools on daily basis (Banga and te Velde, 2018). In regard to waste, significant costs occur with overproduction, which usually is linked to storage cost. (Shahbazi, 2015). This shows that lower amounts of waste are linked to lower amount of cost as well. This is a big problem, which requires innovative solutions to solve.

Digitalisation is a phenomenon that can help manufacturing lower the production costs. To better understand the effect digitalisation and technologies can have on the cost in the Production Process, De Kruijk (2018) analysed the effect of robotics in the Production Process and the cost reduction associated with the use of this technology. During the study it has been demonstrated, that use of robotic pick & place activities can significantly reduce costs and also decrease lead time. The benefits of this technology are massive, as it was found that "use of automation over manual labour show potential recurring cost saving of 40-50 % compared to the baseline parts" (De Kruijk, 2018). These numbers show that use of robotics benefits cost reduction and it is worth looking into the use of this technology. One other benefit of the use of robotic is also the increase in quality as robotics allow to do the repetitive tasks better and eliminate the majority of human errors (De Kruijk, 2018). In another study it was found that Virtual Reality (VR) can also lower costs, particularly when used for training manufacturing employees (Cohen, Faccio, Pilati, & Yao, 2019). This lower costs and time needed to train new employees as VR allows users to learn in an immersive and real-world scenario. It also can be argued that use of VR increases quality, especially when it comes to new employees as it allows them to learn in a virtual environment as opposed to learning on a real product. In the Production Process there are several costs that can be lowered with the implementation of innovative solutions, referred to as conversion costs, meaning costs that are involved in a production of an item with the raw materials ordered from suppliers (Shivajee, Singh and Rastogi, 2019). These costs include labor costs, that are closely linked to the employees, overhead costs, which is more linked to the machinery and energy and finally material handling costs, linked directly to the materials used for production. Lowering these costs is essential in order to in order to increase the efficiency and profitability of the company. Manufacturing is a competitive industry, therefore companies are constantly looking into ways of cutting unnecessary costs in order to have a more competitive position in the market (Shivajee, *et al.,* 2019). Lower costs of production directly affect the pricing of the products and with this have a competitive advantage in the industry/ Cutting costs is an essential part of improving the Production Process and it can be done with the help of a variety of different technological tools, for example real-time data tracking (Isaksson *et al.* 2018). It allows the company to make quick and necessary adjustments to their Production Process in turn lowering the costs due to possible mistake or defects. With the help of real-time data, it allows to identify the mistakes much sooner due to patterns, which aim to reduce the costs linked to the downtime and maintenance. It also helps with resource allocation as better resource management is possible due to these tools, which allow companies to manage the resources better and reduce costs linked to waste (Isaksson et al. 2018)). This real-time data helps also to manage the inventory, the most important parts of storing or warehousing the goods. It is also worth noting that automation helps with reducing the costs of labour and overhead, as it reduces the number of employees needed for the manual labor (Leksic *et al.,* 2020). This allows companies to cut on costs and hire or retain employees willing to develop needed competencies to use the digital innovations effectively. Although it may pose risks for the employees, as with automation the need of human resources is lower, for the people willing to develop necessary digital competencies, the work becomes easier, as the digital tools can automate the repetitive tasks, allowing workers to be more productive and focus on activities that generate more value for the company. Even though digitalisation seems to have a lot of benefits when it comes to all the metrics covered in this thesis, digital competence of employee is a must to ensure that they can use said innovations to their advantage (Wagner *et al.,* 2017).

In summary cost can be defined as a monetary value of a product or service. Digital technologies are capable of reducing costs in production, as competent employees leverage these innovations based on the needs of the company. This allows company to get more profit and in turn benefits the profitability. Especially robotics, VR, cloud computing and Big Data are the driving factors in reducing costs. However, competent employees are a must in order to leverage these technologies. As this is an important aspect to consider there is a need to analyse the concept of employee digital competencies to see how important it is in order for digitalisation to have a bigger impact on the Production Process of the manufacturing industry.

1.3. Theoretical concept of Employee Digital Competencies

It is important to define what employee digital competencies mean in order to have a clear understanding of its importance. There are many definitions found in research, however for this thesis the term digital competence will be described as "(…) the confident use of electronic media necessary to gain knowledge and skills in personal and professional development, due to a high level of logical and critical thinking aimed at managing the information and communication received" (Bashkireva, T., Bashkireva, A., Morozov, Tsvetkov & Popov, 2020). Due to this we can note that confidence of the use, of these tools is an important factor in determining whether employees have high level of digital competence. It is evident that digital competence is the ability to use digital tools proficiently and in an aging industry of manufacturing having the ability to use multiple digital tools is extremely important and valuable, as this allows to ensure that digitalisation can have an impact on the Production Process. It is very important to have digital competencies in the manufacturing industry specifically, as digitalisation is currently transforming the manufacturing processes, and these digital capabilities will be very important in the near future (Huu, 2023). Digital competence of the employees is an aspect which is often overlooked, however it can determine whether the digital tools can be implemented and used successfully in regards to the phenomenon of Digitalisation. In a recent study it was noted that the recent Covid-19 pandemic has highlighted the importance of digital competencies of employees due to remote work (Huu, 2023). With the heightened focus on the ability of the employees to use digital tools it showed an importance for every industry to have workers able to adapt quickly to ever-changing environments. It is important to note that introducing new technologies create positive environments in which competent employees thrive and are able to showcase their abilities (Barykin, Borovkov, Rozhdestvenskiy, Tarshin & Yadykin, 2020). However, these digital competencies need to be developed by the employees themselves, usually with the help of their managers. To ensure that the workers have positive outlook on digitalisation and are ready to learn more in regard to digital fluency, managers are expected to help them by firstly building warm interpersonal relationships (Huu, 2023). This is very important, because in order to have employees that are ready for change and are eager to adapt new technologies there is a need to look into their expectations and motivations, which are both usually evident through their social interaction. Employees won't be eager to learn, change and develop digital competencies if they will not see the benefit that they can get from it (Huu, 2023). With direct training and assistance in building their digital competencies employees are able to work more efficiently and contribute more to the production processes with the help of digital tools (Barykin *et al.,* 2020). That is why digitalisation itself provides a framework that allows employees to get needed results – improved outcomes. The support of the company is crucial in order to develop needed skills which are the main and direct contributor to the successful integration of digital tools in the Manufacturing industry (Barykin *et al.,* 2020).

It seems that digital savviness will be a must in the near future for those motivated to work in the ever-changing manufacturing industry. Due to globalization and manufacturing slowly transitioning to Industry 4.0, it is extremely important to develop digital competencies, that are required in order to use the new digital tools effectively. With the technological advancement in IoT, AI and big data in manufacturing, businesses aim to retain employees that are flexible and technologically savvy, in order to have employees competent enough to use complex systems, understand the analytics of data and use the technologies to their advantage (Schumacher, Erol and Sihn, 2016). A crucial in part in identifying whether employees possess needed digital competencies lies in the correct assessment of the competencies through a variety of tests and questions, which becomes a critical part of successful technology implementation. It is important to understand that digital competencies in the manufacturing industry are not only classified as essential and basic IT skills, like a proficient use of programs and knowledge of the virtual environment, but also rather focus on ability to work with complex ERP systems, have basics in data analytics and ability or willingness to participate in the process automation (Schumacher *et al.,* 2016). It is important to note that these digital competencies are not based on the hierarchical position a person has in the company, rather that all levels need to have these competencies to a degree, especially the people working directly with these innovations. This assures that the workers are competent enough to have a high level of independency with their decision-making and having the knowledge to solve issues or any discrepancies themselves.

It is important to also highlight what are types of digital competencies found in previous research, like digital autonomy, which allows workers to have full power and freedom to use the tools for their convenience or innovative work behaviour, which encompasses trying out new things and allowing more creativity in their line of work (Huu, 2023). It is strongly linked to technical proficiency which allows the workers to be able to effectively operate and manage the digital tools and systems based on the needs of the company (Schumacher *et al.,* 2016). This ensures that the decision maker is the employee and based on their competencies important decisions in production process is made. The data literacy measure allows to check the level of proficiency and technological savviness, that allows the employees to make independent decisions based on their knowledge and ability to interpret data (Schumacher *et al.,* 2016). Due to large number of different digital competencies, the main employee digital competencies that are strongly linked to the manufacturing production process along with the corresponding technologies are listed in the Table 1.

Table 1. *Employee digital competencies & corresponding innovations in manufacturing*

Digital Competencies	Corresponding innovation
IT infrastructure management	Cloud computing, Remote Control/Monitoring
Data processing and analysis	Big data, Machine/Deep Learning
Data security/cybersecurity	Cloud computing
Computer programming/coding	Machine/Deep learning, Internet of things (IoT)
Internet of things and cyber-physical systems	Internet of things (IoT), Wireless sensors, Remote control/monitoring
Automation	Collaborative robots, Remote control/monitoring, IoT
Additive manufacturing	3D printing
Cloud technologies	Cloud computing, Remote control/monitoring
Big data	Big data, Machine/Deep learning
Product simulation	Simulation, Augmented reality (AR)
Process design and simulation	Simulation, AR
Service design and engineering	Simulation, IoT, Remote control/monitoring
Knowledge management	Big data, Cloud computing

Source: compiled by the author, based on Jurczuk & Florea, (2022); Tortorella *et al.,* (2022)

It is important to note that some digital competencies correspond to a couple different technologies due to the nature of these competencies, showing the connection between some digital solutions. Moreover, digital competencies encompass not only specific knowledge of the systems and digital tools but also the ability to quickly adapt to change and new technologies (Huu, 2023). This shows that employees should not focus on sticking to the previous knowledge or even new competencies that they developed recently, as they should keep in mind that the technologies advance in a rapid pace. Due to the ever-changing nature of technologies and innovations it is very important for the employees to have a mindset of continuous learning and improvement (Schumacher *et al.,* 2016). This shows that employers should focus on fostering these types of skills, especially in the manufacturing industry to equip their employees with the best possible technological background. For example, IoT technologies by themselves can have an impact on the production process, however digital competencies allow employees to utilize the innovations better and more efficient outcomes (Butschan, Heidenreich, Weber & Kraemer, 2019). This shows that technologies should be looked at tools that can be effectively used by competent and technologically proficient employees. This also shows that employee digital competencies facilitate adoption of digital solutions, therefore there is a need for companies to invest firstly in the development of these competencies (Butschan et.al., 2019). To do so it is important to introduce training and education allowing employees to develop the needed skills and it is important that this is a continuous cycle in which employees could also improve gradually (Jurczuk & Florea, 2022). The company needs to also encourage employees to show motivation and take part in digital transformation initiatives and reward workers with incentives. This not only allows the company to have a smoother and faster digital transformation but also allows the employees to improve their technical skills and digital competencies. It is important to highlight the importance of encouraging teamwork between different departments, as this not only allows to exchange valuable information but also share valuable insights that could benefit the company in the long-run (Jurczuk & Florea, 2022). Due to these steps, the company and its management are responsible for a healthy and improvement driven environment, that allows employees to develop needed digital competencies and keep improving them in the long run. The study touched upon digital autonomy, which refers to the freedom and flexibility that come with using the technologies to perform work duties (Huu, 2023). The author highlighted that the bigger digital autonomy directly results in more creativity and in turns allows the employees to grow and propose new ideas which results in improvement. It is important for the companies to ensure that the employees have autonomy and allow them to propose new ideas, solutions, tools or systems, which could develop into frameworks that can solve major issues of the process. In order to keep the employees possessing valuable and important digital competencies, it is important to encourage them to apply and pass down their knowledge in more leadership or mentoring focused role, that allows them to not only share their expertise but also lead a team of professionals (Schumacher *et al.,* 2016). This shows that management should also look into improving their current competencies in order to keep their positions and be able to grown further in their careers. As it stands, digital competencies are needed to a degree for each and every department in order to have a smooth and successful digital transformation.

In summary Employee Digital Competencies can be defined as confident use of digital tools or technologies. The competencies of the employees are key factors that allow to leverage and facilitate the adoption of digital technologies, which in turn help to improve the Production Process. The companies need to be proactive and develop the digital competencies in their employees as this results in smoother implementation of new innovations and after the initial stages it allows the employees themselves be fully responsible for the process and even the maintenance of said technologies. This results in more freedom and autonomy for the employees and better Production Process results for the company.

1.4. Effect of Digitalisation on Production Process Results

Digitalisation as a phenomenon influences the Production Process results with the use of new innovations and various digital solutions. A variety of different digital solutions like Internet of Things (IoT), artificial intelligence (AI) and cloud computing are used in order to positively transform the production process into a more effective operation (Hanenkamp and Zipse, 2023). In a recent study it was noted that digitalisation was linked to high expectations in regard to better efficiency (Horvat, Kroll, & Jäger, 2019). It was found that even though the expectations were high, the positive effect of used technologies was much smaller than expected. It was due to digital tools interfering with the current Production Process and automation rather than improving existing processes (Horvat *et al.,* 2019). This study had a short-term outlook which could explain why in the short-term the results did not meet expectations. It showed that the digitalisation as a phenomenon itself is not enough, and other factors need to be considered in order to get the full potential of this process. The study offers some important insights as it reports that "(…) digitalization is but one, albeit central, factor in the Production Process that is and remains contingent on others" (Horvat *et al.,* 2019). The effect of digitalisation in this case was positive, however high expectations did contribute to a study which offered a critical view on this process and resulted in valuable insights gathered. On the other hand, in another source, it was found that some digital solutions improve the production, especially the decision-making aspect at all stages (Hanenkamp and Zipse, 2023). In this source several positive outlooks were identified, as for example AI was useful and productive in analyzing the data received from the Production Process, which is linked to IoT devices, that ensure that any faults and inefficiencies are identified, analyzed with AI and solved in a timely manner. The term digital twins is another example, which means that firstly the production is planned and optimized in a virtual simulation and only then the physical process of production starts (Hanenkamp & Zipse, 2023). This ensures that any mistakes or problems identified during the virtual simulations can be fixed before starting the production, which reduces Cost, eliminates Waste and improves Quality. It is also worth mentioning that digitalization contributes to sustainability, and it is one of the key benefits of this area. With the help of smart digital solutions companies reduce the consumption of resources which makes the whole process more efficient and simultaneously minimizes waste (Durakovic *et al.,* 2018). With the help of predictive analytics and automation companies can reduce the waste and become more energy efficient, which shows the strategic transition to a more sustainable production methods. With the help of various technologies and digital solutions the companies can improve their processes, track the sustainable goals and pivot to a more eco-friendly environment, that helps not only in reaching their financial goals but also reducing their carbon footprint at the same time (Hanenkamp and Zipse, 2023).

In another study, the use of “cobots”, or collaborative robots was tested, and it was found that these are great helpers for workers in manufacturing that work hand in hand with them to assist in difficult, repetitive or even ergonomically dangerous tasks (Cohen, Faccio, Pilati, & Yao, 2019). With the help of the “cobots” the workers do their work faster, more efficiently and most importantly it benefits the quality of their work which in turn lowers costs. The use of robotics enables workers to have an assistant that manages to help them in every-day tasks, simultaneously benefitting the Production Process (Horvat *et al.,* 2019). It is yet another benefit, which is closely linked to efficiency, quality and cost. A big problem in manufacturing is waste, which usually occurs due to wasting materials after one or another production step in a form of leftovers. To eliminate this kind of waste an innovative solution is needed that produces needed parts without any leftovers. In a study written about digital manufacturing the idea on the use of 3D printers was presented. (Cohen *et al.,* 2019). It was discussed that it is a quick and cost-effective way to print needed materials, to avoid any delays in production, however it is also worth mentioning that the process of use in 3D printers is layer based, meaning that only the needed amount of material is used each time. This ensures that there are no leftovers or and it helps to eliminate waste in the Production Process. It is worth mentioning that the concept of mass customization is possible with the help of digital technologies, which essentially means that the digital systems put in place can adapt to changes much faster and meet the demands of the customer immediately, regardless of the quantity or the complexity of the products (Hanenkamp & Zipse, 2023). These are huge benefits, because industry of manufacturing relies on fast adaptation and fulfilment of the needs the customer has. This allows companies to have a competitive advantage which directly impacts the profitability. The efficiency of the Production Process relies heavily on the machines and workers, therefore the technologies are used to identify and predict any problems that may arise in the future. Two technologies, IoT and AI, together can help implement predictive maintenance, that allows to anticipate and react proactively to any faults in the machines, that can result in unexpected breakdowns that can hinder the production of goods (Hanenkamp & Zipse, 2023). It is also worth noting that the speed of production and implementation of any innovations is higher due to the use of some digital tools like 3D printing or simulations, due to the ability to get the necessary outcome much faster than in the alternative case of human work. These technologies not only allow to implement the innovative solutions much faster, but also aid in fixing current issues faster and more efficiently. (Hanenkamp & Zipse, 2023). Due to these technologies the Production Process is not only faster, but more efficient, which is the goal for any manufacturer. However, to ensure that the innovative solutions are used correctly and effectively it is important to understand, that human impact and their competencies are essential in order for these tools to work correctly.

Effective human interaction with digital technologies is essential in order to get the needed results from the Production Process. However, it is important to note that in this industry the technologies will not replace human workers, but rather foster collaboration between human workers and digital solutions, making repetitive tasks easier and overall enhancing the productivity (Hanenkamp & Zipse, 2023). It is important to highlight the skills, that are changing due to digitalization, as companies are finally realizing that employees need to develop digital literacy and other digital competencies first to successfully use any new innovation. It is important to note that these skills need to up-to-date to ensure that employees realize the everchanging nature of technology (Ngereja and Hussein, 2022). This is not only a concern of the worker to learn but it shows that companies need to invest in their employees and provide a good environment for them to learn and develop new skills first (Hanenkamp & Zipse, 2023). Due do that, digitalization does not only change the Production Process but also the skills needed in the manufacturing industry. The digital transformation in the company depends on the ability of employees to effectively learn and apply their knowledge into their daily work (Ngereja and Hussein, 2022). The implementation of any new technology or innovation requires some upfront cost, which not every manufacturing company can afford immediately, however in this case the changes can occur gradually. It is also important to consider the risks of cyberattacks as with any technology the sensitive data needs to be thoroughly protected (Hanenkamp & Zipse, 2023). The overall productivity and efficiency of the production process depends on the level of proficiency that the employees have in regards to digital technologies, as the employees having good training and an environment in which they continuously learn and improve their skills allows them to handle the complex everyday task better and more efficiently (Kraus *et al.,* 2021). It is worth noting, that even though the effect of the technological solutions is positive, it would not be possible without the ability of the workers to effectively use previously mentioned tools.

1.5. Effect of Employee Digital Competencies on Digitalisation

Many benefits of Digitalisation were identified in previous research, and it is important to note, that digital competencies are very important if the goal is to use digitalisation correctly to improve Quality, Cost and Waste. In a recent study on digital competencies, an idea was proposed which noted that we should assume "(…) individuals are not only affected by digitalization but can actively shape it" (Blanka, Krumay, & Rueckel, 2022). This means that employees that have competencies in the technological field will be able to guide the technologies in the needed direction and will be the ones responsible for their effectiveness. It shows a need for the employees to develop these competencies to have a competitive advantage in the job market. In the same study it was found that researchers usually are focusing on the standalone technology and its application and not on human resources that are as important (Blanka, *et al.,* 2022). After the research was concluded, it was determined that having proficiency in digital skills, basic knowledge of technologies and the understanding of the effect digitalisation has on the processes, can significantly improve existing processes and even transform organisations. It is important to highlight the importance of developing digital competencies as without them, the benefits of digitalisation, such as improved decision making, increased efficiency and enhanced productivity cannot be fully realized (Ngereja and Hussein, 2022). This shows that employees that developed strong digital competence first are more likely to manage complex systems and everyday tasks. It is understandable, as having a strong digital background is beneficial for both the employee himself and the organisation in which he works (Barykin et.al., 2020). As previously researchers focused mainly on technologies, this study showed the need to investigate the human aspect to ensure that the level of employee digital competence is measured before starting to implement any technology. This in turn allows to reduce unnecessary risks than can be associated with technological faults or disruptions, because it allows to determine beforehand whether employees are ready to tackle these challenges (Ngereja and Hussein, 2022). It is also worth noting that digitalisation is a "transformational process and a cyclical, rather than stepwise, development", which shows the need to have a long-term approach and not only look into improving the technology but also increasing the digital proficiency of the workers (Blanka, *et al.,* 2022).

In a dynamic environment like manufacturing, it is extremely important not only to develop digital competencies but also to retain and continuously improve them. There is a need for companies to invest in ongoing training programs, that are focused not on traditional learning methods, but rather on digital learning as a way for employees to acquire any necessary digital competencies (Kraus *et al.,* 2021). This training needs to be regular, so employees are up to date and ready to tackle any challenges. The development of such technologies usually come with challenges, as a lot of employees could suffer from resistance to change and in turn slowdown the digital transformation of companies (Ngereja and Hussein, 2022). However, tackling this obstacle allows companies to have workers ready to have an immediate positive effect on the Production process due to their newly acquired digital competencies. Employees which develop and continuously improve their digital proficiency do not only contribute to their own individual success and better results but also enhance communication and collaboration with the help of a digital manufacturing environment (Barykin *et al.,* 2020). This ensures that the communication is much more efficient and allows colleagues to not only minimize their mistakes but also react to any possible problems in the future with the predictive analysis systems in place. This shows that digital skills are not only based on the technical knowledge but also on the ability to communicate effectively and efficiently in a digital environment (Chaka, 2020). It is worth noting that the data gathered from various technologies allow the users to share insights in real time, which in turn allows quicker problem solving and improve the decision-making time (Ngereja and Hussein, 2022). This shows that companies willing to invest in the digital competencies of their employees can expect a much smoother and efficient integration of digital solutions, due to digital literacy being a foundation for the employees on which other digital competencies are built (Chaka, 2020). Employees that develop a strong digital literacy are able to identify faults and bottlenecks in the Production Process and in some cases even eliminate them themselves with the help of technology due to having the ability to implement the digital solutions than can help to fix the problem For example, having basic knowledge in programming or data analysis helps to identify the root cause, with which eliminating this problem is possible maybe even without any help. This helps to identify any faults in the machines and make data driven decisions for the future (Chaka, 2020). It is worth mentioning that digital competencies not only allow the employees to make their work easier, but simultaneously more productive, but also helps employees to identify new possibilities, methods and creative solutions that would not be possible without digital technologies and digital competencies (Ngereja and Hussein, 2022). Due to this, employees find creative ways to improve existing processes, by either making them easier or introducing few more steps to make them more efficient. This allows workers to find new ways to use the technology and can help with optimizing the performance of machines or even reducing the consumption of energy (Chaka, 2020). This ensures that the whole company is innovating continuously and ready to tackle any obstacles in the everchanging manufacturing industry.

Digital competencies also provide a good base in the context of digital transformation as with the skills employees possess, with the help of the company, they can overcome any challenges and hurdles due to their adaptability (Kraus *et al.,* 2021). It is important to note that digital competencies allow employees to be completely responsible for their work and to be independent in decision-making and daily tasks. Due to this, employees require less monitoring or micromanaging which saves time and effort for management. However, it important to highlight the importance of having the digital competencies developed at every single level of the company from operators to higher management (Ngereja and Hussein, 2022) It ensures that innovate solutions come not only from the workers side but also management can be responsible to innovative changes that are closely linked to leadership. This ability to innovate allows employees to not only focus on doing their part of work but also improve the processes around, which as a result makes the company more effective and in turn more competitive in the market (Ngereja and Hussein, 2022). These digital solutions allow to tackle very complex tasks, which could not be managed by manual labour or human decision-making (Chaka, 2020). The amount of data gathered by various devices require the ability to correctly interpret and use real-time data of machines and other manufacturing devices to ensure that the Production Process is running correctly and smoothly and does not show any potential risks in the near future. The ability to navigate complex digital systems enables employees to manage the production process with a predictive maintenance in mind, ensuring any possibility of disruptions is minimized (Chaka, 2020). In accordance with these research findings the following hypotheses are presented:

$H1_a$ Employee Digital Competencies will improve Quality in the Production Process

$H1_b$ Employee Digital Competencies has a positive impact on the effectiveness of Digitalisation in the Production Process

$H1_c$ Digitalisation will improve Quality in the Production Process

$H1_d$ The relationship between Employee Digital Competencies and Quality in the Production Process is positively mediated by Digitalisation

$H2_a$ Employee Digital Competencies will reduce Waste in the Production Process

$H2_b$ Employee Digital Competencies has a positive impact on the effectiveness of Digitalisation in the Production Process

$H2_c$ Digitalisation will reduce Waste in the Production Process

$H2_d$ The relationship between Employee Digital Competencies and Waste in the Production Process is positively mediated by Digitalisation

$H3_a$ Employee Digital Competencies will reduce Cost in the Production Process

$H3_b$ Employee Digital Competencies has a positive impact on the effectiveness of Digitalisation in the Production Process

$H3_c$ Digitalisation will reduce Cost in the Production Process

$H3_d$ The relationship between Employee Digital Competencies and Cost in the Production Process is positively mediated by Digitalisation

2. RESEARCH METHODOLOGY ON HOW EMPLOYEE DIGITAL COMPETENCIES AFFECT THE QUALITY, WASTE AND COST OF THE MANUFACTURING PRODUCTION PROCESS WITH THE IMPLEMENTATION OF DIGITALISATION

2.1. The aim and objectives of the research, conceptual framework, and hypotheses

The aim of the research is to assess and evaluate the strength of the effect Employee Digital Competencies have on Quality, Waste and Cost in the Manufacturing Production Process where Digitalisation level plays a mediating role.

Research objectives:

1.) Assess the current level of Employee Digital Competencies, current level of Digitalisation and recent outcome results in the Production Process.
2.) Assess the reliability and internal consistency of the research questionnaire using the Chronbach's alpha coefficient.
3.) Determine normality of data distribution by analysing Skewness and Kurtosis measures.
4.) Identify whether Digitalisation has a positive effect on the results of Quality, Waste and Cost measures in the Production Process.
5.) Identify whether the relationship between Employee Digital Competencies and Quality, Waste and Cost in the Production process is mediated by Digitalisation.
6.) Identify whether Employee Digital Competencies have a positive impact on the effectiveness of Digitalisation in the Production Process

The context of the theoretical analysis helped to establish twelve research hypotheses that will be tested in 3 models. The first set of hypotheses was proposed due to the information found in existing sources which shows the importance of Employee Digital Competencies and the effect or impact it has on Digitalisation. In the previous research it was found that companies willing to invest in developing Employee Digital Competencies had an impact on the Digitalisation and solving challenges of successful implementation of said technologies (Barykin *et al.,* 2020; Schumacher *et al.,* 2016; Butschan *et al.,* 2019; Chaka, 2020; Dillinger *et al.,* 2022). It was found that support of the company is essential in developing needed skills and competencies, as it usually results in the successful integration of digital solutions (Barykin *et al.,* 2020). In another sources it was theorized that companies are aiming to attract employees that are flexible and digitally proficient, as these employees are more likely to use complex systems, understand and interpret data and use their skills effectively (Schumacher *et al.,* 2016). It is important to note that companies that are willing to invest in the digital competencies of their workers are more likely to expect a smooth integration of the innovations due to digital literacy as an important foundation on which other competencies are built (Chaka, 2020). It was also discovered that skilled employees have a large advantage in the market as they are always ready to leverage their knowledge in order to excel in using new technologies (Dilinger *et al.,* 2022). This is why it was hypothesized that:

$H1_a$ Employee Digital Competencies will improve Quality in the Production Process

$H1_b$ Employee Digital Competencies has a positive impact on the effectiveness of Digitalisation in the Production Process

$H2_a$ Employee Digital Competencies will reduce Waste in the Production Process

$H2_b$ Employee Digital Competencies has a positive impact on the effectiveness of Digitalisation in the Production Process

$H3_a$ Employee Digital Competencies will reduce Cost in the Production Process

$H3_b$ Employee Digital Competencies has a positive impact on the effectiveness of Digitalisation in the Production Process

The second set of hypotheses was proposed based on previous research, in which it was found that digital solutions may help the Production Process overall when implemented correctly (Hanenkamp & Zipse, 2023; Cohen *et al.,* 2019; Bankar & Nandurkar, 2023, Carnerud & Bäckström, 2021; Alieva & Haartman, 2020; Wagner *et al.,* 2017; De Kruijk 2018). Even though Digitalization can also bring negative aspects, and it is important to note that based on the researchers mentioned previously the correct technology is vital in order to have a positive change. Technologies like Internet of Things (IoT) or cloud computing are implemented to positively affect the production process and make their operation more effective (Hanenkamp and Zipse, 2023). Colaborative robots are great helpers that allow workers to automate repetitive and even dangerous tasks (Cohen *et al.,* 2019). The quality can improve with the correct use and implementation of IoT, based on previous research of positive effects of real-time monitoring (Bankar & Nandurkar, 2023). Overall, it was found that the growing interest in the digital changes in manufacturing is a drive that usually positively influences many manufacturing process, mostly the Production Process. It is very important to look into the following metrics of the Production Process: Quality, Waste and Cost, to determine whether Digitalisation has a positive or negative impact on these metrics. This is why it can be hypothesized that:

H1$_c$ Digitalisation will improve Quality in the Production Process

H2$_c$ Digitalisation will reduce Waste in the Production Process

H3$_c$ Digitalisation will reduce Cost in the Production Process

The third set of hypotheses was proposed in regard to previous research in which it was found that digital competencies of the employees facilitate the correct adoption and implementation of digital solutions (Barykin *et al.,* 2020, Butschan et.al., 2019, Ngereja & Hussein, 2022, Blanka *et al.,* 2022, Pereira *et al.,* 2023). These previous sources looked into the importance of Digitalisation and innovations as a tool which allows competent employees to navigate the hardships of the Production Process more effectively. It was found that introducing new technologies aids in creating new innovative environments in which competent employees can use their skills and time more effectively to improve the Production Process (Barykin et.al., 2020). In another source it was found that the competencies are important and should be developed before the technology adoption, therefore companies need to invest more in the development of the employee digital competencies (Butschan *et al.,* 2019). It was also theorized that competent employees are the ones guiding digital transformation and their competencies are what usually determines the level of the success Digitalisation will have on the Production Process (Ngereja & Hussein, 2022; Pereira *et al,* 2023). Due to these points found in the literature review the following hypothesis was drawn:

H1$_d$ The relationship between Employee Digital Competencies and Quality in the Production Process is positively mediated by Digitalisation

H2$_d$ The relationship between Employee Digital Competencies and Waste in the Production Process is positively mediated by Digitalisation

H3$_d$ The relationship between Employee Digital Competencies and Cost in the Production Process is positively mediated by Digitalisation

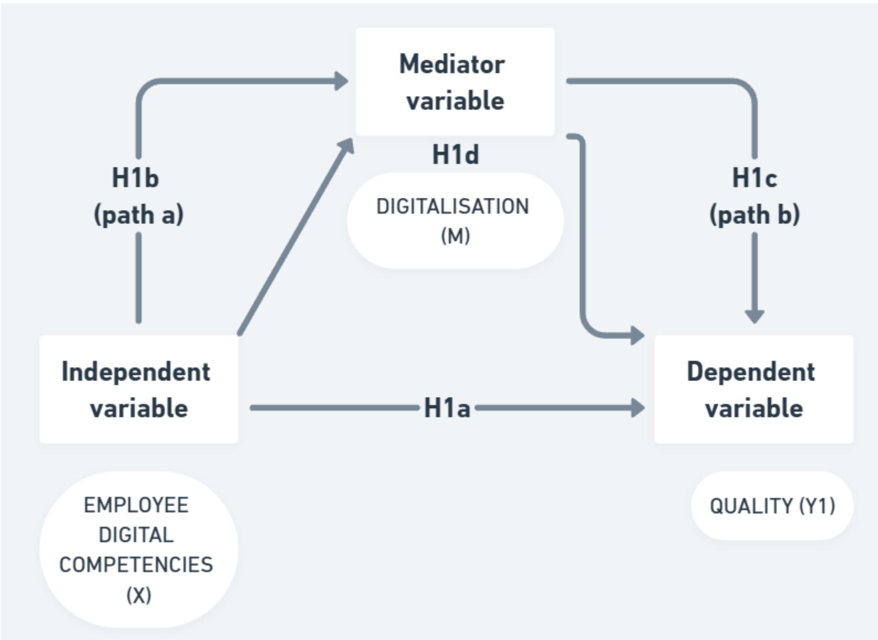
When it comes to independent variables in this thesis, the only independent variable (X) is the Employee Digital Competencies. It serves as an independent variable, because it is the factor that influences the dependent variables, effect on which will be studied in this thesis. The literature analysis helped to establish the theoretical aspects of digital competencies of the workers, which included the definition of said term, identifying the key digital competencies needed in the manufacturing industry and the importance of technological savviness. This serves as a foundation for the research methodology as it provides much needed context of the current situation, that has a major impact on further research development.

When it comes to dependent variables (Y) in this thesis, there are three dependent variables: Quality, Waste and Cost. The selected indicators are chosen, because these dependent variables serve as results and outcomes and can be clearly measured by doing the research, which is pivotal in this case. Each indicator was thoroughly analysed in the literature review chapter to determine the importance of each aspect on the Production Process in the manufacturing industry.

The literature analysis helped to establish the theoretical aspects of digitalisation, which included the definition of this phenomenon, identifying the key technologies used currently in the manufacturing industry and the importance, benefits and drawbacks of their implementation. This phenomenon of digitalisation is the mediator variable (M) in this study. It is an important part of the study as it connects independent variable with the dependent variables through mediation.

Finally, the relationship between the independent, mediator and dependent variables will be analysed to determine what is the strength of the effect Digital Competencies have on the key metrics of the Manufacturing Production Process: Quality, Waste and Cost. This relationship will be studied based on the visualisation of three research models, each having a different dependent variable. The first model provided below included Quality as the dependent variable (Y1) as seen in *Figure 5*.

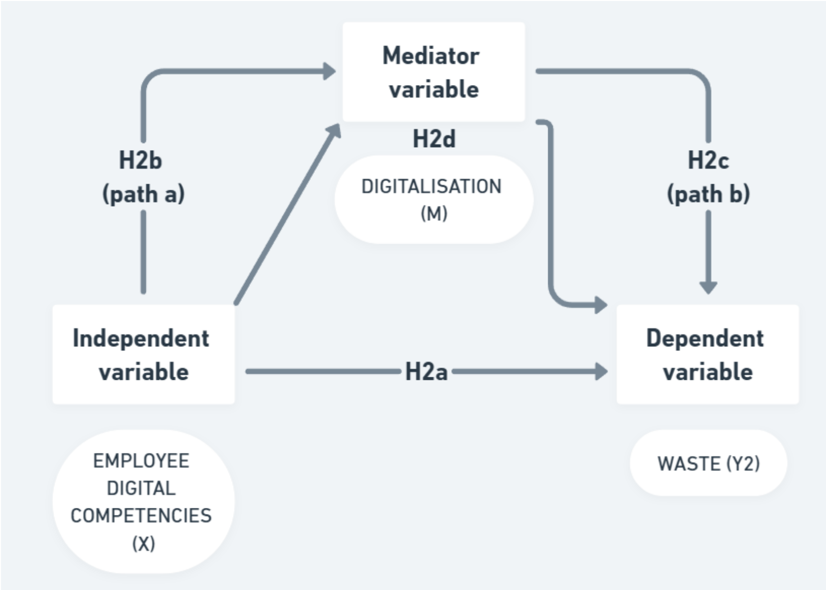
Figure 5. *Research Model 1*



Source: compiled by the author

The second model is provided below in *Figure 6* and includes Waste as the dependent variable (Y2).

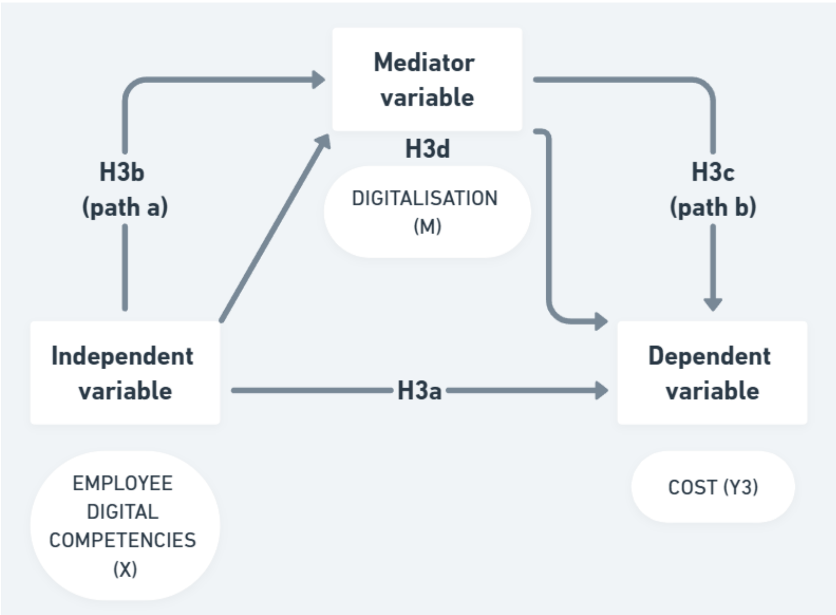
Figure 6. *Research Model 2*



Source: compiled by the author

The third model is provided below in *Figure 7* and includes Cost as the dependent variable (Y3).

Figure 7. *Research Model 3*



Source: compiled by the author

The relationship between Employee Digital Competencies, Digitalisation and Quality, Waste and Cost will be studied to approve or disapprove the hypotheses. Due to the research gaps in which the majority chose a qualitative methodology the quantitative approach is chosen (Huu, 2023; Blanka *et al,* 2022). The research method chosen is the online questionnaire, which will have three sets of questions, each corresponding to the dependent variable. In order to have a deeper understanding on how the research will be carried out, the research strategy needs to be presented.

2.2. Sampling strategy, sample size, and data collection

A quantitative approach is chosen to provide concrete, precise and objective results. It is chosen having research gaps in mind as previous studies were mainly qualitative and lacked a larger sample size (Huu, 2023; Blanka *et al,* 2022). The research method chosen is online questionnaire, that consists of five sets of thematical questions, each based on the corresponding variable: Employee Digital Competencies, Digitalisation, Quality, Waste and Cost. It also involves the sixth section with demographic data. To have the most accurate answers, purposive sampling is chosen to get the opinion of respondents actively working and having experience with Digitalisation in the manufacturing industry, in Lithuania. There is a need to gather the insights of people having expertise and experience in the field, and this survey design is the most suitable for this research. This ensures that the collected data is relevant, and it is an efficient way to gather the data. The questionnaire is prepared in English as the respondents in the manufacturing industry, in Lithuania, are usually capable to answer these questions and share their responses in English. It also enables the testing of the hypotheses as this can determine whether there is a positive effect of Employee Digital Competencies on the Quality, Waste, and Cost in the Production Process.

To achieve needed results there is a need to gather at least 200 respondents from different manufacturing industry sectors to determine what effect the independent variables have on the dependent variables. The number is chosen based on recommendations from previous researchers. Hair *et al.,* (2010) recommends a sample size of at least 200 respondents for stable parameter estimation. Hayes (2017) suggests that a sample size of minimum 200 respondents is needed for models that include mediation or moderation effects, as a larger number of respondents reduces the risk of Type II errors and allows to determine an accurate direct and indirect effects, which is needed for this study. The sampling will be "non-probability". In regard to the data collection, as mentioned before, an online questionnaire is the research method, which consists of structured 46 items total. The questionnaire consists of 6 thematical sections, that cover the following: employee digital competencies, digitalisation, quality, waste, cost, demographics. Each section corresponds to the variable in the research model and demographics is used to get much needed information about the respondents like their age, gender, current job position, their tenure in the current company, size of the organization they are currently working in & level of their education.

The tool used for the questionnaire is Google forms, which is one of the main questionnaire building and sharing tools in the world and Lithuania as well. It included all of the items plus a introductory section in which a brief explanation was introduced as well as the confirmation that this questionnaire will only be used for research purposes and the responses are anonymous. To proceed with the questionnaire respondents needed to confirm that they are familiar with this by clicking the option “NEXT”. The whole questionnaire is provided in Annex 1. To gather the responses the questionnaire was shared with the employees, HR departments & the network of the author, directly or via social media in order to gather the responses of manufacturing industry professionals in Lithuania. After gathering the needed number of responses, the data analysis will commence with the use of SPSS 19 and PROCESS 4.2 by Hayes, a statistical software used to conduct the analysis. In the next section, research measurement scales will be described to show how the abstracts concepts will be standardized.

2.3. Research measurement scales

The measurement scales used for the constructs of Employee Digital Competencies, Digitalisation, and Quality, Waste, Cost were adopted from previous research. The measurement scale for the independent variable **Employee Digital Competencies** was drawn from previous research study which looked into future-oriented digital skills (Jurczuk & Florea 2022). In the study 13 key competencies were identified and developed by the authors, encompassing items from a business and engineering standpoint. The five-point scale was used with value ranging from 1 to 5, meaning: 1 - “no competencies, 2 - “low competencies”, 3 – “medium competencies”, 4 – “high competencies”, 5 – “excellent competencies”. It was used to determine the level of competencies the employees possess which is relevant to the further research development. The questions are provided in the Table 2 below.

Table 2. *Construct X - Employee Digital Competencies (Jurczuk and Florea, 2022)*

Please assess the current level of your digital competencies
IT infrastructure management
Data processing and analysis
Data security/cybersecurity
Computer programming/coding
Internet of things and cyber-physical systems
Automation
Robotics
Additive manufacturing (3d printing)
Cloud technologies and big data
Product simulation
Process design and simulation
Service design and engineering
Knowledge management

Source: compiled by the author based on Jurczuk and Florea (2022)

A scale for the mediating variable **Digitalisation** was found and implemented from a previous study on the impact of Industry 4.0 on relevant constructs (Tortorella *et al.,* 2022). In this study 9 items were highlighted and chosen to show the technologies and innovations used in manufacturing. All items were relevant to this study and also connected to previously mentioned digital competencies and it was selected based on these criteria. In the study 9 main technologies were identified as follows: internet of things (IoT), big data, cloudcomputing, wireless sensors, 3d printing, augmented reality (AR)/simulation, colaborative robots, machine/deep learning, remote control/monitoring (Tortorella *et al.,* 2022). The five-point scale was used with value ranging from 1 to 5, meaning: 1 – "no adoption", 2 – "low adoption" 3 – "moderate adoption", 4 – "high adoption", 5 – "full adoption". It was used to determine the level of adoption of these technologies in the company of the respondent, which is relevant to further research development. The questions are provided in the Table 3 below.

Table 3. *Construct M – Digitalisation (Tortorella et al., 2022)*

Please, indicate the adoption level of the following digital technologies in your company
Internet of things (IoT)
Big data
Cloudcomputing
Wireless sensors
3d printing
Augmented reality (AR)/Simulation
Colaborative robots
Machine/Deep Learning
Remote Control/Monitoring

Source: compiled by the author based on Tortorella *et al.,* (2022)

A scale for the dependent variables **Quality, Waste** and **Cost** was applied from previous research, in which the authors looked into barriers to industry 4.0 adoption (Chauhan *et al.,* 2021). In this study 18 items are noted as production process outcomes or results, which correspond to Quality, Waste and Cost. In this study 18 items total were highlighted, each one corresponding to one of three dependent variables. For further research there was a need to distinguish between all the results and therefore each item was assigned to the corresponding dependent variable. In regard to **Quality** these 6 items were assigned: customer satisfaction, product customisability, improvement in the quality of products, rise in product innovativeness, successful launches of new products, improvement in product capability and performance (Chauhan *et al.,* 2021). These questions are found in Table 4 below.

Table 4. *Construct Y1 – Quality (Chauhan et al., 2021)*

Please indicate your company's improvement in following parameters related to quality in the time period of last 3 years
Customer satisfaction
Product customisability
Improvement in the quality of products
Rise in product innovativeness
Successful launches of new products
Improvement in product capability and performance

Source: compiled by the author based on Chauhan *et al.,* (2021)

In regard to **Waste** these 6 items were assigned: speed of delivery, supply chain responsiveness, notification of advance-ship, dependability in terms of delivery, decrease in time required for creating and delivery of new products, flexibility in delivery. These questions are found in Table 5 below.

Table 5. Construct Y2 – Waste (Chauhan et al., 2021)

Please indicate your company's improvement in following parameters related to waste in the time period of last 3 years
Speed of delivery
Supply chain responsiveness
Notification of advance-ship
Dependability in terms of delivery
Decrease in time required for creating and delivery of new products
Flexibility in delivery

Source: compiled by the author based on Chauhan *et al.,* (2021)

In regard to **Cost** these 6 items were assigned: cost of logistics, return on assets, decrease in operating costs, inventory turn, order flexibility, capacity of order-fill (Chauhan *et al.,* 2021). The five point scale was used value ranging from 1 to 5, meaning: 1 – "worsened significantly", 2 – "somewhat worsened", 3 – "stayed same", 4 – "somewhat improved", 5 – "improved significantly". It was used to determine the improvement of the company in these parameters in the time period of last 3 years. The questions are found in Table 6 below:

Table 6. Construct Y2 – Cost (Chauhan et al., 2021)

Please indicate your company's improvement in following parameters related to cost in the time period of last 3 years
Cost of logistics
Return on assets
Decrease in operating costs
Inventory Turn
Order flexibility
Capacity of order-fill

Source: compiled by the author based on Chauhan *et al.,* (2021)

2.4. Data processing procedures

The data gathered from the responses of manufacturing industry professionals in Lithuania is analysed using the IBM SPSS Statistics version 29. Firstly, in order to assess the reliability of the set of items in the questionnaire or in other words internal consistency, Cronbach's Alpha coefficient is measured. Secondly, in order to evaluate the data distribution, Skewness and Kurtosis values are analysed as well. Thirdly, descriptive statistics are used to analyse the demographics to show the main data (mean, standard deviation, frequencies) and showcase mean and standard deviation of all questionnaire items. Also, a correlation analysis is used to determine the correlation level between variables. Finally, mediation analysis is done to examine the relationship between independent and dependent variables and to approve or disapprove the hypotheses.

2.5. Study limitations

There are some limitations to this study. The limitation lays in choosing only a quantitative approach. Adding qualitative approach would help to have a deeper understanding of the industry as a whole and would add a level of context to the study. This would also add context into the behavioural aspect of innovation adoption, developing employee digital competencies and challenges related to them. It would also provide the information on the motivation behind the current trends in manufacturing.

3. THE EMPRIRICAL RESULTS AND ANALYSIS OF THE IMPACT STRENGTH OF THE EFFECT EMPLOYEE DIGITAL COMPETENCIES HAVE ON QUALITY, WASTE AND COST IN THE MANUFACTURING PRODUCTION PROCESS, WHERE DIGITALISATION LEVEL PLAYS A MEDIATING ROLE

3.1. Demographic characteristics of the respondents

A quantitative questionnaire included a demographic section in which the respondents were asked to anonymously provide the following information: age, gender, job position, tenure in the current company, size of the company and level of education (Annex 2). Summarized results of this section can be found in Table 7.

Table 7. *Demographic characteristics of respondents*

Characteristics	Distribution	Number of Respondents	Percentage of Respondents
Age	20-29	49	19.5%
	30-39	148	59.0%
	40-49	54	21.5%
Gender	Male	145	57.8%
	Female	106	42.2%
Job position	Supervisor/Manager	121	48.2%
	Engineer	86	34.3%
	Operator/Technician	38	15.1%
	Other	6	2.4%
Tenure in the current company	1-5	178	70.9%
	6-10	59	23.5%
	11-15	13	5.2%
	16-20	1	0.4%
Size of the company	Micro (up to 10 employees)	1	0.40%
	Small (10-49 employees)	3	1.20%
	Medium (50-249 employees)	87	34.70%
	Large (more than 249 employees)	160	63.70%
Level of Education	High School Diploma	26	10.40%
	Bachelor's Degree	158	62.90%
	Master's Degree	67	26.70%

Source: compiled by the author according to research data

The questionnaire was answered by 253 respondents total and after data cleaning 2 of the responses were deleted due to invalid responses in regard to age (332 and 1997 accordingly) and 251 respondents was the total amount which remained for further analysis. The table 2 shows some of the main characteristics of the respondents. In regard to age, the majority of respondents were aged in the age group of 30-39 years old (59%), while two other age groups showed similar results: age group of 20-29 years old (19.5%) and age group of 40-49 years old (21.5%). The average respondent was 35 years old. After that, respondents answered the question about gender, which determined that there were more male respondents (57.8%) than female (42.2%). Furthermore, the experts in the manufacturing industry were asked to indicate their job position. The largest amount of respondents represented the Supervisor/Manager position (48.2%), while Engineer (34.3%) showed a large amount of respondents as well. The lowest group of respondents were workers who picked the option "other" as these positions did not represent the three provided options, of which Operator/Technician (15.1%) was the least represented position. The majority of respondents, when asked about the tenure in their current company, answered with the 1-5 years option (70.9%), while workers working in their current organisation for 6-10 years (23.5%) also represented a sizable group. On the other hand, the number of options of 11-15 years (5.2%) and 16-20 years (0.4%) indicated a much smaller respondent group. The average tenure of respondents was around 5 years. Regarding the size of the company, respondents were asked to indicate the size of their company based on the number of employees. The majority of respondents indicated that they work in a large company (63.7%) in which there are more than 249 employees, while medium company (34.7%), in which there are between 50 and 249 employees also represented a sizable number of responses. In regard to two other options, both small company (1.2%) and micro (0.4%) company, which are between 10 and 49, and up to 10 employees respectively indicated a minimal number of respondents. Finally, the level of education question showed the majority of respondents having a Bachelor's degree (62.9%), while workers having a Master's degree (26.7%) represented a lower group. The minority of respondents have picked the High School Diploma option (10.4%).

3.2. Consistency and reliability of the scales

It is important to test the consistency and reliability of the scales used in the research, as this shows how reliable the chosen scales are and whether they can be used for further research. For this reason, Cronbach's alfa (Annex 3) was calculated for every scale that is used in the thesis. The results are provided in the Table 8.

Table 8. *Scales consistency and reliability measure with Cronbach's alfa*

Construct	Cronbach's alpha value
Employee Digital Competencies (X)	0.893
Digitalisation (M)	0.834
Quality (Y1)	0.801
Cost (Y2)	0.836
Waste (Y3)	0.836

Source: compiled by author according to research data

As shown in Table 3 all alpha values are higher than cutoff value 0.7, which is acceptable (Tavakol & Dennick, 2011), meaning that all scales are consistent and reliable, and can be used for further research.

3.3. Assessment of data normality

The next step after confirming the consistency and reliability of scales is to assess the data normality of the questions in the questionnaire, which is needed to do prior to descriptive statistics and data analysis. To determine this, skewness and kurtosis of all items in the scale was calculated (Annex 4). Based on previous researchers remarks the skewness must be between -2 and 2 and kurtosis between -7 and 7 in order to accept data as normally distributed (Byne, 2010; Hair *et al.,* 2010). The first scale used was the future oriented digital skills created by previous researchers, who identified 13 main employee digital competencies linked to the manufacturing industry (Jurczuk & Florea, 2022). The respondents were asked to assess the current level of their digital competencies based on a 5 points scale, in which the values were the following: 1 - “no competencies”, 2 - “low competencies”, 3 – “medium competencies”, 4 – “high competencies”, 5 – “excellent competencies”. The abbreviation “EDC” was used along with a number which showed the variable to which the question corresponds, in this case Employee Digital Competencies, along with the number which depicts the order of the question in the questionnaire. The skewness and kurtosis of the first group of questions and the results of the latent variable are provided in the Table 9.

Table 9. *Data normality of Employee Digital Competencies questionnaire section*

Items of the Questionnaire	Skewness	Kurtosis
EDC1. IT infrastructure management	-0.120	-0.752
EDC2. Data processing and analysis	-0.135	-0.659
EDC3. Data security/cybersecurity	-0.103	-1.000
EDC4. Computer programming/coding	-0.124	-0.676
EDC5. Internet of things and cyber-physical systems	-0.212	-1.085
EDC6. Automation	0.108	-0.939
EDC7. Robotics	0.362	-0.911
EDC8. Additive manufacturing (3d printing)	0.142	-0.975
EDC9. Cloud technologies and big data	-0.371	-0.927
EDC10. Product simulation	0.221	-1.022
EDC11. Process design and simulation	-0.216	-1.084
EDC12. Service design and engineering	-0.169	-1.064
EDC13. Knowledge management	-0.425	-1.019
Results for the latent EDC variable	**-0.764**	**0.123**

Source: compiled by author according to research data

In regard to the normality of the questions corresponding to the independent variable – Employee Digital Competencies, every response in this group had a skewness value between -2 and 2, as the lowest skewness value in this regard was -0.425 and the highest skewness value was 0.362. The results for the latent variable of Employee Digital Competencies showed the value of skewness to be -0.764 which is also acceptable based on previous research (Byne, 2010; Hair *et al.,* 2010). When it comes to kurtosis of each of the question in this section, every single response value is between -7 and 7, as the lowest value is -1.085 and the highest value is -0.659. When it comes to the kurtosis of the latent variable, it is also acceptable as the value is 0.123. Due to both the skewness and kurtosis of all items being appropriate, the responses of the Employee Digital Competencies section are normally distributed.

The second scale used was impact of industry 4.0, in which 9 innovative solutions, specifically for the manufacturing industry, were identified, which are corresponding to the mediating variable of the study – Digitalisation (Tortorella *et al.,* 2022). The respondents were asked to indicate the adoption level of these digital technologies based on a 5 points scale, in which the values were the following: 1 – "no adoption", 2 – "low adoption" 3 – "moderate adoption", 4 – "high adoption", 5 – "full adoption". The abbreviation "DGTL" was used along with a number which showed the variable to which the question corresponds, in this case Digitalisation and the order of the question in the questionnaire. The skewness and kurtosis of the second group of questions and the results of the latent variable are provided in the Table 10.

Table 10. *Data normality of Digitalisation questionnaire section*

Items of the Questionnaire	Skewness	Kurtosis
DGTL14. Internet of Things (IoT)	0.734	0.633
DGTL15. Big data	-0.023	-0.624
DGTL 16. Cloud computing	0.461	-0.093
DGTL 17. Wireless sensors	0.077	-0.467
DGTL 18. 3d printing	0.692	0.520
DGTL 19. Augmented reality/Simulation	0.417	-0.201
DGTL 20. Colaborative robots	0.658	0.503
DGTL 21. Machine/Deep Learning	0.317	-0.335
DGTL 22. Remote Control/Monitoring	0.638	-0.148
Results for the latent DGTL variable	**0.212**	**0.053**

Source: compiled by author according to research data

When it comes to normality of the questions in section two, which corresponds to the mediating variable – Digitalisation, every response has a skewness value between -2 and 2, which is the appropriate value based on previous research (Byne, 2010; Hair *et al.,* 2010). The lowest value in this section is -0.023, while the highest value is 0.734. In regard to the result for the latent variable, the skewness value is 0.212 which is appropriate as well. The kurtosis value of all responses in this group of questions is between -7 and 7, which is the needed value for data normality. The lowest value is -0.624, while the highest value is 0.633. Following this is the result for the latent mediating variable – Digitalisation, which is of the appropriate value as well – 0.212. This indicates that all responses in this variable are normally distributed.

Prior to proceeding with the next scale, it is important to note, that the third scale consisted of 18 items total, which were assigned equally to three dependent variables – Cost, Waste and Quality (Chauhan *et al.,* 2021). Due to this each section of the following questions in the questionnaire consisted of 6 items for each dependent variable and were linked to results of the Production Process. Firstly, in regard to Cost, 6 items were assigned, and the respondents were asked to indicate their company's improvement in following parameters related to cost in the time period of the last three years based on a 5 points scale, in which the values were the following: 1 – "worsened significantly", 2 – "somewhat worsened", 3 – "stayed same", 4 – "somewhat improved", 5 – "improved significantly" (Chauhan *et al.*, 2021). The abbreviation "CST" was used along with a number which showed the variable to which the question corresponds, in this case Cost and the order of the question in the questionnaire. The skewness and kurtosis of this third group of questions and the results of the latent variable are provided in the Table 11.

Table 11. *Data normality of Cost questionnaire section*

Items of the Questionnaire	Skewness	Kurtosis
CST 23. Cost of logistics	-0.581	-0.201
CST 24. Return on assets	-0.392	-0.221
CST 25. Decrease in operating costs	-0.761	0.261
CST 26. Inventory Turn	-0.724	0.065
CST 27. Order flexibility	-0.784	0.189
CST 28. Capacity of order-fill	-0.545	-0.447
Results for the latent CST variable	**-1.261**	**1.628**

Source: compiled by author according to research data

In the third section, corresponding to the first dependent variable – Cost, data the skewness value of every response is between -2 and 2, which is an acceptable value based on previous research remarks (Byne, 2010; Hair *et al.,* 2010). The lowest skewness value in the section was -0.784 and the highest value was -0.392. The overall result for the latent computed variable of CST was -1.261, which also falls in the appropriate interval. In regard to kurtosis of this section every response has a kurtosis value between -7 and 7, which is appropriate, lowest kurtosis value being -0.447 and the highest kurtosis value being 0.261. Similarly, the overall result for the latent variable indicated the kurtosis value to be 1.628. This shows that this section is also normally distributed.

In regard to another dependent variable – Waste, 6 items were assigned with the same question. The abbreviation ”WST” was used along with a number which showed the variable to which the question corresponds, in this case Waste and the order of the question in the questionnaire. The skewness and kurtosis of this fourth group of questions and the results of the latent variable are provided in the Table 12.

Table 12. *Data normality of Waste questionnaire section*

Items of the Questionnaire	Skewness	Kurtosis
WST 29. Speed of delivery	-0.439	-0.467
WST 30. Supply chain responsiveness	-0.552	-0.459
WST 31. Notification of advance-ship	-0.906	0.592
WST 32. Dependability in terms of delivery	-0.794	0.127
WST 33. Decrease in time required for creating and delivery of new products	-0.779	-0.016
WST 34. Flexibility in delivery	-0.695	-0.092
Results for the latent WST variable	**-1.310**	**1.441**

Source: compiled by author according to research data

In this fourth section, in which questions and responses corresponded to another dependent variable – Waste, skewness value of all responses was between -2 and 2, which according to previous research is a valid interval for data normality (Byne, 2010; Hair *et al.,* 2010). The lowest skewness value in this section was -0.906 and the highest value was -0.439. In regard to the entire variable the skewness value was equal to -1.310, which is also appropriate for further research. When it comes to kurtosis, all responses had a kurtosis value between -7 and 7, lowest value being -0.467 and the highest value being 0.592. The overall variable kurtosis value was equal to 1.441 which is appropriate as well. This concludes that this section is also normally distributed.

Regarding the last dependent variable – Quality, 6 items were assigned and the respondents were asked to indicate their company's improvement in following parameters related to Quality in the time period of the last three years based on a 5 points scale, in which the values were the following: 1 – "worsened significantly", 2 – "somewhat worsened", 3 – "stayed same", 4 – "somewhat improved", 5 – "improved significantly" (Chauhan *et al.,* 2021). The abbreviation ”QLT” was used along with a number which showed the variable to which the question corresponds, in this case Waste, and the order of the question in the questionnaire. The skewness and kurtosis of this fifth group of questions and the results of the latent variable are provided in the Table 13.

Table 13. *Data normality of Quality questionnaire section*

Items of the Questionnaire	Skewness	Kurtosis
QLT 35. Customer satisfaction	-0.817	0.045
QLT 36. Product customisability	-0.641	-0.163
QLT 37. Improvement in the quality of products	-0.804	0.350
QLT 38. Rise in product innovativeness	-0.741	0.132
QLT 39. Successful launches of new products	-0.826	0.170
QLT 40. Improvement in product capability and performance	-0.840	0.494
Results for the latent QLT variable	**-1.354**	**1.856**

Source: compiled by author according to research data

In the last fifth section, corresponding to the dependent variable – Quality, skewness value of every response was between -2 and 2, which is appropriate based on prior research (Byne, 2010; Hair *et al.,* 2010). The lowest skewness value was -0.840 and the highest value was -0.641. The overall result for the latent variable showed a skewness value of -1.354, which is suitable as well. When it comes to kurtosis, all responses had the kurtosis value between -7 and 7. The lowest kurtosis value in this section was -0.163 and the highest value was 0.494. The overall value of the latent variable was 1.856, which is appropriate. Based on this, the fifth and last set of questions and responses indicate normal distribution. To summarize, every single item of the questionnaire was normally distributed, which is an important step after which the data analysis can commence, and we can proceed with the descriptive statistics.

3.4. Descriptive data statistics

After the data normality of all questionnaire items is confirmed, descriptive statistics can be done. For each questionnaire section corresponding to the variable mean value and standard deviation was calculated to see the answers of the respondents, their averages and variability (Annex 4). Firstly, we are looking into the Employee Digital Competencies, as the independent variable, in which a 13-item scale is adopted, that talks about 13 digital competencies linked to manufacturing industry (Jurczuk & Florea, 2022). The respondents were asked to assess the current level of their digital competencies in regard to 13 digital competencies, based on a 5-point scale, in which the values were the following: 1 - “no competencies, 2 - “low competencies”, 3 – “medium competencies, 4 – “high competencies”, 5 – “excellent competencies”. The results of mean and standard deviation measures are provided in the Table 14.

Table 14. *Descriptive statistics of Employee Digital Competencies questionnaire section*

Items of the Questionnaire	Mean	Std. Deviation
EDC1. IT infrastructure management	3.00	1.147
EDC2. Data processing and analysis	3.02	1.147
EDC3. Data security/cybersecurity	3.02	1.193
EDC4. Computer programming/coding	3.04	1.162
EDC5. Internet of things and cyber-physical systems	3.21	1.292
EDC6. Automation	2.90	1.252
EDC7. Robotics	2.60	1.227
EDC8. Additive manufacturing (3d printing)	2.84	1.289
EDC9. Cloud technologies and big data	3.23	1.244
EDC10. Product simulation	2.82	1.280
EDC11. Process design and simulation	3.17	1.307
EDC12. Service design and engineering	3.19	1.288
EDC13. Knowledge management	3.44	1.353
Results for the entire EDC variable	**3.04**	**0.825**

Source: compiled by author according to research data

Regarding the first section of the questionnaire, corresponding to the independent variable, Employee Digital Competencies, the overall result of the entire variable shows a mean value of 3.04. This shows that on average respondents rated their competencies level as "medium competencies". Looking further into each response, it is highlighted that knowledge management (mean 3.44), cloud technologies and big data (mean 3.23) and internet of things & cyber-physical systems (mean 3.21) were competencies which the employees of the manufacturing company highlighted as their strongest. On the other hand, robotics (mean 2.60), product simulation (mean 2.82) and additive manufacturing (3d printing) (mean 2.84) showed competencies which were noted as the weakest from the respondents. This showed a tendency of more well known and popular technologies being the ones in which the respondents had more experience and knowledge, while the lesser known or used technologies being less favourable, based on the responses. In regard to standard deviation, the whole computed variable showed a standard deviation of 0.825, which based on previous research remarks falls into the category of 68% of data points, that fall into an interval of -1 to 1 standard deviation (Byne, 2010; Hair *et al.,* 2010). This is used with normal distribution, which was confirmed in the previous subchapter. Regarding the standard deviation of the responses, all responses fell into the interval between 1.1 and 1.4 which based on the researchers is suitable with normal distribution, as 98,5% of data points fall into an interval of -2 to 2 standard deviation, indicating a predictable and consistent spread of data (Byne, 2010; Hair *et al.,* 2010).

Secondly, there is a need to look into the mediating variable, Digitalisation, in which a 9-item scale is adopted, which shows 9 main digital solutions used in manufacturing industry. (Tortorella *et al.,* 2022). The respondents were asked to indicate the adoption level of these digital technologies based on a 5 points scale, in which the values were the following: 1 – "no adoption", 2 – "low adoption" 3 – "moderate adoption", 4 – "high adoption", 5 – "full adoption". The results of mean and standard deviation measures are provided in the Table 15.

Table 15. *Descriptive statistics of Digitalisation questionnaire section*

Items of the Questionnaire	Mean	Std. Deviation
DGTL14. Internet of Things (IoT)	2.37	0.840
DGTL15. Big data	2.38	0.923
DGTL 16. Cloud computing	2.53	0.905
DGTL 17. Wireless sensors	2.46	0.904
DGTL 18. 3d printing	2.25	0.922
DGTL 19. Augmented reality/Simulation	2.18	0.919
DGTL 20. Collaborative robots	2.02	0.855
DGTL 21. Machine/Deep Learning	2.42	0.990
DGTL 22. Remote Control/Monitoring	2.59	1.118
Results for the entire DGTL variable	**2.35**	**0.612**

Source: compiled by author according to research data

Regarding the second section of the questionnaire, corresponding to the mediating variable, Digitalisation, the overall result of the entire variable is 2.35. This shows that on average the respondents indicated that the adoption level of these digital solutions is closer to the "low adoption" level. Looking further into each response it is evident that remote control/monitoring (mean 2.59), cloud computing (mean 2.53) and wireless sensors (2.46) are the technologies which had the highest adoption level of this section. On the other hand, collaborative robots (2.02), augmented reality (2.18) and 3d printing (2.25) were the technologies that had the lower adoption level. It is also important to note that other technologies which situated in the middle based on the mean vale, were closer to the higher value, which shows that most of the innovations are prioritized more than the lowest value ones. Overall, it shows that lesser-known technologies and innovations are adopted less, which can be linked to lack of knowledge and popularity on this topic. In regard to standard deviation, the whole computed variable showed the value of 0.612, which along with all questions fell into the interval of -2 to 2, which based on prior research is the acceptable value (Byne, 2010; Hair *et al.,* 2010). This indicates a predictable and consistent spread of data in this section as well.

Thirdly, we need to look into the third variable, dependent variable, Cost, in which there are 6 total questions, in which the respondents were asked to indicate their company's improvement in parameters related to Cost, in the time period of the last three years, based on a 5 points scale, in which the values were the following: 1 – “worsened significantly”, 2 – “somewhat worsened”, 3 – “stayed same”, 4 – “somewhat improved”, 5 – “improved significantly” (Chauhan *et al.,* 2021). The results of mean and standard deviation measures are provided in the Table 16.

Table 16. *Descriptive statistics of Cost questionnaire section*

Items of the Questionnaire	Mean	Std. Deviation
CST 23. Cost of logistics	3.41	0.887
CST 24. Return on assets	3.76	0.946
CST 25. Decrease in operating costs	3.83	0.965
CST 26. Inventory Turn	3.88	1.009
CST 27. Order flexibility	3.83	1.015
CST 28. Capacity of order-fill	3.84	1.024
Results for the entire CST variable	**3.76**	**0.722**

Source: compiled by author according to research data

Regarding the third section of the questionnaire, corresponding to the dependent variable, Cost, the overall result of the entire variable is 3.76. This shows that on average the respondents highlighted that the production process results linked to Cost “somewhat improved”. When looking into the responses, it is evident that both the inventory turn (mean 3.88) and capacity of order-fill (mean 3.84) saw the best improvement, while cost of logistics (mean 3.41) saw the worst improvement of this section. Other three responses had a mean value close to the best improved results, therefore it shows that almost the whole variable saw a similar improvement. In regard to standard deviation, the whole computed variable showed the value 0.722, which along with all questions fell into the interval of -2 to 2, which based on prior research is the acceptable value (Byne, 2010; Hair *et al.,* 2010). This indicates a predictable and consistent spread of data in this section too.

Also, we need to look into the fourth variable, dependent variable, Waste, in which there are 6 total questions, where the respondents were asked to asked to indicate their company’s improvement in parameters related to Waste, in the time period of the last three years, based on a 5 points scale, in which the values were the following: 1 – “worsened significantly”, 2 – “somewhat worsened”, 3 – “stayed same”, 4 – “somewhat improved”, 5 – “improved significantly” (Chauhan *et al.,* 2021). The results of mean and standard deviation measures are provided in the Table 17.

Table 17. *Descriptive statistics of Waste questionnaire section*

Items of the Questionnaire	Mean	Std. Deviation
WST 29. Speed of delivery	3.53	1.074
WST 30. Supply chain responsiveness	3.80	1.030
WST 31. Notification of advance-ship	3.81	1.004
WST 32. Dependability in terms of delivery	3.88	1.017
WST 33. Decrease in time required for creating and delivery of new products	3.76	1.094
WST 34. Flexibility in delivery	3.86	0.994
Results for the entire WST variable	3.77	0.768

Source: compiled by author according to research data

Regarding the fourth section of the questionnaire, which corresponds to another dependent variable, Waste, the result for the entire variable is 3.77, which is slightly larger than the result for the Cost variable and signals that the production process results related to Waste "somewhat improved". This shows that overall, Waste is impacted more than Cost, and this claim is further backed by the mean values of the questions in this section, with the largest improvement being in dependability in terms of delivery (mean 3.88) and flexibility in delivery (mean 3.86). On the other hand, speed of delivery (mean 3.53) was improved the least for this section. The other responses in this question group showed similar mean values to the highest improvements, highlighting that the overall improvement in Waste is larger than Cost. In regard to standard deviation, the whole computed variable showed the value 0.768, which along with all questions fell into the interval of -2 to 2, that based on prior research is the proper value (Byne, 2010; Hair *et al.,* 2010). This indicates a predictable and consistent spread of data in this section as well.

Finally, the last, fifth variable needs to be analysed. This final dependent variable is Quality, in which there are 6 total questions, where the respondents were asked to answer the same question as with Cost and Waste. The results of mean and standard deviation measures are provided in the Table 18.

Table 18. *Descriptive statistics of Quality questionnaire section*

Items of the Questionnaire	Mean	Std. Deviation
QLT 35. Customer satisfaction	3.79	1.083
QLT 36. Product customisability	3.88	1.010
QLT 37. Improvement in the quality of products	3.84	0.995
QLT 38. Rise in product innovativeness	3.83	0.999
QLT 39. Successful launches of new products	3.83	1.042
QLT 40. Improvement in product capability and performance	3.93	0.971
Results for the entire QLT variable	**3.85**	**0.721**

Source: compiled by author according to research data

Regarding the fifth section, which corresponds to the final dependent variable, Quality, the result for the entire variable is 3.85, a result which is the highest of all three dependent variables, showing that Quality also "somewhat improved". It also shows that the improvement in this variable was the largest, which is further highlighted in the mean values of the questions, as the improvement in product capability and performance (mean 3.93) had the largest mean value of the whole questionnaire. Other questions had a similar mean value, however the lowest of them was customer satisfaction (mean 3.79), which showed the lowest improvement. In regard to standard deviation, the whole computed variable showed the value 0.721, which along with all questions fell into the interval of -2 to 2, that based on prior research is the proper value (Byne, 2010; Hair *et al.,* 2010). This shows a consistent and predictable spread of data in this section as well.

In summary, the standard deviation of all response of the questionnaire showed values in the interval of -2 to 2, which is an appropriate value with which all of the questionnaire entries can be summarised as consistent and predictable. Regarding the mean value, the responses corresponding to the independent variable, Employee Digital Competencies, showed that the respondents highlighted on average medium level of digital competencies, with the highest level of them being linked to technologies which had a higher level of adoption as highlighted in the mean values corresponding to the mediating variable – Digitalisation. Due to lesser-known technologies having a lower level of digital competencies and thus a lower level of adoption in the companies it shows a lack of practical knowledge and information about them in Lithuania, which could explain the results. The higher level of Employee Digital Competencies in relation to Digitalisation, proves that the competencies facilitate the adoption of the technologies, as the manufacturing professionals in Lithuania, who took part in this questionnaire, showed that they have a higher level of competencies which in turn drives further adoption of the technologies. This explains why the higher Employee Digital Competencies mean value corresponded to higher adoption level of the corresponding technology, as this was highlighted in previous research (Barykin *et al.,* 2020; Blanka, *et al.,* 2022; Butschan *et al.,* 2019; Chaka, 2020; Ngereja & Hussein, 2022). When it comes to the production results, Quality had the biggest improvement, followed by Waste and Cost. All dependent variables showed that in the period of last three years they have somewhat improved, which would be higher with a higher level of digital competencies and in turn also a higher level of innovation adoption.

3.5. Correlation analysis

Correlation analysis is needed between all computed variables in order to determine the direction and the strength of the relationship between variables (Byne, 2010; Hair *et al.,* 2010). In this subchapter, all five variables are be tested: Employee Digital Competencies (EDC), Digitalisation (DGTL), Cost (CST), Waste (WST), Quality (QLT) (Annex 5). Based on previous research remarks, there are three main intervals in regards to correlation: first one notes weak relationship in which the correlation coefficient (r) is from 0 to either -0.3 or 0.3, the second one highlights a moderate relationship when the interval of correlation coefficient (r) is either 0.3 to 0.7 or -0.3 to -.0.7, the third one shows a strong relationship in which the correlation coefficient (r) is in the interval of either 0.7 to 1.0 or -0.7 to -1.0 (Byne, 2010; Hair *et al.,* 2010). The Correlation analysis results are provided in Table 19.

Table 19. *Correlation analysis of all variables*

Correlation analysis	EDC	DGTL	CST	WST	QLT
EDC					
DGTL	0.279				
CST	0.345	0.356			
WST	0.342	0.381	0.825		
QLT	0.346	0.280	0.764	0.781	

Source: compiled by author according to research data

Firstly, it is important to note that all values are positive, which shows that an increase in one variable, results with an increase in another. In regard to the level of the relationship between variables one variable pair shows a weak positive relationship, in this case the independent variable - Employee Digital Competencies (EDC) and mediating variable - Digitalisation (DGTL) notes a correlation of 0.279, which based on previous research remarks is considered a low correlation (Byne, 2010; Hair *et al.,* 2010). As the relationship is positive, based of the gathered data, this shows that when Employee Digital Competencies increase, Digitalisation tends to increase only slightly. This is also the case when looking into correlation of mediating variable Digitalisation (DGTL) and one of the dependent variables – Quality (QLT), as the relationship shows a correlation of 0.280. It is important to note that these findings depict a different situation in Lithuania compared to previous research on similar topics worldwide. Based on Table 14 a strong positive relationship is depicted between two dependent variables Waste (WST) and Cost (QST) in which the correlation is 0.825. This strong positive correlation shows a close association between the variables, which is consistent with prior research, however it is important to highlight that this relationship does not imply redundancy as Waste and Cost are clearly separated but interrelated aspects of production (Ohno, 2019). The rest of the pairs shows a moderate positive correlation which shows that when one variable increases, the other tends to increase too, however the relationship is not extremely strong. These findings shows that each variable is connected due to all values showing a positive correlation value.

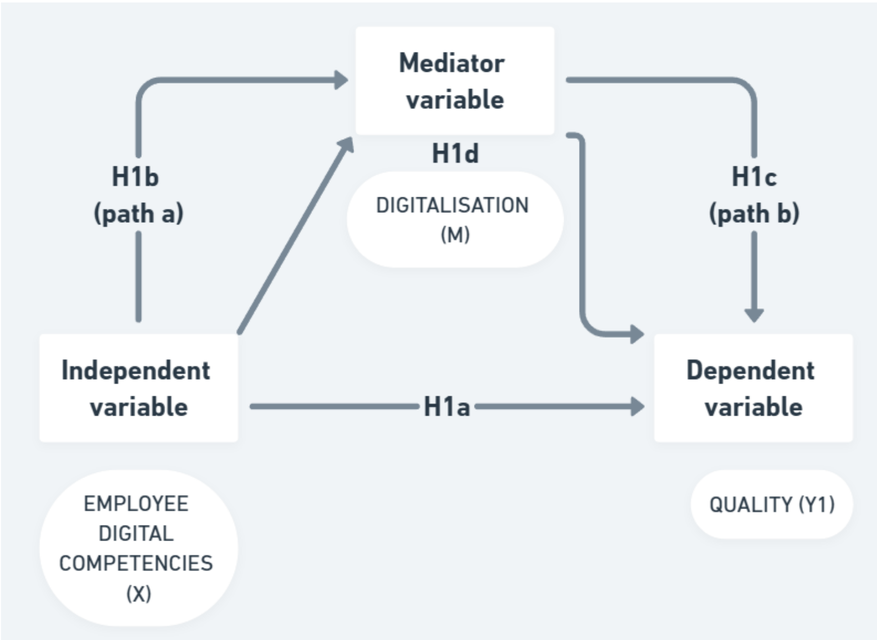
3.6. The mediating effect of Digitalisation

To assess the relationship between the independent variable – Employee Digital Competencies and the dependent variables – Quality, Cost and Waste, the relationship between the independent variable Employee Digital Competencies and mediating variable Digitalisation, and the mediating effect of Digitalisation between the independent and dependent variables a mediating analysis was performed (Annex 6). It was done using SPSS version 29 with the use of plugin 4.2 version process macro by Andrew F. Hayes, model 4. Due to the study having three research models, each model and corresponding hypotheses were analysed separately.

Model 1

The research Model 1 is analysed, in which Quality is the dependent variable as per the research model provided in Figure 8.

Figure 8. *Research Model 1. Quality (Y1)*



Source: compiled by the author

In accordance to research Model 1 mediating analysis is done to confirm or reject the following hypotheses:

$H1_a$ Employee Digital Competencies will improve Quality in the Production Process

$H1_b$ Employee Digital Competencies has a positive impact on the effectiveness of Digitalisation in the Production Process

$H1_c$ Digitalisation will improve Quality in the Production Process

$H1_d$ The relationship between Employee Digital Competencies and Quality in the Production Process is positively mediated by Digitalisation

To approve or disapprove the first hypothesis of Model 1, linear regression analysis is done, results of which are provided in Table 20.

Table 20. *Direct effect of Employee Digital Competencies (X) on Quality (Y1)*

Independent variable (X)	Dependent variable (Y1)	b	β	R sq.	T value	P value	LLCI	ULCI
Employee Digital Competencies	Quality	0.254	0.291	0.156	4.789	0.000	0.150	0.359

Source: compiled by author according to research data

Based on the findings, the unstandardized coefficient (*b*) in this regression analysis is 0.254 and indicates a positive direct effect, showing that an increase in Employee Digital Competencies results in increase of Quality by 0.254 units, controlling for other variables in the model (Hayes, 2017). The standardized coefficient (*β*) in this regression analysis is 0.291, which shows a small-to-moderate positive relationship between these variables, indicating that increase in Employee Digital Competencies corresponds to the increase of Quality by approximately 0.29 standard deviations, when controlling for other predictors in the model. R square in this mediation analysis is 0.156, which means that 15.6% of the variance can be explained, so the model fits the data. The T value is higher than 2 as it is 4.789, which means that the effect is statistically significant. The p value of 0.000 shows a significant effect. The interval between LLCI and ULCI values is between 0.150 and 0.359, the values are positive and don't cross 0, therefore the effect is significant and positive. In conclusion this analysis proves that **$H1_a$ is approved**.

To approve or disapprove the second hypothesis of Model 1, linear regression analysis is done, results of which are provided in Table 21.

Table 21. *Indirect pathway (path a) of relationship between Employee Digital Competencies (X) and Digitalisation (M)*

Independent variable (X)	Variable (M)	b	β	R sq.	T value	P value	LLCI	ULCI
Employee Digital Competencies	Digitalisation	0.207	0.279	0.078	4.590	0.000	0.118	0.296

Source: compiled by author according to research data

Based on the findings, the unstandardized coefficient (*b*) in this regression analysis is 0.207 and indicates a positive effect, showing that an increase in Employee Digital Competencies results in increase of Digitalisation by 0.207 units, controlling for other variables in the model.

The standardized coefficient (*β)* in this regression analysis is 0.279, which shows a small-to-moderate positive relationship between these variables, indicating that increase in Employee Digital Competencies corresponds to the increase of Digitalisation by approximately 0.28 standard deviations, when controlling for other predictors in the model. R square in this mediation analysis is 0.078, which means that 7,8% of the variance can be explained, so the model fits the data. The T value is higher than 2 as it is 4.590, which means that the effect is statistically significant. The p value of 0.000 shows a significant effect. The interval between LLCI and ULCI values is between 0.118 and 0.296, the values are positive and don't cross 0, therefore the effect is significant and positive. In conclusion this analysis proves that **$H1_b$ is approved**.

To approve or disapprove the third hypothesis of Model 1, linear regression analysis is done, results of which are provided in Table 22.

Table 22. *Indirect pathway (path b) of relationship between Digitalisation (M) and Quality (Y1)*

Mediator variable (M)	Dependent variable (Y1)	b	β	R sq.	T value	P value	LLCI	ULCI
Digitalisation	Quality	0.233	0.198	0.156	3.267	0.001	0.093	0.374

Source: compiled by author according to research data

Regarding the results, the unstandardized coefficient (*b*) in this regression analysis is 0.233 and indicates a positive effect, showing that an increase in Digitalisation results in increase of Quality by 0.233 units, controlling for other variables in the model (Hayes, 2017). The standardized coefficient (*β)* in this regression analysis is 0.198, which shows a small positive relationship between these variables, indicating that increase in Digitalisation corresponds to the increase of Quality by approximately 0.20 standard deviations, when controlling for other predictors in the model. The R square value is 0.156, which means that 15.6% of the variance can be explained, so the model fits the data. The T value is bigger than 2 and is 3.267, meaning that the effect is statistically significant. The p value of 0.001 also shows a significant effect. Finally, LLCI and ULCI interval is between 0.093 and 0.374 and as the values do not cross 0, the effect is significant and positive, due to both values being larger than 0. Based on these findings it can be concluded that Digitalisation has a positive effect on Quality. As based on this mediation analysis Digitalisation has a positive effect on Quality the **$H1_c$ is approved**.

To approve or disapprove the fourth hypothesis of Model 1, analysis is done, results of which are provided in Table 23.

Table 23. *Mediation Analysis of the effect Employee Digital Competencies (X) have on Quality (Y1) through Digitalisation (M)*

Total effect						
b	se	t	p	LLCI	ULCI	β
0.302	0.052	5.826	0.000	0.200	0.405	0.346

Continuation Table 23

Direct effect						
b	se	t	p	LLCI	ULCI	β
0.254	0.053	4.789	0.000	0.150	0.359	0.291
Indirect effect						
b	BootSE	t	p	BootLLCI	BootULCI	β
0.048	0.022	-	-	0.012	0.097	0.108

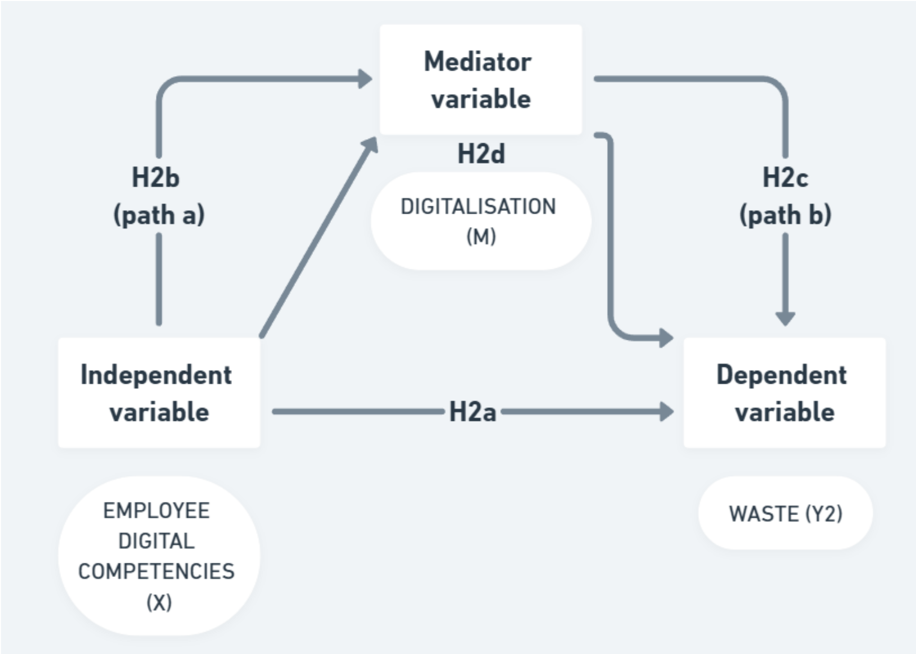
Source: compiled by author according to research data

The first measure is the unstandardized coefficient (*b*) and in the total effect section, it equals 0.302, which based on previous research, indicates a positive relationship between variables, as the increase can be measured by 0.302 of the units (Hayes, 2017). Also, the standard error shows a value of 0.052 and as the smaller value is better, it shows a precision of the effect estimate. The T value should be bigger than 2, and in this case is 5.826, meaning that the effect is statistically significant. The p value of 0.000 shows a significant effect too. Finally, LLCI and ULCI interval is between 0.200 and 0.405, which depicts that values do not cross 0, and due to that, the effect is significant and also positive, as both values are larger than 0. Regarding standardized coefficient (β), the value of 0.346 is positive, because it signals a positive relationship between the variables, meaning that for every one standard deviation increase of the independent variable, dependent variable increases by 0.346 standard deviations showing a moderate effect. Secondly, in regard to the direct effect it shows similar results with some changes: almost all values are lower, except of standard error which is slightly higher than in the total effect at 0.053. This also shows that the relationship is positive, and the effect is statistically significant. In this regard there is also measure of (β), which shows a value of 0.291, indicating small-to-moderate direct effect based on previous research. Lastly, the indirect effect results describe a much smaller (*b*) value of 0.048. Even though the effect value is smaller, as the interval of both BootLLCI and BootULCI results exclude zero, the indirect effect is statistically significant even when the effect value is lower. The BootSE value shows a value of 0.022 and due to that indicates, that the indirect effect is estimated with reasonable precision. Based on these findings as both the direct and indirect effects of Employee Digital Competencies on Quality are positive and statistically significant, a partial mediation between the variables is found. Based on these findings **$H1_d$ is approved.** In summary, based on the findings of the mediation analyses done, all four hypotheses of Model 1 were approved.

Model 2

The research Model 2 is analysed, in which Waste is the dependent variable as per the research model provided in Figure 9.

Figure 9. *Research Model 2. Waste (Y2)*



Source: compiled by the author

In accordance to research Model 2 mediating analysis is done to confirm or reject the following hypotheses:

$H2_a$ Employee Digital Competencies will reduce Waste in the Production Process

$H2_b$ Employee Digital Competencies has a positive impact on the effectiveness of Digitalisation in the Production Process

$H2_c$ Digitalisation will reduce Waste in the Production Process

$H2_d$ The relationship between Employee Digital Competencies and Waste in the Production Process is positively mediated by Digitalisation

To approve or disapprove the first hypothesis of Model 2, linear regression analysis is done, results of which are provided in Table 24.

Table 24. *Direct effect of Employee Digital Competencies (X) on Waste (Y2)*

Independent variable (X)	Dependent variable (Y2)	b	β	R sq.	T value	P value	LLCI	ULCI
Employee Digital Competencies	Waste	0.238	0.255	0.205	4.330	0.000	0.130	0.346

Source: compiled by the author according to research data

Based on the findings, the unstandardized coefficient (*b*) in this regression analysis is 0.238 and indicates a positive direct effect, showing that an increase in Employee Digital Competencies results in increase of Waste by 0.238 units, controlling for other variables in the model (Hayes, 2017). The standardized coefficient (*β)* in this regression analysis is 0.255, which shows a small-to-moderate positive relationship between these variables, indicating that increase in Employee Digital Competencies corresponds to the increase of Waste by approximately 0.26 standard deviations, when controlling for other predictors in the model. Regarding the R square, in this mediation analysis, it is equal to 0.205, meaning that 20.5% of the variance can be explained, so the model fits the data. The T value is higher than 2 as it is 4.330, which means that the effect is statistically significant. The p value of 0.000 shows a significant effect. The interval between LLCI and ULCI values is between 0.130 and 0.346, the values are positive and don't cross 0, therefore the effect is significant and positive. In conclusion this analysis proves that **$H2_a$ is approved**.

To approve or disapprove the second hypothesis of Model 2, linear regression analysis is done, results of which are provided in Table 25.

Table 25. *Indirect pathway (path a) of relationship between Employee Digital Competencies (X) and Digitalisation (M)*

Independent variable (X)	Variable (M)	b	β	R sq.	T value	P value	LLCI	ULCI
Employee Digital Competencies	Digitalisation	0.207	0.279	0.078	4.590	0.000	0.118	0.296

Source: compiled by the author according to research data

Based on the findings, the unstandardized coefficient (*b*) in this regression analysis is 0.207 and indicates a positive effect, showing that an increase in Employee Digital Competencies results in increase of Digitalisation by 0.207 units, controlling for other variables in the model (Hayes, 2017). The standardized coefficient (*β)* in this regression analysis is 0.279, which shows a small-to-moderate positive relationship between these variables, indicating that increase in Employee Digital Competencies corresponds to the increase of Digitalisation by approximately 0.28 standard deviations, when controlling for other predictors in the model. Regarding R square, in this mediation analysis it is 0.078, which means that 7,8% of the variance can be explained, so the model fits the data. The T value is higher than 2 as it is 4.590, which means that the effect is statistically significant. The p value of 0.000 shows a significant effect. The interval between LLCI and ULCI values is between 0.118 and 0.296, the values are positive and don't cross 0, therefore the effect is significant and positive. In conclusion this analysis proves that **$H2_b$ is approved**.

To approve or disapprove the third hypothesis of Model 2, linear regression analysis is done, results of which are provided in Table 26.

Table 26. Indirect pathway (path b) of relationship between Digitalisation (M) and Waste (Y2)

Mediator variable (M)	Dependent variable (Y2)	b	β	R sq.	T value	P value	LLCI	ULCI
Digitalisation	Waste	0.389	0.310	0.205	5.256	0.000	0.243	0.534

Source: compiled by the author according to research data

Based on the mediation analysis results, the unstandardized coefficient (*b*) in this regression analysis is 0.389 and indicates a positive direct effect, showing that an increase in Digitalisation results in increase of Waste by 0.389 units, controlling for other variables in the model (Hayes, 2017). The standardized coefficient (*β)* in this regression analysis is 0.310, which shows a moderate positive relationship between these variables, indicating that increase in Digitalisation corresponds to the increase of Waste by 0.31 standard deviations, when controlling for other predictors in the model. Also, the R square value is 0.205, meaning that 20.5% of the variance is explained, so the model fits the data. The T value is bigger than 2, as the value is 5.256, which shows statistical significance. The p-value is 0.000 and this also indicated a strong level of significance. In regard to the LLCI and ULCI interval, we can observe that the values are in an interval between 0.243 and 0.534, meaning that due to both values being positive, there is a positive effect and due to the interval not crossing 0, the effect is also significant. Based on these finding it can be concluded that Digitalisation has a positive effect on Waste, therefore **$H2_c$ is approved**.

To approve or disapprove the fourth hypothesis of Model 2, mediation analysis is done, results of which are provided in Table 27.

Table 27. *Mediation Analysis of the effect Employee Digital Competencies (X) have on Waste (Y2) through Digitalisation (M)*

Total effect						
b	se	t	p	LLCI	ULCI	β
0.318	0.055	5.739	0.000	0.209	0.427	0.342
Direct effect						
b	se	t	p	LLCI	ULCI	β
0.238	0.055	4.330	0.000	0.130	0.346	0.255
			Indirect effect			
b	BootSE	t	p	BootLLCI	BootULCI	β
0.081	0.027	-	-	0.034	0.14	0.087

Source: compiled by the author according to research data

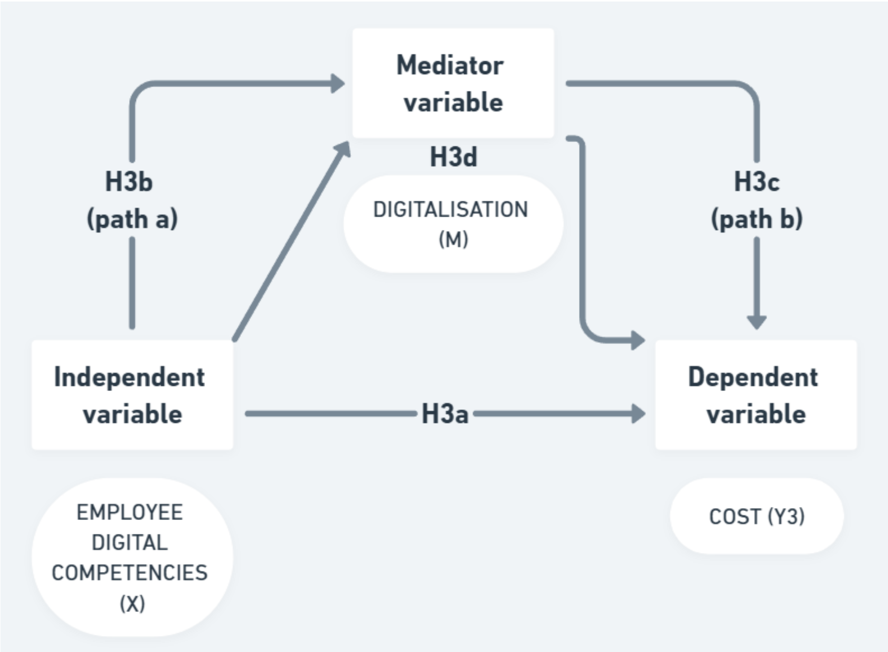
Based on the results, the unstandardized coefficient (*b*) value in the total effect section equals 0.318, which based on previous research remarks signals a positive relationship between variables, as the increase can be measured by 0.318 of the units (Hayes, 2017). Standard error in this case is 0.055 and as the smaller value is better, it shows precision of the effect estimate. The T value needs to be bigger than 2 and in this case is 5.379, meaning that the effect is statistically significant. The p value of 0.000 shows a significant effect as well. Finally, LLCI and ULCI interval is between 0.209 and 0.427, and as the values do not cross 0, the effect is significant and positive, due to both values being larger than 0. In regard to standardized coefficient (β), the value of 0.342 is positive as it signals a positive relationship between the variables, meaning that for every one standard deviation increase of the independent variable, dependent variable increases by 0.342 standard deviations which shows a moderate effect. Secondly, regarding the direct effect it shows similar results with some changes: almost all values are lower, except of standard error which remains the same as in the total effect. This also shows that the relationship is positive, and the effect is statistically significant. In this regard value of (β) is 0.255, which indicates small to moderate direct effect. Lastly, the indirect effect results note a much smaller (*b*) value of 0.081. However, as the interval of both BootLLCI and BootULCI results exclude zero, the indirect effect is statistically significant even when the effect value is lower. The BootSE value shows a value of 0.027 and in turn indicates that the indirect effect is estimated with reasonable precision. Based on these findings as both the direct and indirect effects of Employee Digital Competencies on Waste are positive and statistically significant, a partial mediation between the variables is found, therefore **$H2_d$ is approved**.

In summary, based on the findings of the mediation analyses done, all four hypotheses of Model 2 were approved.

Model 3

The research Model 3 is analysed, in which Cost is the dependent variable as per the research model provided in Figure 10.

Figure 10. *Research Model 3. Cost (Y3)*



Source: compiled by the author

In accordance to research Model 3 mediating analysis is done to confirm or reject the following hypotheses:

$H3_a$ Employee Digital Competencies will reduce Cost in the Production Process

$H3_b$ Employee Digital Competencies has a positive impact on the effectiveness of Digitalisation in the Production Process

$H3_c$ Digitalisation will reduce Cost in the Production Process

$H3_d$ The relationship between Employee Digital Competencies and Cost in the Production Process is positively mediated by Digitalisation

To approve or disapprove the first hypothesis of Model 3, linear regression analysis is done, results of which are provided in Table 28.

Table 28. *Direct effect of Employee Digital Competencies (X) on Cost (Y3)*

Independent variable (X)	Dependent variable (Y3)	b	β	R sq.	T value	P value	LLCI	ULCI
Employee Digital Competencies	Cost	0.233	0.266	0.192	4.482	0.000	0.131	0.336

Source: compiled by the author according to research data

Based on the findings, the unstandardized coefficient (*b*) in this regression analysis is 0.233 and indicates a positive direct effect, showing that an increase in Employee Digital Competencies results in increase of Cos by 0.233 units, controlling for other variables in the model (Hayes, 2017). The standardized coefficient (*β)* in this regression analysis is 0.266, which shows a small-to-moderate positive relationship between these variables, indicating that increase in Employee Digital Competencies corresponds to the increase of Waste by approximately 0.27 standard deviations, when controlling for other predictors in the model. Regarding the R square, in this mediation analysis, it is equal to 0.192, meaning that 19.2% of the variance can be explained, so the model fits the data. The T value is higher than 2 as it is 4.482, which indicates that the effect is statistically significant. The p value of 0.000 shows a significant effect. The interval between LLCI and ULCI values is between 0.131 and 0.336, the values are positive and don’t cross 0, therefore the effect is significant and positive. In conclusion this analysis proves that **$H2_a$ is approved**.

To approve or disapprove the second hypothesis of Model 3, linear regression analysis is done, results of which are provided in Table 29.

Table 29. *Indirect pathway (path a) of relationship between Employee Digital Competencies (X) and Digitalisation (M)*

Independent variable (X)	Mediator variable (M)	b	β	R sq.	T value	P value	LLCI	ULCI
Employee Digital Competencies	Digitalisation	0.207	0.279	0.078	4.590	0.000	0.118	0.296

Source: compiled by the author according to research data

Based on the findings, the unstandardized coefficient (*b*) in this regression analysis is 0.207 and indicates a positive effect, showing that an increase in Employee Digital Competencies results in increase of Digitalisation by 0.207 units, controlling for other variables in the model (Hayes, 2017). The standardized coefficient (*β)* in this regression analysis is 0.279, which shows a small-to-moderate positive relationship between these variables, indicating that increase in Employee Digital Competencies corresponds to the increase of Digitalisation by approximately 0.28 standard deviations, when controlling for other predictors in the model. The R square in this mediation analysis is 0.078, which means that 7,8% of the variance can be explained, so the model fits the data (Hayes, 2017). The T value is higher than 2 as it is 4.590, which means that the effect is statistically significant. The p value of 0.000 shows a significant effect. The interval between LLCI and ULCI values is between 0.118 and 0.296, the values are positive and don't cross 0, therefore the effect is significant and positive. In conclusion this analysis proves that **$H3_b$ is approved**.

To approve or disapprove the third hypothesis of Model 3, mediation analysis is done, results of which are provided in Table 30.

Table 30. Indirect pathway (path b) of relationship between Digitalisation (M) and Cost (Y3)

Mediator variable (M)	Dependent variable (Y3)	b	β	R sq.	T value	P value	LLCI	ULCI
Digitalisation	Cost	0.332	0.281	0.192	4.732	0.000	0.194	0.470

Source: compiled by the author according to research data

Based on the mediation analysis results, the unstandardized coefficient (*b*) in this regression analysis is 0.332 and indicates a positive direct effect, showing that an increase in Digitalisation results in increase of Cost by 0.332 units, controlling for other variables in the model (Hayes, 2017). The standardized coefficient (*β)* in this regression analysis is 0.281, which shows a small-to-moderate positive relationship between these variables, indicating that increase in Digitalisation corresponds to the increase of Cost by approximately 0.28 standard deviations, when controlling for other predictors in the model. In this case the value of R square is 0.192, which shows a meaningful effect in regard to variance as 19.2% of variance is explained, which shows that the model fits the data. Regarding T value, value larger than 2 represents a statistical significance and in this case, this is evident, as the T value is 4.732. Regarding the p value it is

0.000 which also indicates a stronger level of significance. Also, LLCI and ULCI values are important as when the interval between these values excludes 0, it indicates that the effect is significant, and if the values are larger than 0 it shows a positive effect. This is the case with the effect of Digitalisation on Cost, as the LLCI and ULCI interval is between 0.194 and 0.470, meaning it excludes 0 and both values are positive. This shows a significant positive effect on Cost. Therefore, it can be summarized that Digitalisation has a positive effect on Cost, due to which **H3$_c$ is approved.**

To approve or disapprove the fourth hypothesis of Model 3, mediation analysis is done, results of which are provided in Table 31.

Table 31. *Mediation Analysis of the effect Employee Digital Competencies (X) have on Cost (Y3) through Digitalisation (M)*

Total effect						
b	se	t	p	LLCI	ULCI	β
0.302	0.052	5.800	0.000	0.200	0.405	0.345
Direct effect						
b	se	t	p	LLCI	ULCI	β
0.233	0.052	4.482	0.000	0.131	0.336	0.266
Indirect effect						
b	BootSE	t	p	BootLLCI	BootULCI	β
0.069	0.024	-	-	0.029	0.120	0.079

Source: compiled by the author according to research data

The results show the unstandardized coefficient (*b*) to have a value of 0.302, which based on previous research remarks signals a positive relationship between variables, as the increase can be measured by 0.302 of the units (Hayes, 2017). Standard error in this case is 0.052 and, in this case, this smaller value is better as it shows precision of the effect estimate. The T value is bigger than 2 and is 5.800, meaning that the effect is statistically significant. The p value of 0.000 also shows a significant effect. Finally, LLCI and ULCI interval is between 0.200 and 0.405, and as the values do not cross 0, the effect is significant and also positive, due to both values being larger than 0. In regard to standardized coefficient (β), this measure shows the completely standardized total effect. The value of 0.345 is positive and it signals a positive relationship between the variables, which means that for every one standard deviation increase of the independent variable, dependent variable increases by 0.345 standard deviations which shows a moderate effect. Secondly, in regard to the direct effect it shows similar results with notable changes: almost all values are lower, except of standard error which stays the same. This also shows that the relationship is positive, effect is statistically significant. In this regard the value of (β) is equal to 0.266, which indicates small to moderate direct effect. Lastly, the indirect effect results shows a much smaller (*b*) value of 0.069, which is a smaller value, however as the interval of both

BootLLCI and BootULCI results exclude zero which shows that the indirect effect is statistically significant even when the effect value is lower. The BootSE value shows a value of 0.024 which indicates that the indirect effect is estimated with reasonable precision (Hayes, 2017). Based on these findings as both the direct and indirect effects of Employee Digital Competencies on Cost are positive and statistically significant, a partial mediation between the variables is found, therefore **$H3_d$ is approved.**

In summary, based on the findings of the mediation analyses done, all four hypotheses of Model 3 were approved.

Overall, 12 hypotheses were tested, 4 for each research model. The results of this subchapter are summarized and provided in the Table 32 below.

Table 32. *Hypotheses testing results*

Model 1					
Hypothesis	Relationship	Std. beta	T value	P value	Decision
$H1_a$	EDC --> QLT	0.291	4.789	0.000	Approved
$H1_b$	EDC --> DGTL	0.279	4.590	0.000	Approved
$H1_c$	DGTL --> QLT	0.198	3.267	0.001	Approved
$H1_d$	EDC --> DGTL --> QLT	0.108	-	-	Approved
Model 2					
Hypothesis	Relationship	Std. beta	T value	P value	Decision
$H2_a$	EDC --> WST	0.255	4.330	0.000	Approved
$H2_b$	EDC --> DGTL	0.279	4.590	0.000	Approved
$H2_c$	DGTL --> WST	0.310	5.256	0.000	Approved
$H2_d$	EDC --> DGTL --> WST	0.087	-	-	Approved
Model 3					
Hypothesis	Relationship	Std. beta	T value	P value	Decision
$H3_a$	EDC --> CST	0.266	4.482	0.000	Approved
$H3_b$	EDC --> DGTL	0.279	4.590	0.000	Approved
$H3_c$	DGTL --> CST	0.281	4.732	0.000	Approved
$H3_d$	EDC --> DGTL --> CST	0.079	-	-	Approved

Note: EDC – Employee Digital Competencies, DGTL – Digitalisation, QLT – Quality, WST – Waste, CST – Cost.

Source: compiled by the author according to research data

Based on these results, provided in the table above, all 12 hypotheses of this study were approved. The results indicate that Digitalisation serves as a significant mediator, however the lower effects means that it partially mediates the relationships and there are other factors that influence the relationship between Employee Digital Competencies and Production Process measures.

3.7. Research results summary and discussion

Regarding the research, the demographic characteristic showed that the majority of the respondents were between the age of 30 and 39 years old, about 58% of the respondents were male, working either as an Engineer or a Supervisor/Manager. The tenure in their current company showed that the manufacturing industry experts worked in their current company between 1 to 5 years and the majority of them were a part of a large company, which has more than 249 employees. Lastly, the education level of Bachelor's degree was the most common. Furthermore, all questionnaire scales were consistent and reliable as approved by Cronbach's alpha values. Skewness and Kurtosis values showed that every single item of the questionnaire was normally distributed as well. Descriptive statistics showed that all items are consistent and predictable, based on standard deviation and mean value showed that employess posses a medium level of competencies, while the adoption level of the technologies is lacking behind, as the mean values highlighted it to be closer to low level of adoption. The production process results – Quality, Waste and Cost have somewhat improved, showing a positive effect despite the lower-than-expected Employee Digital Competencies and the adoption level of Digitalisation. The Quality was the measure that improved the most, followed by Waste and then Cost. The Correlation analysis showed most relationships between variables to have a moderate level of correlation, while the relationship between Cost and Waste showed a high level of correlation. Conversely, a low level of correlation was found between Employee Digital Competencies and Digitalisation, which was surprising, as it contradicts the findings that were found in literature review (Butschan et.al., 2019; Ngereja & Hussein, 2022; Blanka, et al., 2022). Finally, the mediation analysis has managed to approve all twelve hypothesis.

It is important to highlight, that partial mediation of Digitalisation was found, indicating that there are other factors that could possibly mediate the relationship, which is a good indicator for future research on the topic. The research question: What is the strength of the effect Employee Digital Competencies have on Quality, Waste and Cost in the Manufacturing Production Process, where Digitalisation level plays a mediating role? Was answered: The strength of the effect Employee Digital Competencies have on Quality, Waste and Cost in the Manufacturing Production Process, where Digitalisation level plays a mediating role is **small-to-moderate**, as based on research Digitalisation partially mediates the effect, however a significant direct effect remains between the independent and dependent variables, meaning that other factors are involved.

Discussion. All twelve hypotheses were approved, however the mediation analysis showed a partial mediation which was a surprising outcome based on prior research. It shows how complex the relationship between all variables is and implies that there are other factors which need to be addressed in future research. This discrepancy may be due to the lower level of technology adoption level than expected, which is different regarding conditions of previous research. However, this research findings contribute to the study of the topic in Lithuania, providing a framework of what could be a good way to assess the strength of the effect of Employee Digital Competencies on Cost, Waste and Quality in the Production process through Digitalisation. The study clearly states which Employee Digital Competencies facilitate the adoption of which technologies, how these relationships can be tested and indicates, that there can be further research on the topic in a different geographical environment or with the assessment of different Production Process measures, digital technologies or Employee Digital Competencies. As the mediation is partial it shows a possibility for further exploration, looking into other mechanisms or factors that influence the Production Process and mediate the relationship between the Employee Digital Competencies and Production Process results.

CONCLUSIONS & RECOMMENDATIONS

Conclusions:

1. Based on the findings in the research data analysis chapter, the mean value of 3.04 indicates that the employees in the Manufacturing industry in Lithuania possess a moderate level of Employee Digital Competencies.
2. Based on the findings in the research data analysis chapter, the mean value of 2.35 shows that the adoption level of digital solutions in the Manufacturing industry, in Lithuania, is low, suggesting a low Digitalisation level overall in the industry.
3. Based on the findings in the research data analysis chapter, the mean value of 3.84 shows that Quality in the Production Process in the last three years have somewhat improved, followed by the mean value of Waste (mean 3.77) and Cost (mean 3.76). This indicates that even with moderate level of Employee Digital Competencies and low level of Digitalisation the Production Process results have somewhat improved in the last three years.
4. Based on the findings in the research data analysis chapter, it was found that Employee Digital Competencies have a positive direct effect on Quality, Waste and Cost in the Production Process, as in all three cases a moderate positive effect was found. This suggests that an increase in the level of Employee Digital Competencies would positively impact Quality, Waste and Cost.
5. Based on the findings in the research data analysis chapter, it was found that Employee Digital Competencies have a positive direct effect on Digitalisation, as the relationship between these variables showed a small-to-moderate positive effect. This indicates that increase of the level of Employee Digital Competencies positively effects the Digitalisation level of the companies in the Manufacturing industry, in Lithuania.
6. Based on the findings in the research data analysis chapter, it was found that Digitalisation has a positive direct effect on Quality, Waste and Cost in the Production Process. It was found that Digitalisation has a small positive effect on Quality, moderate positive effect on Waste and small to moderate effect on Cost. It suggests that Digitalisation improves Waste the most, followed by Cost and finally Quality.
7. Based on the findings in the research data analysis chapter, it was found that the strength of the effect Employee Digital Competencies have on Quality, Waste and Cost in the Manufacturing Production Process, where Digitalisation level plays a mediating role is **small-to-moderate**, as based on research Digitalisation **partially mediates the effect,**

meaning that a significant direct effect remains between the independent and dependent variables.

Recommendations:

1. Based on the findings in the research data analysis chapter, moderate level of Employee Digital Competencies in the Manufacturing industry of Lithuania indicates, that managers need to create a digital environment in which competent employees could improve the Production Process results with the effective use of digital solutions.
2. Based on the findings in the research data analysis chapter, a low Digitalisation level in the manufacturing industry in Lithuania indicates, that stakeholders need to look into implementing various digital solutions into their companies and allow digital transformation.
3. Based on the findings in the research data analysis chapter, even with moderate level of Employee Digital Competencies and low level of Digitalisation the Quality, Cost and Waste has somewhat improved, suggesting that companies need to further develop the Employee Digital Competencies and integrate new digital solutions to the existing business processes.
4. Based on the findings in the research data analysis chapter, a positive direct effect of Employee Digital Competencies on Quality, Waste and Cost, suggests that employees need to upgrade their existing competencies in order to improve the Production Process.
5. Based on the findings in the research data analysis chapter, a positive direct effect of Employee Digital Competencies on Digitalisation suggests that managers need to invest in training, as competent employees are able to facilitate the digital solutions much better.
6. Based on the findings in the research data analysis chapter, a small positive effect of Digitalisation on Quality, moderate positive effect on Waste and small to moderate effect on Cost indicates, that top management need to ensure that digital transformation is included in the overall vision and aligns with the future goals of the company.
7. Based on the findings in the research data analysis chapter, **small-to-moderate** strength of the effect Employee Digital Competencies have on Quality, Waste and Cost in the Manufacturing Production Process, where Digitalisation level plays a mediating role indicates that there are other factors which can possibly influence these relationships, showing possible research gaps for future researchers.

LIST OF REFERENCES

Al-Hattami, H. M., Kabra, J. D., & Lokhande, M. A. (2020). Reducing costs in manufacturing firms by using target costing technique. *International Journal of Business Excellence, 22*(1), 69-82. Internet access: https://doi.org/10.1504/IJBEX.2020.109216

Alieva, J., & von Haartman, R. (2020). Digital MudA-The new form of waste by Industry 4.0. In *Proceeding International Conference on Operations and Supply Chain Management (OSCM)* (Vol. 13, No. 3, pp. 269-278). OCSM. Internet access: http://doi.org/10.31387/oscm0420268

Banga, K., & te Velde, D. W. (2018). *Digitalisation and the Future of Manufacturing in Africa*. London: ODI. Internet access: https://set.odi.org/wp-content/uploads/2018/03/SET_Digitalisation-and-future-of-African-manufacturing_Final.pdf

Bankar, V. R., & Nandurkar, K. N. (2023). Implementation of IoT technology for quality improvement in an automotive industry. *Materials Today: Proceedings*. Internet access: https://doi.org/10.1016/j.matpr.2023.03.485

Barykin, S., Borovkov, A., Rozhdestvenskiy, O., Tarshin, A., & Yadykin, V. (2020, September). Staff competence and training for digital industry. In IOP Conference Series: Materials Science and Engineering (Vol. 940, No. 1, p. 012106). IOP Publishing. Internet access: https://doi.org/10.1088/1757-899X/940/1/012106

Bashkireva, T., Bashkireva, A., Morozov, A., Tsvetkov, S., & Popov, A. (2020, November). Problems of the formation of digital competence in the modern educational space. In *Journal of Physics: Conference Series* (Vol. 1691, No. 1, p. 012130). IOP Publishing. Internet access: https://doi.org/10.1088/1742-6596/1691/1/012130

Blanco-Encomienda, F. J., Rosillo-Díaz, E., & Muñoz-Rosas, J. F. (2021). Importance of quality control implementation in the production process of a company. Internet access: https://doi.org/10.26417/ejes.v10i1.p248-252

Blanka, C., Krumay, B., & Rueckel, D. (2022). The interplay of digital transformation and employee competency: A design science approach. *Technological Forecasting and Social Change, 178*, 121575. Internet access: https://doi.org/10.1016/j.techfore.2022.121575

Buer, S. V., Semini, M., Strandhagen, J. O., & Sgarbossa, F. (2021). The complementary effect of lean manufacturing and digitalisation on operational performance. *International Journal of Production Research, 59*(7), 1976- 1992. Internet access: https://doi.org/10.1080/00207543.2020.1790684

Butschan, J., Heidenreich, S., Weber, B., & Kraemer, T. (2019). Tackling hurdles to digital transformation—The role of competencies for successful industrial internet of things (IIoT) implementation. International Journal of Innovation Management, 23(04), 1950036. Internet access: https://doi.org/10.1142/S1363919619500361

Byrne, B. M. (2013). *Structural equation modeling with EQS: Basic concepts, applications, and programming*. Routledge.

Calarge, F. A., Pereira, F. H., & Carretero, E. G. S. L. E. (2012). Evaluation of Lean Production System by using SAE J4000 standard: Case study in Brazilian and Spanish automotive component manufacturing organizations. *African Journal of Business Management, 6*(49), 11839. Internet Access: https://doi.org/10.5897/AJBM12.465

Carnerud, D., & Bäckström, I. (2021). Four decades of research on quality: summarising, Trendspotting and looking ahead. *Total Quality Management & Business Excellence*, *32*(9-10), 1023-1045. Internet access: https://doi.org/10.1080/14783363.2019.1655397

Chaka, C. (2020). Skills, competencies and literacies attributed to 4IR/Industry 4.0: Scoping review. *IFLA journal*, *46*(4), 369-399. Internet access: https://doi.org/10.1177/0340035219896376

Chauhan, C., Singh, A., & Luthra, S. (2021). Barriers to industry 4.0 adoption and its performance implications: An empirical investigation of emerging economy. *Journal of cleaner production*, *285*, 124809. Internet access: https://doi.org/10.1016/j.jclepro.2020.124809

Clancy, R., Ahern, M., O'Sullivan, D., & Bruton, K. (2020). Systematic mapping study of digitization and analysis of manufacturing data. International Journal of Industrial and Systems Engineering, 14(9), 717-731. Internet access: https://www.researchgate.net/publication/345940485_Systematic-Mapping-Study-of-Digitization-and-Analysis-of-Manufacturing-Data-

Cohen, Y., Faccio, M., Pilati, F., & Yao, X. (2019). Design and management of digital manufacturing and assembly systems in the Industry 4.0 era. *The International Journal of Advanced Manufacturing Technology, 105*, 3565-3577. Internet access: https://doi.org/10.1007/s00170-019-04595-0

De Kruijk, J. C. (2018). Automated composite manufacturing using robotics lowers cost, lead-time and scrap rate.
Internet access: https://hdl.handle.net/10921/1484

Dillinger, F., Bernhard, O., & Reinhart, G. (2022). Competence requirements in manufacturing companies in the context of lean 4.0. Procedia Cirp, 106, 58-63. Internet access: https://doi.org/10.1016/j.procir.2022.02.155

Durakovic, B., Demir, R., Abat, K., & Emek, C. (2018). Lean manufacturing: Trends and implementation issues. *Periodicals of Engineering and Natural Sciences, 6*(1), 130-143. Internet access: http://dx.doi.org/10.21533/pen.v6i1.45

Esmaeilian, B., Behdad, S., & Wang, B. (2016). The evolution and future of manufacturing: A review. *Journal of manufacturing systems, 39*, 79-100. Internet access: https://doi.org/10.1016/j.jmsy.2016.03.001

Fernández-Macías, E. (2018). Automation, digitalisation and platforms: Implications for work and employment. Internet access: https://hdl.handle.net/1813/87388

Fremont, V. (2021). *The digital transformation of the manufacturing industry: metamorphic changes and value creation in the industrial network* (Doctoral dissertation, Acta Universitatis Upsaliensis). Internet access: https://uu.diva-portal.org/smash/record.jsf?pid=diva2%3A1584539&dswid=8283

Fu, Q. (2022). How does digital technology affect manufacturing upgrading? Theory and evidence from China. *Plos one, 17*(5), e0267299. Internet access: https://doi.org/10.1371/journal.pone.0267299

Fundin, A., Bergquist, B., Eriksson, H., & Gremyr, I. (2018). Challenges and propositions for research in quality management. *International Journal of Production Economics*, *199*, 125-137. Internet access: https://doi.org/10.1016/j.ijpe.2018.02.020

Frigo, M. A., da Silva, E. C., & Barbosa, G. F. (2016). Augmented reality in aerospace manufacturing: A review. *Journal of Industrial and Intelligent Information, 4*(2). Internet access: https://doi.org/10.18178/jiii.4.2.125-130

Hanenkamp, N., & Zipse, O. (2023). Sustainability in Manufacturing Transforming: Envisioning the Factory of the Future. In *Road to Net Zero: Strategic Pathways for Sustainability-Driven Business Transformation* (pp. 187-214). Cham: Springer International Publishing. Internet access: https://doi.org/10.1007/978-3-031-42224-9

Hair, J.F., Black, W.C., Babin, B.J., & Anderson, R.E. (2010). *Multivariate data analysis: A global perspective*. Prentice Hall.

Hayes, A. F. (2017). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. Guilford publications.

Hernandez-de-Menendez, M., Morales-Menendez, R., Escobar, C. A., & McGovern, M. (2020). Competencies for industry 4.0. International Journal on Interactive Design and Manufacturing (IJIDeM), 14, 1511-1524. Internet access: https://doi.org/10.1007/s12008-020-00716-2

Horvat, D., Kroll, H., & Jäger, A. (2019). Researching the effects of automation and digitalization on manufacturing companies' productivity in the early stage of industry 4.0. *Procedia Manufacturing, 39*, 886-893.
Internet access: https://doi.org/10.1016/j.promfg.2020.01.401

Huu, P. T. (2023). Impact of employee digital competence on the relationship between digital autonomy and innovative work behavior: a systematic review. *Artificial Intelligence Review, 56*(12), 14193-14222.
Internet access: https://doi.org/10.1007/s10462-023-10492-6

Isaksson, O., Hallstedt, S. I., & Rönnbäck, A. Ö. (2018). Digitalisation, sustainability and servitisation: Consequences on product development capabilities in manufacturing firms. *DS 91: Proceedings of NordDesign 2018, Linköping, Sweden, 14th-17th August 2018*. Internet access:

https://www.designsociety.org/publication/40920/Digitalisation%2C+sustainability+and+servitisation%3A+Consequences+on+product+development+capabilities+in+manufacturing+firms

Jurczuk, A., & Florea, A. (2022). Future-oriented digital skills for process design and automation. *Human Technology*, *18*(2), 122-142. Internet access: https://doi.org/10.14254/1795-6889.2022.18-2.3

Knudtzon, W. W. (2018). Integrating Lean Manufacturing and Digital Technologies: A Survey of Norwegian Manufacturing Companies (Master's thesis, NTNU). Internet access: http://hdl.handle.net/11250/2562113

Kraus, S., Jones, P., Kailer, N., Weinmann, A., Chaparro-Banegas, N., & Roig-Tierno, N. (2021). Digital transformation: An overview of the current state of the art of research. Sage Open, 11(3), 21582440211047576. Internet access: https://www.doi.org/10.1177/21582440211047576

Leksic, I., Stefanic, N., & Veza, I. (2020). The impact of using different lean manufacturing tools on waste reduction. *Advances in production engineering & management, 15*(1). Internet access: https://doi.org/10.14743/apem2020.1.351

Mostafa, S., & Dumrak, J. (2015). Waste elimination for manufacturing sustainability. *Procedia manufacturing, 2*, 11-16. Internet access: https://doi.org/10.1016/j.promfg.2015.07.003

Ngereja, B. J., & Hussein, B. (2022). Employee learning in the digitalization context: An evaluation from team members' and project managers' perspectives. *Procedia Computer Science*, *196*, 902-909. Internet access: https://doi.org/10.1016/j.procs.2021.12.091

Ohno, T. (2019). *Toyota production system: beyond large-scale production*. Productivity press. Internet access: https://doi.org/10.4324/9780429273018

Pereira, A. C., Alves, A. C., & Arezes, P. (2023). Augmented reality in a lean workplace at smart factories: a case study. *Applied Sciences, 13*(16), 9120. Internet access: https://doi.org/10.3390/app13169120

Potemkin, V., & Rasskazova, O. (2020, September). Digital competence of employees and the value of human resources in the development strategy of enterprises. In IOP conference series: Materials Science and Engineering (Vol. 940, No. 1, p. 012098). IOP Publishing. Internet access: https://doi.org/10.1088/1757-899X/940/1/012098

Sanders, A., Elangeswaran, C., & Wulfsberg, J. P. (2016). Industry 4.0 implies lean manufacturing: Research activities in industry 4.0 function as enablers for lean manufacturing. *Journal of Industrial Engineering and Management (JIEM), 9*(3), 811-833. Internet access: https://doi.org/10.3926/jiem.1940

Schumacher, A., Erol, S., & Sihn, W. (2016). A maturity model for assessing Industry 4.0 readiness and maturity of manufacturing enterprises. *Procedia Cirp*, *52*, 161-166. Internet access: https://doi.org/10.1016/j.procir.2016.07.040

Shahbazi, S. (2015). *Material efficiency management in manufacturing* (Doctoral dissertation, Mälardalen University). Internet access: https://www.diva-portal.org/smash/record.jsf?pid=diva2%3A813564&dswid=7096

Shivajee, V., Singh, R. K., & Rastogi, S. (2019). Manufacturing conversion cost reduction using quality control tools and digitization of real-time data. *Journal of Cleaner Production*, *237*, 117678. Internet access: https://doi.org/10.1016/j.jclepro.2019.117678

Steinlechner, M., Schumacher, A., Fuchs, B., Reichsthaler, L., & Schlund, S. (2021). A maturity model to assess digital employee competencies in industrial enterprises. Procedia CIRP, 104, 1185-1190. Internet access: https://doi.org/10.1016/j.procir.2021.11.199

Strietska-Ilina, O., Chun, H. K., Aleksynska, M., Kriechel, B., Kofol, C., Dull, N., & Vetter, T. (2021). *Changing demand for skills in digital economies and societies: literature review and case studies from low-and middle-income countries*. ILO. Internet access: https://www.ilo.org/publications/changing-demand-skills-digital-economies-and-societies-literature-review

Stucke, M. E., & Ezrachi, A. (2020). Digitalisation and its impact on innovation. *R&I paper series.* Internet access: https://ir.law.utk.edu/utklaw_facpubs/959/

Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. International journal of medical education, 2, 53. Viewed on 2023-11-29. Internet access: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4205511/

Tidd, J., & Bessant, J. (2018). Innovation management challenges: From fads to fundamentals. *International Journal of Innovation Management*, *22*(05), 1840007. Internet access: https://doi.org/10.1142/S1363919618400078

Tercan, H., & Meisen, T. (2022). Machine learning and deep learning based predictive quality in manufacturing: a systematic review. *Journal of Intelligent Manufacturing, 33*(7), 1879-1905. Internet access: https://doi.org/10.1007/s10845-022-01963-8

Tortorella, G., Saurin, T. A., Fogliatto, F. S., Tlapa, D., Moyano-Fuentes, J., Gaiardelli, P., ... & Forstner, F. F. (2022). The impact of Industry 4.0 on the relationship between TPM and maintenance performance. *Journal of Manufacturing Technology Management*, *33*(3), 489-520. Internet access: https://doi.org/10.1108/JMTM-10-2021-0399

Valamede, L. S., & Akkari, A. C. S. (2020). Lean 4.0: A new holistic approach for the integration of lean manufacturing tools and digital technologies. *International Journal of Mathematical, Engineering and Management Sciences, 5*(5), 851. Internet access: https://doi.org/10.33889/IJMEMS.2020.5.5.066

Valenduc, G., & Vendramin, P. (2017). Digitalisation, between disruption and evolution. *Transfer: European Review of Labour and Research, 23*(2), 121-134. Internet access: https://doi.org/10.1177/1024258917701379

Wagner, T., Herrmann, C., & Thiede, S. (2017). Industry 4.0 impacts on lean production systems. *Procedia Cirp*, *63*, 125-131. Internet access: https://doi.org/10.1016/j.procir.2017.02.041

THE EFFECT OF EMPLOYEE DIGITAL COMPETENCIES ON QUALITY, WASTE AND COST IN THE MANUFACTURING PRODUCTION PROCESS: THE MEDIATING ROLE OF DIGITALISATION

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Master Thesis

Business Process Management programme

Vilnius University, Faculty of Economics and Business Administration

Supervisor – Asst. Prof. Dr. Darius Ruželė, Vilnius, 2024

SUMMARY

80 pages, 32 tables, 10 figures, 6 Annexes, 56 references.

The main aim of the Master thesis is to assess and evaluate the effect Employee Digital Competencies have on Quality, Waste and Cost in the Manufacturing Production Process where Digitalisation level plays a mediating role.

The thesis consists of the following parts: scientific research analysis or literature review, research methodology and empirical research results. It also includes introduction, conclusions and recommendations.

The literature analysis highlights the concepts of Employee Digital Competencies, Digitalisation, Cost, Waste, Quality and the Production Process. It explores the prior research on these concepts to gather strong theoretical background on the topic and explores the relationship between these variables.

Based on the findings of literature analysis a framework was developed which showed the need to conduct quantitative research in order to assess and evaluate the strength of the effect Employee Digital Competencies have on Quality, Waste and Cost in the Manufacturing Production Process, where Digitalisation level plays a mediating role. A questionnaire was prepared for manufacturing industry professionals in Lithuania, which gathered the outlook of 253 respondents, 251 of which were eligible for the data analysis. Statistical data analysis was processed with SPSS and included the following tests: Cronbach's Alpha, to determine the reliability and consistency of the measurement scales, descriptive statistics (means, frequencies, standard deviation, kurtosis, skewness), correlation analysis to explore the relationship between variables. The mediation analysis was carried out using the IBM SPSS

4.2 process macro version 65 by Andrew F. Hayes, in order to approve or disapprove the hypotheses.
The analysis confirmed that Employee Digital Competencies have a positive effect on Digitalisation, Digitalisation has a positive effect on Quality, Cost and Waste in the Production Process and that Digitalisation has a mediating effect on the relationship between Employee Digital Competencies and Quality, Waste and Cost in the Production process, even though the mediation is partial.
The summary of the literature review and scientific data analysis is provided in the conclusions and recommendations chapter.

Keywords: Employee Digital Competencies, Digitalisation, Quality, Waste, Cost, Production Process.

DARBUOTOJŲ SKAITMENINIŲ KOMPETENCIJŲ POVEIKIS KOKYBEI, ŠVAISTYMUI IR KAŠTAMS GAMYBOS PROCESE MEDIJUOJANT SKAITMENIZAVIMO LYGIUI

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Magistro baigiamasis darbas

Verslo procesų valdymo magistro programa

Vilniaus Universitetas, Ekonomikos ir Verslo Administravimo Fakultetas

Darbo vadovas - Asst. Prof. Dr. Darius Ruželė, Vilnius, 2024

SANTRAUKA

80 puslapių, 32 lentelės, 10 paveikslų, 6 priedai, 56 literatūros šaltiniai.

Pagrindinis magistro darbo tikslas yra nustatyti ir įvertinti, kokį poveikį darbuotojų skaitmeninės kompetencijos turi kokybei, švaistymui ir kaštams gamybos procese, kai skaitmeninimo lygis atlieka medijuojantį vaidmenį.

Magistro darbą sudaro šios dalys: mokslinio tyrimo analizė arba literatūros apžvalga, tyrimo metodologija ir empirinio tyrimo rezultatai. Ją taip pat sudaro įvadas, išvados ir rekomendacijos.

Literatūros analizėje pabrėžiama darbuotojų skaitmeninių kompetencijų, skaitmeninimo, kaštų, švaistymo, kokybės ir gamybos proceso sąvokos. Joje nagrinėjami ansktesni šių aspektų tyrimai bei siekiama surinkti tvirtą teorinį pagrindą šia tema, nagrinėjant ryšį bei sąveiką tarp šių kintamųjų.

Remiantis literatūros analizės gairėmis buvo nuspręsta atlikti kiekybinį tyrimą, kad būtų galima nustatyti ir įvertinti, kokio stiprumo poveikį darbuotojų skaitmeninės kompetencijos turi kokybei, švaistymui ir kaštams gamybos procese, kur skaitmeninimo lygis atlieka medijuojantį vaidmenį. Buvo parengtas klausimynas skirtas Lietuvos gamybos pramonės specialistams, kuris surinko 253 respondentų, iš kurių 251 buvo tinkami duomenų analizei. Statistinė duomenų analizė buvo atliekama naudojant SPSS programą ir apėmė šiuos elementus: Cronbach alfa, siekiant nustatyti skalių patikimumą ir nuoseklumą, aprašomoji statistika (vidurkiai, dažniai, standartinis nuokrypis, kurtozė, asimetrijos koficientas), koreliacijos analizė, siekiant ištirti ryšį tarp kintamųjų. Mediacijos analizė atlikta naudojant IBM SPSS 4.2 proceso makrokomandos 65 versija, kurią parengė Andrew F. Hayesas, siekiant patvirtinti arba paneigti

hipotezes.

Analizė patvirtino, kad darbuotojų skaitmeninės kompetencijos turi teigiamą poveikį skaitmeninimui, skaitmeninimas turi teigiamą poveikį kokybei, kaštams ir švaistymui gamybos procese ir kad skaitmeninimas turi tarpininkaujantį poveikį ryšiui tarp darbuotojųskaitmeninių kompetencijų ir kokybės, atliekų ir sąnaudų gamybos procese, nors tarpininkavimas ir yra dalinis.

Literatūros apžvalgos apibendrinimas ir mokslinių duomenų analizės apibendrinimas pateikiamas išvadų ir rekomendacijų skyriuje.

Raktiniai žodžiai: Darbuotojų skaitmeninis kompetencijos, skaitmeninimas, kokybė,švaistymas, kaštai, gamybos procesas.

ANNEXES

Annex 1. Research Questionnaire

Dear Participant,

You are invited to participate in a study that explores how employee digital competencies affect quality, waste and cost in manufacturing processes, with a focus on the role of digitalisation as a mediator. Your input will provide valuable insights into how digital skills are shaping production outcomes in our manufacturing industry.

The survey will take approximately 10-15 minutes to complete and your participation is entirely voluntary. Please be assured that all responses will be kept confidential and used strictly for academic purposes. The results will be presented in aggregate form, with no identifying information disclosed.

This study is being conducted by Lukaš Kuzminski as part of my Master's thesis at Vilnius University. Should you have any questions or require further information, feel free to contact me at lukas.kuzminski@evaf.stud.vu.lt.

Thank you for considering this opportunity to contribute to meaningful research!

By clicking "NEXT," you confirm that you have read the information provided and willingly agree to take part in this study.

- o NEXT

Please assess the current level of your digital competencies where 1 means "no competencies", 2 - "low competencies", 3 - "excellent competencies", 4 - "high competencies", 5 - "excellent competencies"

- o IT infrastructure management
- o Data processing and analysis
- o Data security/cybersecurity
- o Computer programming/coding
- o Internet of things and cyber-physical systems
- o Automation
- o Robotics
- o Additive manufacturing (3d printing)
- o Cloud technologies and big data
- o Product simulation
- o Process design and simulation
- o Service design and engineering
- o Knowledge management

Please, indicate the adoption level of the following digital technologies in your company:

1 - No adoption, 2 - Low adoption, 3 - Moderate adoption, 4 - High adoption, 5 -Full adoption

- o Internet of things (IoT)
- o Big data
- o Cloudcomputing
- o Wireless sensors
- o 3d printing
- o Augmented reality (AR)/Simulation
- o Colaborative robots
- o Machine/Deep Learning
- o Remote Control/Monitoring

Please indicate your company's improvement in following parameters related to cost in the time period of last 3 years on a scale: 1 - worsened significantly, 2 - Somewhat worsened, 3 - Stayed same, 4 - Somewhat improved, 5 - improved significantly.

- o Cost of logistics
- o Return on assets
- o Decrease in operating costs
- o Inventory Turn
- o Order flexibility
- o Capacity of order-fill

Please indicate your company's improvement in following parameters related to waste in the time period of last 3 years on a scale: 1 - worsened significantly, 2 - Somewhat worsened, 3 - Stayed same, 4 - Somewhat improved, 5 - improved significantly.

- o Speed of delivery
- o Supply chain responsiveness
- o Notification of advance-ship
- o Dependability in terms of delivery
- o Decrease in time required for creating and delivery of new products
- o Flexibility in delivery

Please indicate your company's improvement in following parameters related to quality in the time period of last 3 years on a scale: 1 - worsened significantly, 2 - Somewhat worsened, 3 - Stayed same, 4 - Somewhat improved, 5 - improved significantly.

- o Customer satisfaction
- o Product customisability
- o Improvement in the quality of products
- o Rise in product innovativeness
- o Successful launches of new products
- o Improvement in product capability and performance

Demographics

What is your age in years? (write a number)

What is your gender?

- o Male
- o Female

What is your current job position?

- Operator/Technican
- Supervisor/Manager
- Engineer
- Other…

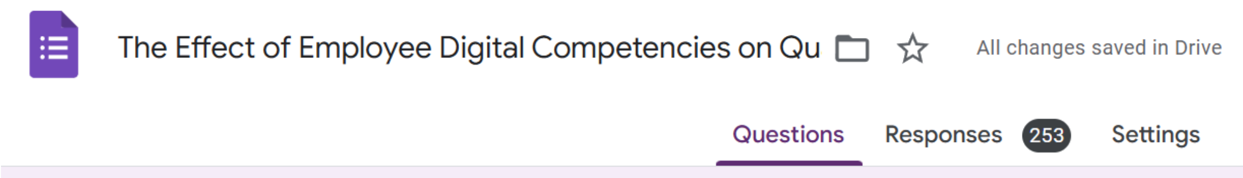
How many years have you been working in your current position? (write a number)

What is the size of your company? (based on number of employees)

- Micro (up to 10 employees)
- Small (10-49 employees)
- Medium (50-249 employees)
- Large (more than 249 employees)

What level of education do you have?

- High school diploma
- Bachelor’s degree
- Master’s degree
- PhD



Annex 2. Demographic respondent statistics

Statistics

	N Valid	N Missing	Mean
What is your age in years? (write a number)	251	0	35.43
What is your gender?	251	0	
What is your current job position?	251	0	
How many years have you been working in your current position? (write a number)	251	0	5.09
What is the size of your company? (based on number of employees)	251	0	
What level of education do you have?	251	0	

What is your age in years? (write a number)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	23	2	.8	.8	.8
	24	1	.4	.4	1.2
	25	7	2.8	2.8	4.0
	26	3	1.2	1.2	5.2
	27	12	4.8	4.8	10.0
	28	11	4.4	4.4	14.3
	29	13	5.2	5.2	19.5
	30	9	3.6	3.6	23.1
	31	9	3.6	3.6	26.7
	32	9	3.6	3.6	30.3
	33	14	5.6	5.6	35.9
	34	9	3.6	3.6	39.4
	35	13	5.2	5.2	44.6
	36	16	6.4	6.4	51.0
	37	22	8.8	8.8	59.8
	38	23	9.2	9.2	68.9
	39	24	9.6	9.6	78.5
	40	14	5.6	5.6	84.1
	41	8	3.2	3.2	87.3
	42	9	3.6	3.6	90.8
	43	3	1.2	1.2	92.0
	44	7	2.8	2.8	94.8
	45	9	3.6	3.6	98.4
	47	1	.4	.4	98.8
	49	3	1.2	1.2	100.0
	Total	251	100.0	100.0	

What is your gender?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	106	42.2	42.2	42.2
	Male	145	57.8	57.8	100.0
	Total	251	100.0	100.0	

How many years have you been working in your current position? (write a number)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	10	4.0	4.0	4.0
	2	25	10.0	10.0	13.9
	3	55	21.9	21.9	35.9
	4	44	17.5	17.5	53.4
	5	44	17.5	17.5	70.9
	6	20	8.0	8.0	78.9
	7	19	7.6	7.6	86.5
	8	4	1.6	1.6	88.0
	9	5	2.0	2.0	90.0
	10	11	4.4	4.4	94.4
	11	5	2.0	2.0	96.4
	12	1	.4	.4	96.8
	13	1	.4	.4	97.2
	15	5	2.0	2.0	99.2
	20	1	.4	.4	99.6
	41	1	.4	.4	100.0
	Total	251	100.0	100.0	

What is your current job position?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Administrator	1	.4	.4	.4
	DevOps Engineer	1	.4	.4	.8
	Engineer	86	34.3	34.3	35.1
	ERP system administrator	1	.4	.4	35.5
	Key account manager	1	.4	.4	35.9
	Key Account manager	1	.4	.4	36.3
	Operator/Technican	38	15.1	15.1	51.4
	Product designer	1	.4	.4	51.8
	Supervisor/Manager	121	48.2	48.2	100.0
	Total	251	100.0	100.0	

What is the size of your company? (based on number of employees)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Large (more than 249 employees)	160	63.7	63.7	63.7
	Medium (50-249 employees)	87	34.7	34.7	98.4
	Micro (up to 10 employees)	1	.4	.4	98.8
	Small (10-49 employees)	3	1.2	1.2	100.0
	Total	251	100.0	100.0	

What level of education do you have?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Bachelor's degree	158	62.9	62.9	62.9
	High school diploma	26	10.4	10.4	73.3
	Master's degree	67	26.7	26.7	100.0
	Total	251	100.0	100.0	

Annex 3. Reliability of the variables

Reliability Statistics

Cronbach's Alpha	N of Items
.836	6

Reliability Statistics

Cronbach's Alpha	N of Items
.836	6

Reliability Statistics

Cronbach's Alpha	N of Items
.801	6

Reliability Statistics

Cronbach's Alpha	N of Items
.834	9

Reliability Statistics

Cronbach's Alpha	N of Items
.893	13

Annex 4. Descriptive statistics and data normality

Statistics

	N Valid	N Missing	Mean	Std. Deviation	Skewness	Std. Error of Skewness	Kurtosis	Std. Error of Kurtosis
EDC 1. Current level of digital competencies (IT infrastructure management)	251	0	3.00	1.147	-.120	.154	-.752	.306
EDC 2. Current level of digital competencies (Data processing and analysis)	251	0	3.02	1.147	-.135	.154	-.659	.306
EDC 3. Current level of digital competencies (Data security/cybersecurity)	251	0	3.02	1.193	-.103	.154	-1.000	.306
EDC 4. Current level of digital competences (Computer programming/coding)	251	0	3.04	1.162	-.124	.154	-.676	.306
EDC 5. Current level of digital competencies (Internet of things and cyber-physical systems)	251	0	3.21	1.292	-.212	.154	-1.085	.306
EDC 6. Current level of digital competencies (Automation)	251	0	2.90	1.252	.108	.154	-.939	.306
EDC 7. Current level of digital competencies (Robotics)	251	0	2.60	1.227	.362	.154	-.911	.306
EDC 8. Current level of digital competences (Additive manufacturing)	251	0	2.84	1.289	.142	.154	-.975	.306
EDC 9. Current level of digital competences (Cloud technologies and big data)	251	0	3.23	1.244	-.371	.154	-.927	.306
EDC 10. Current level of digital competences (Product simulation)	251	0	2.82	1.280	.221	.154	-1.022	.306
EDC 11. Current level of digital competences (Process design and simulation)	251	0	3.17	1.307	-.216	.154	-1.084	.306
EDC 12. Current level of digital competences (Service design and engineering)	251	0	3.19	1.288	-.169	.154	-1.064	.306
EDC 13. Current level of digital competences (Knowledge management)	251	0	3.44	1.353	-.425	.154	-1.019	.306
DGTL 14. Adoption level of digital technologies (Internet of things (IoT)	251	0	2.37	.840	.734	.154	.633	.306
DGTL 15. Adoption level of digital technologies (Big data)	251	0	2.38	.923	-.023	.154	-.624	.306
DGTL 16 Adoption level of digital technologies (Cloudcomputing)	251	0	2.53	.905	.461	.154	-.093	.306
DGTL 17 Adoption level of digital technologies (Wireless sensors)	251	0	2.46	.904	.077	.154	-.467	.306
DGTL 18 Adoption level of digital technologies (3d printing)	251	0	2.25	.922	.692	.154	.520	.306
DGTL 19 Adoption level of digital technologies (Augmented reality/Simulation)	251	0	2.18	.919	.417	.154	-.201	.306
DGTL 20 Adoption level of digital technologies (Colaborative robots)	251	0	2.02	.855	.658	.154	.503	.306
DGTL 21 Adoption level of digital technologies (Machine/Deep Learning)	251	0	2.42	.990	.317	.154	-.335	.306
DGTL 22 Adoption level of digital technologies (Remote Control/Monitoring)	251	0	2.59	1.118	.638	.154	-.148	.306
CST 23 Company's improvement related to cost in last 3 years (Cost of logistics)	251	0	3.41	.887	-.581	.154	-.201	.306
CST 24 Company's improvement related to cost in last 3 years (Return on assets)	251	0	3.76	.946	-.392	.154	-.221	.306
CST 25 Company's improvement related to cost in last 3 years (Decrease in operating costs)	251	0	3.83	.965	-.761	.154	.261	.306
CST 26 Company's improvement related to cost in last 3 years (Inventory Turn)	251	0	3.88	1.009	-.724	.154	.065	.306
CST 27 Company's improvement related to cost in last 3 years (Order flexibility)	251	0	3.83	1.015	-.784	.154	.189	.306
CST 28 Company's improvement related to cost in last 3 years (Capacity of order-fill)	251	0	3.84	1.024	-.545	.154	-.447	.306
WST 29 Company's improvement related to waste in last 3 years (Speed of delivery)	251	0	3.53	1.074	-.439	.154	-.467	.306
WST 30 Company's improvement related to cost in last 3 years (Supply chain responsiveness)	251	0	3.80	1.030	-.552	.154	-.459	.306
WST 31 Company's improvement related to cost in last 3 years (Notification of advance-ship)	251	0	3.81	1.004	-.906	.154	.592	.306
WST 32 Company's improvement related to cost in last 3 years (Dependability in terms of delivery)	251	0	3.88	1.017	-.794	.154	.127	.306
WST 33 Company's improvement related to cost in last 3 years (Decrease in time required for creating and delivery of	251	0	3.76	1.094	-.779	.154	-.016	.306
WST 34 Company's improvement related to cost in last 3 years (Flexibility in delivery)	251	0	3.86	.994	-.695	.154	-.092	.306
QLT 35 Company's improvement related to quality in last 3 years (Customer satisfaction)	251	0	3.79	1.083	-.817	.154	.045	.306
QLT 36 Company's improvement related to quality in last 3 years (Product customisability)	251	0	3.88	1.010	-.641	.154	-.163	.306
QLT 37 Company's improvement related to quality in last 3 years (Improvement in the quality of products)	251	0	3.84	.995	-.804	.154	.350	.306
QLT 38 Company's improvement related to quality in last 3 years (Rise in product innovativeness)	251	0	3.83	.999	-.741	.154	.132	.306
QLT 39 Company's improvement related to quality in last 3 years (Successful launches of new products)	251	0	3.83	1.042	-.826	.154	.170	.306
QLT 40 Company's improvement related to quality in last 3 years (Improvement in product capability and performance)	251	0	3.93	.971	-.840	.154	.494	.306

Statistics

	N Valid	N Missing	Mean	Std. Deviation	Skewness	Std. Error of Skewness	Kurtosis	Std. Error of Kurtosis
EDC_M	251	0	3.0371	.82503	-.764	.154	.123	.306
DGTL_M	251	0	2.3541	.61247	.212	.154	.053	.306
CST_M	251	0	3.7576	.72297	-1.261	.154	1.628	.306
WST_M	251	0	3.7749	.76805	-1.310	.154	1.441	.306
QLT_M	251	0	3.8499	.72053	-1.354	.154	1.856	.306

Annex 5. Correlation Analysis

Correlations

Pearson Correlation

	EDC_M	DGTL_M	CST_M	WST_M	QLT_M
EDC_M	1	.279**	.345**	.342**	.346**
DGTL_M	.279**	1	.356**	.381**	.280**
CST_M	.345**	.356**	1	.825**	.764**
WST_M	.342**	.381**	.825**	1	.781**
QLT_M	.346**	.280**	.764**	.781**	1

**. Correlation is significant at the 0.01 level (2-tailed).

Annex 6. Mediation Analysis

```
Model  : 4
   Y  : CST_M
   X  : EDC_M
   M  : DGTL_M

Sample
Size:  251

**************************************************************************
OUTCOME VARIABLE:
 DGTL_M

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .279       .078       .347     21.070      1.000    249.000       .000

Model
              coeff         se          t          p       LLCI       ULCI
constant      1.724       .142     12.131       .000      1.444      2.004
EDC_M          .207       .045      4.590       .000       .118       .296

Standardized coefficients
         coeff
EDC_M     .279

OUTCOME VARIABLE:
 CST_M

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .438       .192       .426     29.462      2.000    248.000       .000

Model
              coeff         se          t          p       LLCI       ULCI
constant      2.267       .199     11.418       .000      1.876      2.658
EDC_M          .233       .052      4.482       .000       .131       .336
DGTL_M         .332       .070      4.732       .000       .194       .470

Standardized coefficients
         coeff
EDC_M     .266
DGTL_M    .281

*************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X O

Total effect of X on Y
     Effect         se          t          p       LLCI       ULCI       c_cs
       .302       .052      5.800       .000       .200       .405       .345

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI      c'_cs
       .233       .052      4.482       .000       .131       .336       .266

Indirect effect(s) of X on Y:
          Effect     BootSE   BootLLCI   BootULCI
DGTL_M      .069       .024       .029       .120

Completely standardized indirect effect(s) of X on Y:
          Effect     BootSE   BootLLCI   BootULCI
DGTL_M      .079       .025       .034       .132
```

```
Model  : 4
   Y  : WST_M
   X  : EDC_M
   M  : DGTL_M

Sample
Size:  251

**************************************************************************
OUTCOME VARIABLE:
 DGTL_M

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .279       .078       .347     21.070      1.000    249.000       .000

Model
              coeff         se          t          p       LLCI       ULCI
constant      1.724       .142     12.131       .000      1.444      2.004
EDC_M          .207       .045      4.590       .000       .118       .296

Standardized coefficients
         coeff
EDC_M     .279

OUTCOME VARIABLE:
 WST_M

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .453       .205       .473     32.042      2.000    248.000       .000

Model
              coeff         se          t          p       LLCI       ULCI
constant      2.138       .209     10.224       .000      1.727      2.550
EDC_M          .238       .055      4.330       .000       .130       .346
DGTL_M         .389       .074      5.256       .000       .243       .534

Standardized coefficients
         coeff
EDC_M     .255
DGTL_M    .310

*************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y ***************

Total effect of X on Y
     Effect         se          t          p       LLCI       ULCI       c_cs
       .302       .052      5.826       .000       .200       .405       .346

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI      c'_cs
       .254       .053      4.789       .000       .150       .359       .291

Indirect effect(s) of X on Y:
          Effect     BootSE   BootLLCI   BootULCI
DGTL_M      .048       .022       .012       .097

Completely standardized indirect effect(s) of X on Y:
          Effect     BootSE   BootLLCI   BootULCI
DGTL_M      .055       .024       .014       .108
```

```
**************************************************************************
Model  : 4
   Y  : QLT_M
   X  : EDC_M
   M  : DGTL_M

Sample
Size:  251

**************************************************************************
OUTCOME VARIABLE:
 DGTL_M

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .279       .078       .347     21.070      1.000    249.000       .000

Model
              coeff         se          t          p       LLCI       ULCI
constant      1.724       .142     12.131       .000      1.444      2.004
EDC_M          .207       .045      4.590       .000       .118       .296

Standardized coefficients
         coeff
EDC_M     .279

OUTCOME VARIABLE:
 QLT_M

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .395       .156       .442     22.966      2.000    248.000       .000

Model
              coeff         se          t          p       LLCI       ULCI
constant      2.529       .202     12.507       .000      2.130      2.927
EDC_M          .254       .053      4.789       .000       .150       .359
DGTL_M         .233       .071      3.267       .001       .093       .374

Standardized coefficients
         coeff
EDC_M     .291
DGTL_M    .198

*************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y ***************

Total effect of X on Y
     Effect         se          t          p       LLCI       ULCI       c_cs
       .318       .055      5.739       .000       .209       .427       .342

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI      c'_cs
       .238       .055      4.330       .000       .130       .346       .255

Indirect effect(s) of X on Y:
          Effect     BootSE   BootLLCI   BootULCI
DGTL_M      .081       .027       .033       .139

Completely standardized indirect effect(s) of X on Y:
          Effect     BootSE   BootLLCI   BootULCI
DGTL_M      .087       .027       .037       .144
```