MASTER'S THESIS

Strategic Management, Radboud University

Knowledge management 4.0: the rise of artificial intelligence

A mixed-methods study across manufacturing industries

Student: Len Eising

Student number: s1085300

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Supervisors:

Dr. Ligthart, P. E. M.

Prof. Dr. Aalbers, H. L.

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1. Introduction

The industrial revolutions transformed economies worldwide, with each having different impacts on industries and its performances (Kagermann, Helbig, Hellinger, & Wahlster, 2013; Maresova, Soukal, Svobodová, Hedvicakova, Javanmardi, Selamat, & Krejcar, 2018). The first industrial revolution encompasses mechanization of production (Kagermann et al., 2013; Clark, 2007), which had a profound impact on the operational performance of factories by increasing labour productivity and machine efficiency, leading to significant reductions in production costs and the prices of goods (Clark, 2007). The second industrial revolution involved the widespread use of electricity and the development of the assembly line (Kagermann et al., 2013; Hounshell, 1984), resulting in significant improvement of operational performance in terms of increased speed and efficiency of production, enabling mass production of standardized goods and reducing transportation costs (Hounshell, 1984). Following, the third industrial revolution, also called the digital revolution, was characterized by the development of computer technology, the internet, and automation (Kagermann et al., 2013; Rifkin, 2011), which allowed more efficient and accurate processes, better inventory management, and increased customization of products, leading to an overall improvement of the operational performance (Rifkin, 2011). Each industrial revolution, thus, has had an impact on operational performance. We are now amid the next, industrial revolution, called Industry 4.0, which entails the digitalization of all physical assets and the massive integration of value chain participants (PWC, 2016; Pagliosa, Tortorella, & Ferreira, 2019).

The advent of the fourth industrial revolution is the embodiment of the latest technological innovations such as artificial intelligence, robotics, the Internet of Things, 3D printing, genetic engineering, big data, cloud technology, and much more technologies (Rymarczyk, 2022; Sako, 2020; Zheng, Ardolino, Bacchetti, & Perona, 2021). Industry 4.0 is to bring about enormous improvements in efficiency and productivity (Sako, 2020; Sharma, Jabbour, & De Sousa Jabbour, 2020) and is therefore deemed a great opportunity to make operational production perform better (Hofmann & Rüsch, 2017). Literature research (Moeuf, Pellerin, Lamouri, Tamayo-Giraldo, and Barbaray, 2018) reviewed different cases from the literature reporting on Industry 4.0 pilot projects and found that the most commonly reported performance benefits were increased flexibility and efficiency, improved productivity and quality, and reduced cost and delivery time. Furthermore, Tortorella, Mac Cawley, Kumar, and Sawhney (2020) show results that Industry 4.0 has an impact on achieving higher operational performance levels. In addition, results have been found that Industry 4.0 indeed does have a significant impact on operational performance (Tortorella, Miorando, Caiado, Nascimento, & Staudacher, 2021; Tortorella et al., 2020).

Diving deeper into Industry 4.0, a part is about the technology of artificial intelligence. Artificial intelligence is a field of computer science that focusses on creating intelligent systems capable of performing tasks that usually require human intelligence (Russell & Norvig, 2016). According to the authors, it involves the creation and implementation of algorithms and models that enable machines to learn, reason, and adapt autonomously, ultimately mimicking human abilities. This varies from mechanical systems in machines to algorithms in software, to eventually self-learning machines and systems. The current problem with artificial intelligence is that this in itself is a very broad concept with a lot of possible applications (Zheng et al., 2021). Sako (2020) argues that the concept of Industry 4.0 is going to be an enormous improvement on operational performance, but, since Industry 4.0 involves several innovation processes as mentioned before, the question remains on the effect of just artificial intelligence on operational performance. Several studies show that artificial intelligence indeed is beneficial for a company's operations (Khan, Yu, Sarwat, Godil, Amin, & Shujaat, 2021; Queiroz, Pereira, Telles, & Machado, 2021; Umar, Khan, Yusliza, Ali, & Yu, 2021; Yu, Khan, & Umar, 2021). Artificial intelligence has witnessed major developments the past decades. These developments have triggered a debate on the present and future impact of AI on society (Makridakis, 2017; Damioli, Van Roy, & Vertesy, 2021). According to Damioli et al. (2021), artificial intelligence has the potential to disrupt almost all industries and businesses on a worldwide scale. Besides, many studies have found positive associations between artificial intelligence and performance (Wamba-Taguimdje, Wamba, Kamdjoug, & Wanko, 2020; Oke, 2008; Miller, 2017; Li & Zheng, 2018; Michaels, 2018). Artificial intelligence is measured in multiple aspects of the manufacturing process in several studies (Baryannis, Validi, Dani, & Antoniou, 2019; Zhang et al., 2019; Sahu et al., 2021). Artificial intelligence strategies have been utilised in all aspects of the manufacturing process and supply chain, from design, operations management, and production to maintenance and assembly (Baryannis et al., 2019; Zhang, Ming, Liu, Yin, Chen, & Chang, 2019; Sahu, Young, & Rai, 2021). These AI methods can be used by companies to aid in designing manufacturing systems to reach the highest efficiency (Stocker, Schmidt, & Reinhart, 2019). Further, it can be applied and utilised for improvements in operations management (Sahu et al., 2021), supply chain risk management (Baryannis et al., 2019), production decision-making and support (Palmer, Usman, Canciglieri, Malucelli, & Young, 2018), and scheduling and production in assembly lines (Huo, Zhang, & Chan, 2020).

The question is why not every company is already implementing artificial intelligence in whatever form if it seems such an improvement on performance. Acharya (2019) contradicts the before mentioned positive findings by inferring a negative association between artificial intelligence and operational performance. Furthermore, Forgione and Migliardo (2022) state that there is less consensus on the positive impact of the technology on firm performance and argue that artificial intelligence also has negative effects on firm performance. Brynjolfsson, Rock, and Syverson, (2021) in turn argue that an innovative technology such as artificial intelligence does not change the productivity level, while Venturini (2022) states that a great deal of attention has been paid to the effects associated with the adoption of artificial intelligence whilst the impact associated with the production has remained almost unexplored. Additionally, artificial intelligence needs to be provided with data, the better the quality and quantity of the data, the more accurate it can process the data (Bellapu, 2021). Bellapu (2021) argues that an explanation why not every company is implementing artificial intelligence, is that artificial intelligence needs a lot of data. For companies as Amazon or IBM, which have to deal with enormous amounts of data on a regular basis makes sense. However, not all companies have the data to the extent that there is a requirement for artificial intelligence to be deployed. Insufficient data or bad quality data is one of the reasons why these projects fail (Bellapu, 2021). The author gives another reason why a company does not dare taking on artificial intelligence, namely the absence of internal expertise. The absence of internal expertise could be eliminated through recruitment of specialists or specialised training of the current workforce, entailing more time and costs for the company. Although artificial intelligence is the intelligence of machines that is being put to work, the base is still human intelligence. It is important to have employees with the right skills, talent, and mindset to make the idea of moving ahead with artificial intelligence smooth. Without such expertise and knowledge, artificial intelligence is meaningless and useless to a company (Bellapu, 2021). According to Bughin, Hazan, Ramaswamy, Chui, Allas, Dahlstrom, Henke, & Trench (2017), in order for firms to implement an effective artificial intelligence program they are required to address certain elements of a digital transformation: identify a business case, set up the right data ecosystem, build or buy appropriate AI tools, and modify workflow processes, capabilities, and culture. Their survey shows that leadership, management and technical capabilities, and easy data access are key enablers for artificial intelligence to work properly. However, despite its promising advantages, artificial intelligence also presents challenges for firms. For one, the workforce needs to be reskilled and stimulated to exploit AI rather than compete with it (Bughin et al., 2017).

Addressing the knowledge in organisations, Alavi and Leidner (2001) suggest that much knowledge in an organisation remains uncodified and that the mapping of internal expertise as an application of knowledge management can expose this knowledge. In accord, Bencsik (2021) argues that knowledge management is a closely related concept regarding artificial intelligence. Knowledge management is a strategic approach to identifying, capturing, creating, sharing, and effectively using an organization's knowledge assets and can ensure enhancements on an organization's competitiveness by leveraging knowledge to improve inter alia a firm's efficiency and therefore operational performance (Alavi & Leidner, 2001; Liao, Chuang, & To, 2011). Artificial intelligence has been increasingly used in the manufacturing industry to support knowledge management processes. These technologies can help organizations capture, store, and analyse knowledge, leading to better decision-making and innovation (Alavi & Leidner, 2001). A study by Zhang et al. (2019) found that artificial intelligence can help manufacturing companies integrate knowledge management into business processes, leading to increased performance. Bencsik (2021) argues that there is an interaction between knowledge management and artificial intelligence, namely that former makes the understanding of knowledge possible, while the latter provides the tools to expand and use this knowledge.

According to different studies (Jarrahi, Askay, Eshraghi, & Smith, 2022; Pai, Shetty, Shetty, Bhandary, Shetty, Nayak, Dinesh, & D'souza, 2022; Rhem, 2017), there is both an overlap and distinction between human driven knowledge management and artificial intelligence driven knowledge management. Human driven knowledge management is directly concerned with managing knowledge in organizations, while artificial intelligence driven knowledge management is primarily focused on developing systems that can mimic human knowledge and learning activities (Jarrahi et al., 2022). Both forms are connected to knowledge, yet differ in how they approach knowledge. While artificial intelligence driven knowledge management offers machines the ability to learn, human driven knowledge management offers a platform to better understand knowledge (Pai et al., 2022). Human driven knowledge management allows an understanding of knowledge to occur, while artificial intelligence driven knowledge management provides the capabilities to expand, use, and create knowledge (Rhem, 2017). The rapid advance of artificial intelligence and its systems within the field of knowledge management has created a tension between the current knowledge management in companies and artificial intelligence integrated knowledge management (Pai et al., 2022).

Regarding the above given information, several studies are arguing for benefits of artificial intelligence on operational performance, while other studies plead for the opposite, therefore creating a contradiction in the existing literature on the effect of the use of artificial intelligence on operational performance. Furthermore, taking into account the role of knowledge management, the literature distinguishes as well as states overlap between human knowledge management and artificial intelligence knowledge management, creating a certain tension. Considering the mentioned contradiction in the literature regarding artificial intelligence and knowledge management and their impact on operational performance, this will be this research its focus. As Bughin et al. (2017) stated, proper management and stimulation and reskilling of the workforce are key to enable a successful artificial intelligence program. The conundrum as how to go about that, will attempted to be solved by this study.

Research question

Considering the effects of the past revolutions on operational performance, the use of artificial intelligence can also be of significant influence on operational performance. The problem is that the literature is contradicting regarding this influence. As a part of this fourth revolution, the question is whether and, if so, how artificial intelligence will have significant effects on operational performance, as the other revolutions did. Hereby taken into consideration, is the role of knowledge management. Hence, the objective of this research is to examine the influences of artificial intelligence and knowledge management on operational performance. The research question to be answered reads:

RQ: Does artificial intelligence have an impact on the use of knowledge management on operational performance in manufacturing companies, and -if so- how is it implemented within these firms?

Outline

Further in this paper, the theoretical background will be discussed in chapter 2. Here, the concepts of artificial intelligence, knowledge management, and operational performance will be elaborated on through literature review, as well as the relationships between these concepts. In addition, the question on the influences between the concepts will be answered with hypotheses a priori. Next, the research method will be explained in chapter 3 as to how and where data is gathered using a mixed-method study. Subsequently, the findings of the quantitative analysis, followed by the qualitative analysis will be presented in chapter 4, supporting or rejecting the hypotheses. After the presentation of the results, a summary of the findings will be given of the analyses to answer the research question. In the same chapter, the discussion will give theoretical and practical implications of this research, followed by the limitations and possible future research and ending with the ethical reflection.

2. Theoretical background

Considering the introduction, there are a few concepts that need further explaining. In this chapter, the concepts of artificial intelligence, knowledge management, and operational performance will be elaborated on. Hypotheses will be derived out of these elaborations and the connections between the concepts, whereafter a conceptual model is made up.

2.1 Knowledge management

Knowledge management can be applied in various areas of the manufacturing industry, such as product development, process improvement, supply chain management, and customer service. Moreover, knowledge management can facilitate knowledge transfer and learning between different generations of employees and ensure that knowledge is not lost when experienced employees retire or leave the organisation (Zimmer & Madeja, 2019). Furthermore, according to Othman, Al-Kake, Diah, Othman, & Hasan (2019), it is essential to mention that the management of knowledge mainly consists of the creation of knowledge, the sharing of this knowledge, the access to the acquired knowledge, and the capturing as well as the application of the interrelated knowledge. In other words, knowledge management can be seen as a set of activities that create, store, disseminate, and apply knowledge in an organisation (Chow, Choy, Lee, & Chan, 2005). It is the process by which companies create and use their institutional or collective knowledge (Civi, 2000). Similarly, knowledge management can be defined as a set of processes and activities that support, facilitate, and exploit the development and use of knowledge (Dalkir, Wiseman, Shulha, & McIntyre, 2007). Basically, according to the above, four knowledge management processes can be derived: (1) generating knowledge, (2) using knowledge, (3) storing knowledge, and (4) sharing knowledge. This research will seek to add knowledge about where – in which knowledge management process – and how the use of artificial intelligence can help this human centred knowledge management. Note that the concept of knowledge management refers to human based knowledge management, without the incorporation of artificial intelligence.

2.2 Artificial intelligence

Artificial intelligence involves a system, or systems, to model intelligent behaviour (Wamba-Taguimdje et al., 2020; Zheng et al., 2021; Benotsmane, Kovács, & Dudás, 2019). Artificial intelligence entails the use of technology aimed at the cognitive ability of humans to achieve objectives via an autonomous way (Wamba-Taguimdje et al., 2020; Benotsmane et al., 2019). This implies that computers and machines can learn from what data tells them and decide what to do next, which results in intelligent computers and machines taking on more and more traditionally human tasks (Zheng et al., 2021).

A study by Frank, Mendes, Ayala, and Gehzzi (2019) differentiates nine configurations. The implementation of artificial intelligence in manufacturing companies can be attributed to the configuration called ‘factory-integrated substituting services’, which is a combination of a high level of digitization and substituting service as a service offering type. Frank et al. (2019) describe this configuration as the one that focuses on feedbacks for the manufacturing process. Feedback data on own processes serves to develop newly generated solutions by the manufacturing process itself. Therefore, Frank et al. (2019) classify this configuration as “the only one that pursues the complete value of the Industry 4.0 concept”, and furthermore that this configuration has a very high complexity of business implementation. This high complexity of digitization requires more specialised knowledge for employees of an organisation regarding the implementation as well as the use of it.

To add to that, Dhamija and Bag (2020) classified artificial intelligence studies on operations in six clusters: (1) Artificial intelligence and optimization, (2) Industrial engineering and automation, (3) Operational performance and machine learning, (4) Sustainable supply chains and sustainable development, (5) Technology adoption and green supply chain management, and (6) Internet of Things and reverse logistics. This research will focus on the theme of the first cluster of artificial intelligence and optimization. The authors mention that future research has to be done to understand how artificial intelligence can lead to optimization, especially across different sectors/industries (Dhamija & Bag, 2020). Furthermore, a study of Nishant, Kennedy, and Corbett (2020) argued that artificial intelligence has three capabilities: (1) data analysis and learning, (2) human cognition, and (3) emotions and thinking. This research will use artificial intelligence in terms of its first capability, namely the data analysis and learning of machines and other systems within manufacturing companies,. This could mean, on a less advanced scale, the use of artificial intelligence could be described as the automatic storage, use, and sharing of operating data in production processes by machines and other systems.

2.3 Operational performance

Today’s market is characterised by shorter product life cycles and the increasing individualisation of products. Together with increasing global competition, this puts pressure both on manufacturing companies’ flexibility and on resource efficiency to meet customer demand and stay competitive (Lasi, Fettke, Kemper, Feld, & Hoffmann, 2014; Buer, Semini, Strandhagen, & Sgarbossa, 2021). To meet these challenges, manufacturing companies are forced to continuously seek new approaches to improve their operational performance if they wish to grow as a company (Buer et al., 2021). Operational performance can be described as the degree to which a focal firm is better than its competitors in its responsiveness and generation of productivity improvements (Rai, Patnayakuni, & Seth, 2006; Younis, Sundarakani, & Vel, 2016). Slack, Brandon-Jones, and Johnston (2016) and Ahmad and Schroeder (2003) consider operational performance is measured in five important key performance indicators. These indicators are speed, quality, flexibility, dependability, and cost.

2.4 Knowledge management and operational performance

Knowledge can be considered a company's most valuable resource, the only sustainable source of competitive advantage that improves decision-making capabilities and thus its effective action (Alavi & Leidner, 2001). In the current manufacturing environment, companies are more and more focusing on managing knowledge assets rather than physical assets to improve their performance (Gunasekaran and Ngai, 2007). The knowledge management processes, as mentioned before, are being increasingly adopted by manufacturing companies through their ability to positively impact a company's operational performance (Tan & Wong, 2015). In addition, several studies indeed found that knowledge management has a significant direct and positive relationship with operational performance (Tan & Wong, 2015; Marqués & Simón, 2006; Rašula, Vukšić, & Štemberger, 2012). Effective knowledge management practices can lead to improved decision-making, increased innovation, enhanced problem-solving capabilities, and a better collaboration within a company (Alavi & Leidner, 2001; Davenport & Prusak, 1998). These authors also state that by capturing, organising, and sharing knowledge efficiently, organisations can reduce redundancy, save time, avoid costly mistakes, and leverage collective expertise, eventually contributing to improved operational performances.

However, knowledge management can also have negative impacts on operational performance. Yang (2007) gives four reasons on how poor management of knowledge can have a negative impact through knowledge losing its value. These are first, employees quit without transferring their knowledge; second, existing organisational knowledge becomes obsolete; third, knowledge is incompletely transferred; and fourth, organisational knowledge is difficult to access for employees (Yang, 2007). According to Hitt, Bierman, Shimizu, and Kochhar (2001), investments made by organisation in training employees initially generates a negative effect on results, resulting in the organisation not enjoying positive effects until the knowledge learned is transferred. The transfer of knowledge, i.e. the productive use of acquired knowledge and skills, acquired during the training must take place effectively to realize the full benefits (Dirani, 2012).

Thus, proper knowledge management seems to have significant effects on operational performances, although there are reasons where these effects could fade out. Considering both the positive and negative expected effects of the influence of knowledge management on operational performance, the positive effects are more profound and substantiated in current literature. Therefore, the first hypothesis reads:

Hypothesis 1: Knowledge management has a positive effect on operational performance.

2.5 Artificial intelligence and operational performance

Jallow, Renukappa, and Suresh (2020) claim that the adoption of artificial intelligence systems allows organisations to gain competitive advantage and improve their performance through increased productivity, profitability, and efficiency. For manufacturing companies, artificial intelligence applications enable real-time decision-making and performance improvement by enabling predictive maintenance (Chen, Lim, Tan, Govindan, & Kumar, 2021), and enhanced quality control (Chiarini & Kumar, 2021). In addition, Al-Surmi, Bashiri, and Koliousis (2021) argue that AI strategies improve operational performance. Furthermore, the implementation of artificial intelligence enables coordination, integration, and transparency, which in turn could improve operational performance (Khan et al., 2021; Queiroz et al., 2021; Umar et al., 2021; Yu et al., 2021). This corresponds to what was stated in the introduction. Wamba-Taguimdje et al. (2020) and Dubey, Gunasekaran, Childe, Bryde, Giannakis, Foropon, Roubaud, & Hazen (2019) indeed found positive effects of the implementation of artificial intelligence on operational performance in different areas. Furthermore, they reveal the vastness of its potential in organisations, among which the increase of the efficiency of operations, maintenance, supply chain operations, and the performance overall.

However, artificial intelligence is not always an improvement on operational performance. Rana, Chatterjee, Dwivedi, and Akter (2021) find in their study that artificial intelligence integrated business analytics systems can negatively impact operational performance. This is due to a lack of governance, which is associated with a conception of having a pragmatic legal framework that would help the management of organisations to effectively adopt an AI system in a fair way to achieve the best results. The lack of governance leads to a chance of supply of poor quality data for the system to work with. In addition, the lack of governance also results in inefficient training imparted to the employees of the firm. This generates a possibility of the adoption of a non-transparent solution in the firm (Rana et al., 2021). This is in compliance with Ballapu (2021), mentioned in the introduction. According to the literature (Rana et al., 2021; Ballapu, 2021), ultimately why artificial intelligence could have a negative impact on operational performance, is because of three main things: the lack of governance on artificial intelligence, the lack of internal expertise and thereby proper training of employees, and poor data quality or data sets too small to work with.

Despite the possible negative aspects of artificial intelligence on operational performance, considering both sides, this research hypothesises the effect of artificial intelligence on operational performance as follows:

Hypothesis 2: Artificial intelligence has a positive effect on operational performance.

2.6 Artificial intelligence and knowledge management

As mentioned in the introduction, artificial intelligence and knowledge management are closely related concepts (Bencsik, 2021). Knowledge management is a strategic approach to identifying, capturing, creating, sharing, and effectively using an organization's knowledge assets and can ensure enhancements on an organization's competitiveness by leveraging knowledge to improve inter alia a firm's efficiency and therefore operational performance (Alavi & Leidner, 2001; Liao et al., 2011). Simply put, artificial intelligence refers to the use of computers to mimic the thinking activities of the human brain such as reasoning, learning, and planning to solve complex problems that only human experts could previously tackle (Lei & Wang, 2020). In particular, artificial intelligence enables machines to learn, acquire, process, and use knowledge to perform tasks, therefore improving decision-making processes within organizations by revealing or unlocking knowledge that can be delivered to humans (Camarillo, Ríos, & Althoff, 2018; Grzonka, Jakóbik, Kolodziej, & Pllana, 2018). Put another way, it can extract new knowledge from vast amounts of data, portraying complex mappings as a basis of human decision-making (Paschen, Pitt, & Kietzmann, 2020). Hence, Bencsik (2021) states that there is a close interaction between knowledge management and artificial intelligence, where the former enables the understanding of knowledge, while the latter provides the tools to expand and use the knowledge, as well as to create new knowledge. Liebowitz (2001) further highlights the importance of human input in the development and implementation of artificial intelligence systems. He argues that the use of artificial intelligence based knowledge management should be viewed as a helping hand, complementary to human based knowledge management rather than a replacement, as human expertise is essential in ensuring that artificial systems are accurate and reliable (Liebowitz, 2001). More studies have shown that the integration of artificial intelligence in knowledge management systems can help manufacturing companies to increase efficiency, productivity, and innovation (De Bem Machado, Secinaro, Calandra, & Lanzalonga, 2021; Brynjolfsson & McAfee, 2017). According to these studies, artificial intelligence can assist in the creation, organization, and retrieval of knowledge, making it easier for employees to access the information they need, when they need it. AI-enabled knowledge management systems can also automate routine tasks, freeing up employees to focus on more strategic and creative work (De Bem Machado et al., 2021). Additionally, artificial intelligence can help companies to identify patterns and trends in data, enabling them to make data-driven decisions that improve operational performance (Brynjolfsson & McAfee, 2017). In this regard, modern organisations are increasingly relying on these mechanisms to improve knowledge management processes and performance (Al-Mansoori, Salloum, & Shaalan, 2020). This is due to the ability of artificial intelligence to (1) inductively identify trends and relationships in firm's knowledge bases to create new knowledge, (2) help in the search for new knowledge, and (3) disseminate knowledge to those needing it (Al-Mansoori et al., 2020). Therefore, artificial intelligence can help push knowledge management and thus make knowledge management processes and practices more effective with regard to performances (Liebowitz, 2001; Mittal & Kumar, 2019).

However, artificial intelligence does not seem to have only have positive effects on knowledge management and the performances. According to Bellapu (2021), artificial intelligence does not work properly without data of decent quality and quantity. Issues as incomplete or inaccurate data can lead to flawed insights and recommendations, which can impact overall knowledge management and its relationship on performance in a negative way (Bellapu, 2021). Furthermore, a lack of human involvement as a result of the increasing presence of artificial intelligence in knowledge management can lead to AI systems making decisions that are not aligned with organisational goals and values (Chen, Esperanca, & Wang, 2022). As mentioned by Bughin et al. (2017), workflow processes, capabilities, and the culture need to be changed and the workforce needs to be reskilled and stimulated for a successful implementation of an artificial intelligence program. If not, the use of artificial intelligence in knowledge management can be met with resistance from employees who may feel threatened of fear losing their jobs by becoming redundant. This resistance can lead in turn to a lack of adoption and integration of artificial intelligence systems into knowledge management processes (Liebowitz, 2001; Chen et al., 2022).

Considering that artificial intelligence can be a tool in knowledge management practices to reach better performances, and bearing in mind both positive and negative effects, the third hypothesis reads:

Hypothesis 3: Artificial intelligence has a positive moderating effect on the relationship between knowledge management and operational performance.

2.7 Conceptual model

Based on above found literature and the derived hypotheses, the following conceptual model can be made up (see Figure 1). Beside a direct positive relationship of artificial intelligence and knowledge management on operational performance, there is also a hypothesised positive moderating role of artificial intelligence on the relationship between knowledge management and operational performance. The hypotheses are as follows:

H1: *Knowledge management has a positive effect on operational performance.*

H2: *Artificial intelligence has a positive effect on operational performance.*

H3: *Artificial intelligence has a positive moderating effect on the relationship between knowledge management and operational performance.*

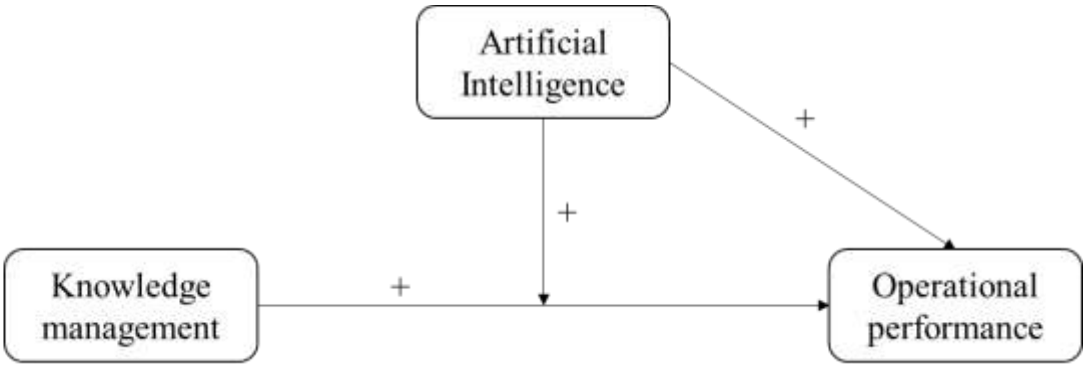

Figure 1: Hypothesised conceptual model

3. Research method

In this chapter the research method is being discussed to eventually arrive at substantiated answers to the research questions. First, the research design will be elaborated on, followed by the research instruments.

3.1 Research design

This research will make use of a mixed methods approach, meaning that a quantitative as well as a qualitative research is going to take place. The quantitative research will be held on the basis of a database regarding Dutch manufacturing companies, which will be explained in the next section. The qualitative research will be held through interviews. Research found through quantitative analysis will be tested in qualitative terms by means of those interviews. This ensures that the found results are being viewed from multiple sides. In addition, through the quantitative data, it will be checked if the hypotheses apply in general. Through the qualitative data, more in depth information on why the hypotheses are being confirmed of rejected, depending on the quantitative results, can be included.

The advantages of a mixed methods research design is that with combining the two types of data there are benefits from both detailed, contextualised insights of qualitative data and generalisable, externally valid insights of quantitative data (George, 2022). Combining different forms of data can give better understanding of the problem and yield more complete evidence, in depth as well as breadth evidence (Jogulu & Pansiri, 2011). Furthermore, Jogulu & Pansiri (2011) mention that a mixed methods research can enable the combination of theory generation and hypothesis testing within a single study.

Downsides of a mixed methods approach could be found in possible conflicting results. If the qualitative and quantitative results do not agree it can be difficult and unclear how to proceed (George, 2022). Additionally, it can also be more complex and difficult to carry out than a qualitative or quantitative study, for example by finding ways to systematically compare the results, putting the data at risk for certain biases in the interpretation (George, 2022).

3.2 Research instruments

In this section, the research instruments regarding both analyses are presented and elaborated on, followed by the corresponding operationalisation of the concepts. This means that corresponding variables and procedures to measure these for each concept are identified (Engel & Schutt, 2014).

3.2.1 Quantitative analysis

During the conduct of the quantitative study, as mentioned, a database will be used for the collection of the required data. This database, called EMS, contains data regarding the modernisation of production in 203 Dutch manufacturing companies. This data comes from a nationwide questionnaire which aims to understand the efforts of industrial companies to modernize their production processes. To process the quantitative data, the statistical computer program SPSS is being used. The data will be analysed through regression and reliability analysis, to determine whether there is an effect of the explanatory variables (knowledge management and artificial intelligence) on the dependent variable (operational performance) and what kind of effect this is. The downside of the EMS database is that it is secondary data, which means that certain data occasionally describes and measures more or less than the definition of the concept in this research.

Table 1: Quantitative operationalisation of the concepts

Concept	Variables	Indicators	EMS database question
Knowledge management	Display Boards	Display boards illustrating work processes and work status	7
	Integration of Tasks	Integration of tasks (integration of planning, operating or controlling functions)	7
	Quality Measures	Methods of assuring quality in production	7
	Job Training	Training on the job (e.g., job rotation or organized exchange of experience with colleagues)	7
	Experimentation	Measures to let employees experiment with new ideas by making worktime, location, and machines available	7
	Maintain Elderly	Measures to maintain elderly or their knowledge for the firm	7
Artificial intelligence	Automatic storage and use of operating data	Machines and systems aimed at: - optimising process data - maintenance planning - resource planning - preparing KPI's - other uses	10.1
Operational performance	Product Lead Time	Production time in days or hours	11
	Not on Time	Percentage of product not delivered on agreed time	11
	Scrap Rate	Percentage of products not passing quality control	11
	Quality Complaints	Percentage of delivered products resulting in quality related complaints	11

Following are the operationalisations for the quantitative analysis regarding the concepts. Table 1 presents the quantitative operationalisation of the concepts. The last column in the table represents the corresponding questions from the questionnaire used to compose the EMS database, which can be found in Appendix B: Questions from the EMS questionnaire.

Knowledge management. The questions used in the questionnaire, and therefore pertaining to the variables, which are being used to define the concept knowledge management are concerning the following. The first is *Display Boards*, this is whether organisations use display boards in production to illustrate work processes and work status, to share knowledge that way. The second is the *Integration of Tasks* and regards whether organisations integrate tasks of their employees, to let them get to learn and know different aspects of the production process. Third, *Quality Measures* concerns whether organisations use certain methods to assure quality in production. Next, *Job Training* pertains whether organisations use training-on-the-job through, for example job rotation or organised experience exchanges with older employees to ensure the capture and use of knowledge. Fifth, *Experimentation* addresses if organisations offer the possibility to employees to experiment in the production with new ideas by making use of working time, location, or machines, with the aim of generating new knowledge. Last, *Maintaining Elderly* aims at the storage of knowledge, whether organisations use instruments to maintain elderly employees or their knowledge, through for example, teams with different age groups, guidance programs, or senior-junior tandems.

Artificial intelligence. One question, and therefore the variable, covered the concept of artificial intelligence in a way of *Automatic storage and use of operating data*. This asked about whether organisations use machines or systems in their production that automatically store and use operating data for the following purposes: (1) optimising production processes, (2) planning of maintenance and repairs, (3) planning of resource utilisation and application, (4) preparing productivity or key performance indicators, or (5) for other uses.

Operational performance. The questionnaire used four variables relating to the concept of operational performance. The first concerned *Product Lead Time*, meaning the average lead time of a firm's main product. The second regarded the percentage of orders which are delivered on time. This indicator has been switched around to *Not on Time*, to ensure uniformity among the variables, where all variables are set negative. The third variable pertains to *Scrap Rate*, asking the percentage of an organisation's products not passing quality control. The last variable is *Quality Complaints*, measured in the percentage of delivered orders that have resulted in quality related complaints.

3.2.2 Qualitative analysis

To gather relevant data for the qualitative part of the study, multiple interviews will be held with employees of manufacturing companies relevant for this research. Which companies and positions these are, are being presented in the results in chapter 4. These semi-structured interviews are based on a questionnaire with a pre-determined set of open questions, derived from different theories, and with the opportunity for the interviewer to explore and question particular themes or responses further. This research will thus use a deductive qualitative method, meaning that the qualitative study is theory driven. It will therefore use a thematic coding, after which open coding follows. This implies applying predetermined codes to the data, after which open codes will be used to specify quotes. These codes are derived from concepts drawn from literature and theory (Bingham & Witkowsky, 2022). The interview (see Appendix A: Interview script) consists of four main themes, corresponding to the concepts of the conceptual model. These themes are knowledge management, artificial intelligence, operational performance, and the effects between the concepts. To process the qualitative data, the interviews will be coded deductively, meaning that the theories previously described will be tested. Based on the coded results of the interviews, the hypotheses will be confirmed or negated.

The interview script, see Appendix A: Interview script shows the operationalisation of the concepts regarding the qualitative analysis.

Knowledge management. As mentioned, this research assumes that knowledge management consists of the following four processes: (1) generating knowledge, (2) using knowledge, (3) storing knowledge, and (4) sharing knowledge. Consequently, these processes will also be the variables for the concept of knowledge management regarding the qualitative analysis. Therefore, these processes will be used as guideline and main themes of the interviews (see Appendix A: Interview script). To generate, use, store, and share knowledge, an organisation can choose to train its employees. Besides the way of generating, using, storing, and sharing knowledge itself, the trainings regarding these processes are also of importance to ensure that knowledge is being handled correctly within a company.

Artificial intelligence. The line of the quantitative analysis is followed for the interview (see Appendix A: Interview script). Therefore, the indicators measured through questions are the automatic storage of operating data by machines or systems (regarding the optimising of process data and the planning of maintenance as well as resources), the visibility of indicators through a system (regarding preparation of KPI’s), the presence of industrial robots and their purpose in the production processes (regarding other uses), and the control of these robots.

Operational performance. For the qualitative analysis, the concept of operational performance is guided by questions regarding what organisations deem important indicators for their performance and how they measure it (see Appendix A: Interview script). This is broad for the reason that organisations often call the same concepts different names. This concept will be measured through the variables of *Speed*, *Quality*, and *Dependability* (Slack et al., 2016).

3.3 Validity and reliability

The validity of the research is ensured by the mixed methods design of this study. Through triangulation, involving the use of theory, qualitative data, and quantitative data the overall validity of the study is enhanced. By comparing all data sources, inconsistencies or similarities can be found, providing a more comprehensive and robust understanding of the problem. The reliability is ensured through the use of several well-defined different variables regarding qualitative and quantitative research. When conducting the quantitative analysis, data is used from factual questions to get factual data, ensuring a more reliable outcome. When conducting the research, it is imperative to address research ethics to ensure integrity and the credibility of the study. For this research, this involves protecting the rights and confidentiality of participants: employees as well as the organisations. Therefore, before the interviews, the participant will be informed and will have to give consent for taping the interview. Furthermore, the interviews conducted will be anonymised. Lastly, the integrity will be ensured by honouring agreements made with the respondents.

4. Results

In this chapter, the results and findings of both analyses will be presented. First, the quantitative analysis is been conducted, structured by the hypotheses, followed by the qualitative analysis, structured by the concepts and hypotheses studied.

4.1 Quantitative analysis

Regression analyses were used to empirically test how operational performance indicators are affected by the use of knowledge management and artificial intelligence. Thereby is controlled for industry type and firm size. In Table 2**Fout! Verwijzingsbron niet gevonden.** there is an overview presented of the descriptive statistics. The majority of the 203 responding manufacturing companies operate in the electronic, metal, and machinery industries and have a median size of 42 employees (the smallest being 10, the largest being 4500 employees). On average, the manufacturing companies use 2.5 knowledge management practices (standard deviation of 1.7) and 0.9 artificial intelligence in the production process (standard deviation of 1.1). The operational performance measures, as dependent variables, have been log transformed to correct for skewed distributions. The median for the dependent variables indicates the measures in units observed. Before commencing the regression analysis, the assumptions were assessed and met, and a reliability test was carried out on the concept of knowledge management (see Appendix C: Assumptions check and reliability test regression analysis).

Table 2: Descriptive statistics of the variables

Descriptive Statistics					
	Mean	Std. Deviation	Median (observed)	Min	Max
Size (log number of employees 2017)	3,769	0,859		2,30	8,41
Size (median observed)	42			10	4500
Industry type					
Metal (base cat.)	19,7%			0	1
Food	8,4%			0	1
Textile	14,3%			0	1
Construction	2,5%			0	1
Chemical	12,8%			0	1
Machinery	19,2%			0	1
Electronic	23,2%			0	1
Knowledge Management					
Knowledge management practices	2,517	1,693		0,00	6,00
Artificial Intelligence					
Automatic storage and use of operating data	0,857	1,149		0,00	4,00
Moderating effect					
Interation KM and AI	0,709	1,880		-4,77	7,80
Dependent variable: Operational Performance					
Product Lead Time (log)	2,460	1,368	2,398	0,12	6,59
Not On Time (log)	2,028	0,980	1,792	0,00	4,51
Scrap Rate (log)	1,591	0,954	1,609	0,00	4,56
Quality Complaints (log)	1,198	0,861	0,789	0,00	4,61

4.1.1 Model fit

Considering the models, all four regression models show significance with Scrap Rate at $p < .016$ and the other three at $p < .001$ (see

Appendix D: Regression analysis SPSS output model fit, Table 13, Table 16, Table 19, and Table 22). The effect size for Product Lead Time is .201 adjusted R^2, for Not on Time .152 adjusted R^2, for Scrap Rate .059 adjusted R^2, and for Quality Complaints .148 adjusted R^2 (see

Appendix D: Regression analysis SPSS output model fit, Table 12, Table 15, Table 18, and Table 21).

4.1.2 Testing hypotheses

Table 3: Regression results models 1 and 2

Regression results

	Model 1				**Model 2**			
	Product Lead Time (B)	Not On Time (B)	Scrap Rate (B)	Quality Complaints (B)	Product Lead Time (B)	Not On Time (B)	Scrap Rate (B)	Quality Complaints (B)
Size (log number of employees 2017)	0.064	0.024	0.153***	-0.039	0.260	0.064	0.161	0.030
Industry type (base: Metal)								
Food	-1.075**	-1.230*	-0.426	-0.762*	-1.047**	-1,224*	-0.425	-0.752*
Textile	-0.100	-0.308	0.140	-0.140	-0.121	-0.312	0.138	-0.147
Construction	0.666	-0.784	0.154	0.599***	0.867	-0.743	0.166	0.663
Chemical	-0.306	-0.230	-0.076	-0.219	-0.295	-0.229	-0.069	-0.226
Machinery	0.999*	0.423***	0.448***	0.532**	0.882*	0.397	0.456***	0.467***
Electronic	-0.013	-0.146	0.401***	0.124	-0.035	-0.151	0.402***	0.113
Knowledge Management								
Knowledge management practices					0.031	0.003	0.019	-0.021
Artificial Intelligence								
Automatic storage and use of operating data					-0.354*	-0.071	-0.022	-0.111***
Moderating effect								
I_KM_CPD								

* significant at p < .001

** significant at p < .01

*** significant at p < .05

Table 4: Regression results model 3

Regression results

	Model 3			
	Product Lead Time (B)	Not On Time (B)	Scrap Rate (B)	Quality Complaints (B)
Size (log number of employees 2017)	0.268**	0.062	0.156	0.028
Industry type (base: Metal)				
Food	-1.054**	-1.223*	-0.421	-0.750*
Textile	-0.124	-0.312	0.141	-0.146
Construction	0.857	-0.741	0.173	0.665
Chemical	-0.312	-0.225	-0.058	-0.223
Machinery	0.875*	0.398	0.460***	0.469***
Electronic	-0.037	-0.150	0.403***	0.114
Knowledge Management				
Knowledge management practices	0.029	0.004	0.020	-0.021
Artificial Intelligence				
Automatic storage and use of operating data	-0.333*	-0.076	-0.036	-0.115***
Moderating effect				
I_KM_CPD	-0.050	0.012	0.033	0.009

* significant at p < .001

** significant at p < .01

*** significant at p < .05

The first hypothesis concerned the positive effect of knowledge management on operational performance. The analysis results (see Table 3 and Table 4) show that knowledge management does not have a significant effect on any of the four dependable variables. Therefore, hypothesis 1 is not supported.

The second hypothesis dealt with the positive effect of artificial intelligence on operational performance. The results (see again Table 3 and Table 4**Fout! Verwijzingsbron niet gevonden.Fout! Verwijzingsbron niet gevonden.**) show that artificial intelligence appears to decrease Product Lead Time (B = -0.333, $p < .001$) and Quality Complaints (B = -0.115, $p < 0.028$). Artificial intelligence has no significant effect on both Not On Time and Scrap Rate. Hence, the second hypothesis is partly supported.

Furthermore, hypothesis 3 regarded the positive moderating effect of artificial intelligence on the relationship between knowledge management and operational performance. The results (Table 4**Fout! Verwijzingsbron niet gevonden.**) show that no interaction effect of both independent variables on the four dependent variables is significant. Thus, hypothesis 3 is not supported.

Control variables

The control variables show that larger firms appear to have longer product lead times and higher scrap rates, but have no significant difference in products delivered on time and quality complaints (see **Fout! Verwijzingsbron niet gevonden.**). As for the industry types, all relative to the metal industry as the reference category, results from **Fout! Verwijzingsbron niet gevonden.** also show that the food industry has a lower product lead time, less products not delivered on time, and less quality complaints. For the construction industry, the products not delivered on time are less and the quality complaints are more, compared to the metal industry. Further, the machinery industry has a significantly higher product lead time, more products delivered too late, higher scrap rates, and more quality complaints than the metal industry. Lastly, the electronic industry has a significantly higher scrap rate than the metal industry has.

4.2 Qualitative analysis

After the quantitative analysis, a qualitative analysis has been conducted to test the quantitative data in practice, and to compare both findings with each other. During the qualitative analysis, five interviews were conducted with different positions at different companies (after each company follows their respective ID regarding the coding of the interviews):

- A project manager at a coffee machine manufacturer, consisting of around 150 employees (#PMCM);
- A category buyer at a bicycle manufacturer, consisting of around 250 employees (#CBBM);
- A process engineer at a metal packaging manufacturer, consisting of around 300 employees locally and 7000 employees worldwide (#PEPM);

- A supply chain specialist at a hatchery machine manufacturer, consisting of around 150 employees (#SCHM);
- A process engineer at a metalworking company, consisting of around 500 employees locally and 1000 employees worldwide (#PEMC).

4.2.1 Knowledge management

Knowledge management is defined as the handling of knowledge, divided in four main processes: generating, using, storing, and sharing knowledge. Table 5 shows the most relevant quotes regarding this concept.

Table 5: Quotes concept knowledge management

Subject		Knowledge Management	
ID	#	QUOTE	OPEN CODERING
#CBBM	1	De master data planner, die verzamelt alle informatie nodig voor planning en voor voorspellingen van de verschillende mensen en afdelingen.	Generating knowledge
#PMCM	2	Zij gaan weer in vergaderingen zitten van nou dit project, dit gaan we doen en zo gaan we het doen.	Sharing knowledge
#PMCM	3	Wij hebben een power BI bord en daarin tonen wij eigenlijk aan hoe hoeveel machines eruit gaan, wat de sales omzet is, wat de ontvangsten zijn en wat de klachten zijn.	Sharing knowledge
#CBBM	4	Er hangen hier en daar in de productie wel van die borden met KPI's erop	Sharing knowledge
#PEPM	5	Hebben we een digitaal overall board	Sharing knowledge
#PEPM	6	We hebben één keer per kwartaal hebben we een meeting van de CEO en daarnaast hebben we ook nog maandelijks een meeting met de plant manager en die schoolt ons bij hoe wij het als bedrijf hebben gedaan	Sharing knowledge
#PEMC	7	Elke ochtend hebben ze een overleg met de hele productie met de ploegleiders en zo om bepaalde indicatoren te bespreken	Sharing knowledge
#PMCM	8	Jira is een bepaald systeem bij ons en dat bord wordt eigenlijk ons verzamelpunt van de gegevens	Storing knowledge
#PEPM	9	Learning en development team die informatie vanuit ervaren mensen gaat verzamelen, gaat borgen en dan over gaat drage naar nieuwe mensen.	Storing knowledge
#SCHM	10	Voor de correcte opslag en verwerking van productdata is dat onze engineering afdeling, en die heeft een hoofd. Die is eindverantwoordelijk en gezamenlijk zorgen ze dan dat alle data actueel is.	Storing knowledge
#PEPM	11	Digital academy waarin veel informatie staat over wat wij allemaal maken, hoe wij dat maken, waarmee wij dat maken.	Using knowledge
#CBBM	12	Vanuit Polen dan die lijn op starten, toen gingen er wel mensen van ons daar naartoe en andersom om elkaar daarin te trainen.	Using knowledge
#PEPM	13	Men heeft eigenlijk niet echt trainingen zo opgezet om de kennis eigenlijk binnen het bedrijf te houden. Het is meer een beetje learning-by-doing om dan zo maar te zeggen.	Using knowledge
#PEMC	14	Omdat eigenlijk ons proces helemaal gestandaardiseerd is en we altijd op dezelfde manier werken kan in principe iedereen aan de machine staan.	Using knowledge
#PEMC	15	Onze werknemers, alle nieuwe werknemers worden opgeleid in onze Academy.	Using knowledge

The findings show that the most common quotes relate to the code of sharing knowledge. The organisations indicated mostly two ways of doing so. The first is through display boards, digital or physical, real-time or updated once a week [quotes #PMCM3; #CBBM4; #PEPM5]. On these boards, important indicators are shown for employees to see how well there are working as a company, or to see in real-time where an error has occurred et cetera. The process engineer at the metal packaging manufacturer indicates having a digital "overall board" where, for example, the overall equipment effectiveness, other key performance indicators, and labour efficiency is shown. In turn, the project manager at the coffee machine manufacturer reports to have a Power BI system which is capable of measuring and showing real-time data regarding their key performance indicators. However, this data is only accessible for management, like the project manager, and not for shop floor employees. To solve that, the project manager keeps his two project coordinators up to date regarding new projects and the real-time data, who in turn meet with the shop floor workers to disperse this information [#PMCM2]. That is, in fact, the second way of sharing information in most of the organisations: meetings and gatherings of the employees. For example, within the metal packaging company, a meeting is scheduled once every month with the plant manager who presents and explains the performance and the important indicators of the past month to all employees [#PEPM6]. At the metalworking company, a meeting is scheduled every day at the start of the day with all production employees to discuss certain indicators from the day before and for the coming day [#PEMC7].

Other two codes appearing are pertaining to the storage and use of knowledge. All firms indicated having a central digital system to store information. Usually, each department was responsible for storing its own relevant information in the right place [#SCHM10]. However, regarding experience and knowledge stored in employees' heads, nearly all firms reported not doing anything to capture this. The project manager at the coffee machine manufacturer admitted that, when a specialist left, a considerable chunk of knowledge was gone and would leave a significant knowledge gap for the other employees, because this knowledge was mostly gained from experience. He reported having a system where all relevant information concerning a project is stored, being the central information point of each project [#PMCM8]. Nevertheless, he also acknowledged that when having a system where experience could be measured or stored digitally, this knowledge could be transferred more easily to new employees. The process engineer at the metal packaging manufacturer agreed to this, mentioning that they are already in a process of trying to capture knowledge gained through experience [#PEPM9]. The idea was that a learning and development team would gather knowledge from the more experienced employees and would store this knowledge in a digital academy for employees [#PEPM11]. This would facilitate knowledge transfer to new employees. Furthermore, the goal was to keep this - now still available - knowledge within the company for the coming few years, even if the experienced employee had left.

As for using knowledge during the production process, most companies indicate that they use their knowledge, besides during their daily work procedures, to train new employees [#CBBM12; #PEMC15]. Therefore, they work with an onboarding program to let new employees get familiar with the way of working, and the work culture and ethics. One firm had set up a new factory in Poland and let the Polish employees first work and train for two weeks in the Netherlands, after which the Dutch employees often went to Poland to ensure the same way of working, resulting in the wanted high quality. Two other firms used an own academy to train new employees so that they can use knowledge in different situations within the production [#PEPM11; #PEMC15]. A process engineer of one of these firms said: *"All new employees are being trained in our Academy to ensure that they know what to do, how to do it, and that they can manage themselves in normal and unexpected situations."*

Defining knowledge management as a set of four main processes, the found results from the interviews were complementary and deepening these processes. Using knowledge was mostly found in the trainings and onboarding programs for new employees, where two respondents even mentioned having an own company academy. Furthermore, using knowledge was just a way of gaining experience in the way of working. Storing knowledge was unanimously done within digital systems, with some firms being more dedicated to filling it than others. Regarding sharing knowledge, the outcome was almost twofold: sharing through display boards and sharing through meetings of employees. The display boards, when present in a company, showed mostly key performance indicators relevant for each company, real-time or weekly updated. The meetings were mostly initiated by managers or team leaders with the goal to let the shop floor employees know about new information or certain results on a daily or monthly basis. However, regarding the generation of knowledge, most companies gather information from customers for their orders, but did not show to have practices to generate new knowledge regarding innovations.

4.2.2 Artificial intelligence

Artificial intelligence is defined as the use of technology to achieve objectives via an autonomous way. This implies that computers and machines can decide and act on data they receive, without interference of humans (Zheng et al., 2021). In other words, artificial intelligence is defined as the automatic storage and use of operating data by machines or systems. In Table 6, the most relevant quotes with their codes are being presented.

Table 6: Quotes concept artificial intelligence

Subject		Artificial Intelligence	
ID	#	QUOTE	OPEN CODERING
#PEMC	16	Mia kijkt dan wat voor producthet is, dat wordt dan herkend en op basis daarvan verder aangestuurd.	Optimising process data
#PEMC	17	Welke locatie die geproduceerd wordt, wie het besteld heeft, dus welke klant, wat voor type product het is. Maar ook de verwachte productietijd, dus deze staat gepland om tussen 1 en 5 juni te gaan produceren. Als je bijvoorbeeld alleen een vlak plaatje bestelt, dan is dat echt voor 24 uur nauwkeurig wordt die gepland.	Optimising process data
#PEMC	18	Heel veel kennis van de werkvloer is in de software verwerkt. En daarom bevordert het de productie en de efficiëntie en al dat soort dingen.	Optimising process data
#PEPM	19	Alles omtrent productie gegevens wordt opgeslagen. Doel daarvan is dus een beetje soort van visibility creëren over je supply chain	Optimising process data
#PEMC	20	Als bijvoorbeeld de bottleneck een AGV is, dan kun je uit de data halen dat het verstandig om een extra AGV rond te laten rijden.	Optimising process data
#PEPM	21	Bijvoorbeeld als ze gaan order wisselen, dan komt de AGV automatisch het oude materiaal ophalen, legt dat terug in het magazijn, en haalt automatisch het nieuwe materiaal op.	Unmanned vehicles
#PEMC	22	Dat heeft Mia dan ook al herkend, dus dat koppelt die er ook al aan en hoeveel buizen je dan bijvoorbeeld nodig hebt. Of hoeveel platen materiaal dat rekent Mia allemaal uit ja.	Resource planning
#CBBM	23	Je moet wel de juiste input geven voor zo'n AI tool om ook de juiste informatie weer te krijgen.	Resource planning
#PEMC	24	Dan gaat Mia aan de slag en die plant alles in en stuurt zo de productie aan.	Resource planning

The interviews revealed that, regarding artificial intelligence, most of the companies were not very far engaged in truly advanced artificial intelligence. Most companies had digital systems and machines, but those were independent systems and were not working together, resulting in human interference. From the interviews, the most common and relevant codes emerging were: systems aimed at optimising process data, resource planning, and unmanned vehicles.

Regarding the use of systems for optimising process data, the main system at the metalworking company, which took care of the work planning and inputs of the production, recognises the kind of product from a 3D model, delivered by a client [#PEMC16; #PEMC17]. It then knows where, when, and how to plan the product so that it can be delivered at a time a client has indicated. This system is in close contact with the rest of the systems and in combination with the digitally transformed knowledge therefore enhances production [#PEMC18]. The process engineer at the packaging manufacturer agreed by stating that it is important to store everything concerning production data. Therefore, he deems it important to create visibility over the supply chain [#PEPM19].

Another code regarding the use of unmanned vehicles, two companies worked with automated guided vehicles (AGV's), which are unmanned forklifts [#PEMC20; #PEPM21]. The AGV's at both firms are driven by systems, where no one actually has to think about it. They get their input from the planning system which tells it to pick something up at a certain location and deliver it at another location. These AGV’s work among the employees and would thus take care of the internal transportation of goods and products.

Furthermore, two companies used systems which made predictions based on given data when and where to buy and allocate resources. At one company, they used a digital tool that predicted and planned procurement moments and quantities [#CBBM23]. The downside to this was that employees still needed to enter the correct input to the system to get the correct results. Another company had a system that handled the front side of the production. This system got information directly from clients and generated accordingly to that the total production planning [#PEMC22; #PEMC24].

The definition of artificial intelligence in manufacturing companies was mainly that of the use of systems and machines to store and use of operating data, without the interference of humans. The interviews showed that all firms still needed human interference in certain parts of their production process. Two companies had automatic guided vehicles that would drive on their own, controlled by the core system of the organisation, without human interaction. Furthermore, one company had a fully automated system that took care of the gathering of data from customers to the planning of the production, also without any employee intervening with it. Those two cases can be regarded confirmatory to the definition. All other companies showed that with every step in the production process, human intervention was needed. This goes against the definition of artificial intelligence as mentioned by this research, therefore implying that those companies are not far enough involved in incorporating artificial intelligence systems into their production systems.

4.2.3 Operational performance

Operational performance can be defined as the degree to which a firm is better than its competitors in its responsiveness and generation of productivity improvements (Rai, Patnayakuni, & Seth, 2006; Younis, Sundarakani, & Vel, 2016). This research measured operational performance in three components: speed of the production, quality of the product, and dependability of the production. When interviewing the companies, questions regarding certain performance indicators were asked. Following, the information from the interviews regarding each measure of operational performance will be discussed. The most relevant quotes are presented in Table 7.

Table 7: Quotes concept operational performance

Subject		Operational Performance	
ID	#	QUOTE	OPEN CODERING
#PEMC	25	We hebben een leverperformance als indicator. Omdat je alles digitaal doet, is het moment van start productie en einde productie altijd beschikbaar	Depedability
#PMCM	26	Wij houden de levertijden bij, dus leverbetrouwbaarheid en daarbij hebben wij een interne en een externe leverbetrouwbaarheid.	Dependability
#SCHM	27	Met name de uitleverperformance, dus leveren wij op tijd en volledig, dat is onze belangrijkste doelstelling voor 2023 als bedrijf.	Dependability
#PEPM	28	OTIF, dat is on-time-in-full levering aan de klant, dus of je op tijd levert en de juiste hoeveelheid aan de klant.	Key performance indicator
#PEPM	29	OEE om het zo te noemen: overall equipment effectiveness. Daarmee kan je zien hoe een lijn draait, wat we draaien, de snelheid daarbij, de kwaliteit, het uitschot al dat soort zaken.	Key performance indicator
#PEMC	30	We doen bij bepaalde machines ook echt de OEE meten.	Key performance indicator
#PMCM	31	We houden de klachten algeheel bij en dan categoriseren we dat ook weer met wat er is gebeurd en hoe vaak.	Quality
#PEPM	32	Gaat men ook kijken op het aantal change-overs dat soort zaken en daar wordt eigenlijk allemaal bijgehouden om dat allemaal invloed heeft op je productieproces om uiteindelijk een zo kwalitatief goed mogelijk product te kunnen maken	Quality
#CBBM	33	Het is vooral het aantal fietsen wat je maakt, of het aantal frames dat gemaakt worden.	Speed
#PEPM	34	Heeft een operator een stilstand gehad dan moet hij dat ook aangeven, met een reden, zodat we de tijden altijd terug kunnen halen	Speed

The findings showed that, regarding the dependability of the production process, all companies kept track of delivery performance, delivery reliability, and delivery times [#PEMC25; #PMCM26; #SCHM27; #PEPM28]. One company reported using an OTIF indicator, meaning ‘On Time, In Full’. This meant that the organisation kept a close eye on whether their deliveries to customers where on time and complete. The hatchery machine manufacturer even stated that improving their delivery performance, regarding the on time and complete delivery of their product to the customer, was their most important goal for 2023.

For most companies, speed was of importance in a way of how fast the product got from begin to finish. For one firm, speed was measured in the amount of products that could be made within a certain time frame [#CBBM33], and another company mentioned to also to control for downtime [#PEPM34]. Furthermore, two companies used an OEE indicator, an ‘overall equipment effectiveness’ [#PEPM29; #PEMC30]. These were measured per machine to show what was being produced, how well it was produced, how fast, and how efficient it was working. These OEE indicators were monitored at both companies to get and keep these numbers as positive possible. Therefore, the OEE was viewed as a way of indicating operational performance.

As for quality of the products, companies measured this through the amount of complaints. Furthermore, the same firm controlling for downtime registered change-overs of machines, because it has an influence on the production process, to eventually produce a product of the highest possible quality [#PEPM32]. The project manager of the coffee machine manufacturer said they keep track of complaints regarding the product quality [#PMCM31]:

"*So we also keep track of that and then categorise and save it with information about what was wrong, what happened, and how often do we get these kind of complaints.*"

The findings from the interviews resulted in a more concrete idea of what organisations used for measuring their operational performance. Most companies used to measure the speed of the production process, with two companies even measuring a more complete OEE indicator. This kept track of production related indicators per machine during production. The quality was mostly measured through quality concerning complaints. The delivery performance of the firms was in all companies used to measure their dependability and reliability. Thus, the results from the interviews is considered to be a deepening and a concretisation of the theoretical definition, mostly to how firms act to be better than their competitors.

4.2.4 Hypotheses explored

Knowledge management is seen as a strategic approach to identifying, capturing, creating, sharing, and effectively using an organization's knowledge assets, while artificial intelligence is seen as a way to enable machines and systems to learn, acquire, and process knowledge to perform tasks autonomously. Therefore, this research assumed that knowledge management enables the understanding of knowledge, while artificial intelligence provides the tools to expand and use this knowledge, as well as to create new knowledge. Furthermore, Liebowitz (2001) highlights the importance of human input in artificial intelligence systems, where artificial based knowledge management and human based knowledge management should be viewed complementary. This study suggests that the three concepts addressed influence each other, making up the three hypotheses. Thus, it was asked how the organisations could see the effects in their companies. Table 8 shows relevant quotes regarding the influences of the concepts, as seen by the companies. After that, the hypotheses will be evaluated and supported or not supported.

Table 8: Quotes regarding relations between the concepts

Subject		Relations between the concepts	
ID	#	QUOTE	OPEN CODERING
#PEPM	35	Dat wordt allemaal aangestuurd door systemen, daar hoeft men eigenlijk niet bij na te denken en kan dan ook minder fouten maken, dus dat heeft denk ik een positieve invloed op je performance.	AI on better OP
#SCHM	36	Dus ja, dat systeem helpt bij het inplannen van de productie, om daardoor dus hogere prestaties te halen.	AI for timeplanning (OP)
#PEPM	37	Ja ik denk voornamelijk systemen is meer om het werk vergemakkelijken.	AI help for KM
#PEMC	38	Heel veel kennis van de werkvloer is in de software verwerkt en we zien dat het de productie en efficiëntie bevordert omdat de verschillende systemen elkaar helpen en zo ervoor zorgen dat het productie proces wordt geoptimaliseerd. Maar het wil niet zeggen dat je alle kennis weg moet halen,	AI help for KM
#PEMC	39	Dus je kan best veel kennis van de werkvloer wegnemen en automatiseren, maar je kunt nooit alles kennis wegnemen.	AI help for KM
#PEMC	40	Tot een bepaalde hoogte kun je kennis automatisch opslaan denk ik. Ja, je hebt altijd expertise nodig.	AI help for KM
#PEPM	41	Daarbij kan zijn dat hoe meer je automatiseert, hoe minder kennis er bij de mensen zelf aanwezig is omdat het allemaal automatisch is dat mensen zich misschien minder bij realiseren hoe het proces allemaal in elkaar steekt.	Negative impact AI on KM
#PEPM	42	En dan zie je ook wel inderdaad dat meer ervaring op de werkvloer kan zorgen voor betere prestaties, met name dus door minder uitval of snellere handelingen.	Experience on OP
#PEPM	43	Als men weet hoe ze machines beter kan instellen, dus dat die kennis daarvan aanwezig is, zal men waarschijnlijk kwalitatief beter of met minder afval productie kunnen realiseren.	KM for better quality (OP)
#PMCM	44	Dan hoef je niet opnieuw weer alles te doen. Dat is allemaal tijd dat je ergens anders beter in kan stoppen.	KM for timesaving (OP)
#PMCM	45	Als je niet weet hoe het product gemaakt wordt of gerealiseerd wordt, of wat voor een tijd het kost of wat iemand op een andere afdeling ervoor moet doen, dan loop je altijd met je planning in de soep, dat gaat altijd fout dan.	KM for timesaving (OP)

The first hypothesis concerns the positive effect of knowledge management on operational performance. Results from interviews show that a proper management of knowledge can ensure that organisations perform better. A code deemed relevant regards the use of knowledge management for improving time management and quality, and thus operational performance. One company stated that, if their sales people knew what to ask their customers and knew what they actually could do themselves as a firm, that it would save a lot of time later on in the process [#PMCM44; #PMCM45]. Furthermore, the presence of knowledge regarding adjusting the machines would result in a qualitatively better product and less waste during production. A project engineer stated that he had seen that more experienced employees had all this knowledge regarding adjusting machines and therefore that it indeed resulted in better performances through less waste and better products than less experienced employees [#PEPM42; #PEPM43]. So, when capturing and storing this experience knowledge, the less experienced could also provide for a higher performance. Considering the above results and the results presented in paragraph 4.2.1 and 4.2.3, the organisations showed to have a positive relationship between their way of managing knowledge on the operational performance, therefore supporting hypothesis 1.

Hypothesis 2 relates to the positive effect of artificial intelligence on operational performance. The relative big absence of codes relating to the use of digital systems on operational performance, shows that the organisations interviewed are not very engaged in the use of artificial intelligence. Although, the AGV's in cooperation with all the other operating systems, results in people not having to think about how to work, the systems tend to do it for them, leading to less chances of human error and therefore a chance of positive influence on a firm's performance [#PEPM35]. Another company used a planning module in their system that would help plan orders in production, therefore creating the most optimal planning [#SCHM36], leading to a better performance in terms of efficiency and lead time. These results and the results presented in 4.2.2 and 4.2.3, mostly come from two of the five interviewed companies. The other three companies do not seem to have advanced digital systems to directly have an effect on operational performance. Therefore, it is not possible to generalise the results over the five respondents, leading to insufficient substantiation to support the effect of artificial intelligence on operational performance. Thus, hypothesis 2 is qualitatively not supported.

Hypothesis 3 dealt with the moderating effect of artificial intelligence on the relationship between knowledge management and operational performance. The most frequent codes were referring to the relation of artificial intelligence and knowledge management. Results found that respondents mostly think that digitalisation, and eventually self-managing systems like artificial intelligence, could help their knowledge management for using and storing knowledge. A process engineer stated [#PEMC38]: "*What happened here is that we have actually incorporated a lot of knowledge from the shopfloor into our software. And we see that it actually promotes production and the efficiency, because these systems help each other and therefore optimise the production process (...)*"
However, most companies agreed that the use of systems is to facilitate an employee's work [#PEPM37], with one acknowledging that knowledge can only be digitalised to a certain extent [#PEMC39; #PEMC40]. The same process engineer added [#PEMC]: *"(...) You can automatically store knowledge to a certain extent. You will always need a bit of human expertise.*" Another process engineer agreed by arguing that the more you store knowledge digitally, the less people need to know and will know about the products and the processes [#PEPM41]. This could be a problem when systems stop working or when there is something wrong with the systems. Taking into account the results, there is enough substantiated evidence that the use of artificial intelligence has a positive influence on knowledge management practices, leading to a better operational performance, hence supporting hypothesis 3.

To conclude the qualitative analysis, the respondents did see the direct link of better use of knowledge management on performances and the effect of digital systems on the use of knowledge management for better performances, but did not seem to see the direct link of artificial intelligence on operational performances. This might be because it would all be speculations of the respondents and therefore not grounded, considering most companies were not really far engaged with artificial intelligence.

4.3 Conclusion findings

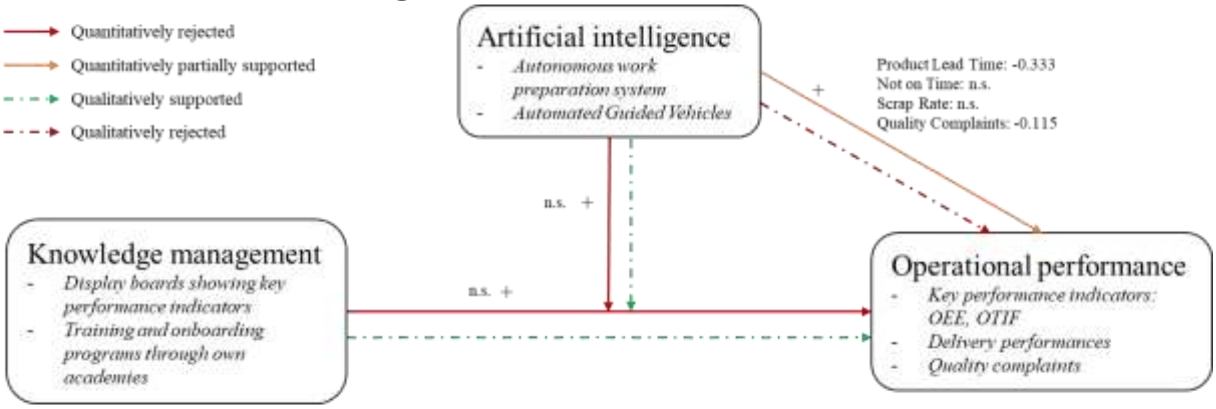

Figure 2: Conceptual model after analyses

To conclude the analyses, the quantitative and qualitative are being compared to each other. Figure 2 shows the conclusion of the analyses in the conceptual model. Quantitative analysis showed that knowledge management practices do not have a significant effect on operational performance indicators. Furthermore, the moderating effect of artificial intelligence on the relationship between knowledge management and operational performance also does not show significant results. Therefore, hypotheses 1 and 3, concerning the effect of knowledge management on operational performance and the moderating effect of artificial intelligence on the relationship between knowledge management and operational performance, are both not supported. However, the results showed partial support for hypothesis 2, meaning that artificial intelligence has a partial significant positive effect on operational performance, specifically for the product lead time and amount of quality related complaints.

The qualitative study revealed that organisations mostly do not consciously think about knowledge management practices for generating, using, sharing, or storing knowledge. There was no company which had a certain program or specific guidelines for managing knowledge, although most companies had certain aspects such as display boards for sharing knowledge and trainings for using knowledge. Each organisation recognised in a way that their ways of generating, using, storing, and sharing knowledge would enhance their performance, therefore supporting hypothesis 1. As for artificial intelligence, the analysis revealed that the companies interviewed were not that far advanced with engaging in and integrating such systems, the most autonomous systems being the Automated Guided Vehicles and an autonomous work preparation system. The results concerning artificial intelligence were deemed not substantial enough, therefore not supporting hypothesis 2. However, it revealed what different indicators companies use to indicate their operational performance and how the use of knowledge and digital systems enhance this. The most important indicators of measuring their operational performance, the interviewed manufacturing companies, indicated to use key performance indicators (such as product lead time, OEE, and OTIF), delivery performances, and the quality of the product (in complaints and passing of quality control). In addition, the qualitative study did gain a deeper insight into the practices regarding knowledge management that organisations use, and the different systems they used with that to eventually enhance their performances, supporting hypothesis 3.

Quantitative analysis rejected hypotheses 1 and 3, and supported 2 partially. Qualitative analysis rejected hypothesis 2, but supported hypotheses 1 and 3. This means that the two studies contradict to each other. There was no significant quantitative effect of knowledge management practices on operational performances, but organisations mentioned that their actions of generating, using, storing and sharing knowledge could certainly lead to better performances. For the use of digital systems and artificial intelligence helping these practices to enhance performances even more, quantitative study also found no significant results, while qualitative study revealed that it is more convenient storing much knowledge digitally and let systems do as much as possible to facilitate employees in their work. For the direct relationship of artificial intelligence on operational performance, quantitative study found a partially significant result, whereas qualitative study did not show enough substantial evidence for digital systems directly impacting operational performance.

5. Summary and discussion

In this chapter, the analyses will be summarised with answering the research question. After the summary, the discussion with theoretical and practical implications will be discussed, followed by the limitations of the study and an ethical reflection.

5.1 Summary

The research question of this study was: *Does artificial intelligence have an impact on the use of knowledge management on operational performance in manufacturing companies, and -if so- how is it implemented within these firms?* Conceptually, according to the theory and literature found before conducting the analyses, the answer is yes. Literature states that artificial intelligence can be used as a tool to enhance knowledge management and facilitate employees in their work, instead of competing with the workforce (Bencsik, 2021; Bughin et al., 2017). When using artificial intelligence systems, knowledge management can be enhanced, resulting in a better operational performance (Liebowitz, 2001; Mittal & Kumar, 2019; Bencsik, 2021).

Empirically speaking, after conducting the analyses, the answer is twofold. Quantitatively analysis showed no significant effect of the moderating effect, therefore the answer would be no. Quantitative analysis only showed significant effects of artificial intelligence on the product lead time and amount of quality complaints in manufacturing organisations. So, the adoption of artficial intelligence has the potential to reduce product lead times by automating production processes, and the potential to reduce the amount of quality related complaints by making and sending fewer bad products to customers.

Nevertheless, the interviews during the qualitative study have shown that certain systems already help with the managing of knowledge and facilitation of work, answering the research question with yes. Companies use different systems for generating, storing, using and sharing knowledge and information, often all connected to each other through an ERP system. According to the theory in paragraph 2.2, another goal of this research was to impart knowledge about in what knowledge management processes artificial intelligence could facilitate human driven knowledge management. According to the findings, organisations interviewed showed particular activities in the processes of using, sharing, and storing of knowledge, with their systems facilitating in these processes. Academies, digital training, and digital handbooks could be used for facilitating the process of using knowledge by new employees or new technologies. As for storing knowledge, all organisations worked with some sort of system storing customer, product, and operating information. However, the input of this data still needed to be done by employees themselves. Lastly, display boards and systems generating and showing performance indicators helped the process of sharing knowledge across the organisations.

5.2 Discussion & implications

This research aims to provide and test a conceptual model where knowledge management and artificial intelligence affect operational performance. Following are theoretical and practical implications that can be drawn for this study.

5.2.1 Theoretical implications

The insights of this study are partially aligned with earlier research showing how the adoption of artificial intelligence can positively influence knowledge management practices in organisations (Liebowitz, 2001; Mittal & Kumar, 2019). It therefore builds on existing evidence of the effect of digitalisation on knowledge management. Furthermore, this study contributes to knowledge management research by adding a new aspect to the concept. It does so by showing that the future of digitalisation, i.e. artificial intelligence, can facilitate in the way knowledge management can be used, to eventually reach higher operational performances. Prior research often only focussed on unfolding the concept of knowledge management (Othman et al., 2019; Chow et al., 2005; Dalkir et al., 2007) and measuring the impact of knowledge management on performances (Yang, 2007; Tan & Wong, 2015; Marqués & Simón, 2006). The future, that is in this case, the use of artificial intelligence and the influence of it on the management of knowledge is often disregarded, as well as the eventual influences of those concepts on reaching higher performances.

Additionally, this study contributes to literature suggesting that artificial intelligence can facilitate the management of knowledge and therefore the carrying out of work for employees. Other research measuring artificial intelligence often do not consider the use of it on operational level and consequently training employees to use it. That is, the aspect of knowledge management is often disregarded in artificial intelligence research. Previous studies are mostly focussed on the influence of artificial intelligence on performances (Rana et al., 2021; Ballapu, 2021; Wamba-Taguimdje et al., 2020; Dubey et al., 2019). This study suggests that artificial intelligence systems can act as a tool, helping the generation, use, storage, and sharing of knowledge and information.

5.2.2 Practical implications

From a practical perspective, the findings imply for manufacturing firms that firstly, a proper management of knowledge (i.e. the way of generating, using, storing, and sharing knowledge) can definitely help with improving work processes and therefore operational performance.

Findings show that the main practice regarding sharing knowledge is a daily or monthly meeting to go through certain indicators of the time period before and the expectations of the period after, to ensure the whole workforce is on the same page and working towards the same goals. Furthermore, the storage of knowledge digitally seemed to have more positive effects resulting in everybody knowing where to find which data, and the use of knowledge is mostly brought to new employees or all employees when there's a new technology via academies and online trainings. Secondly, the use of artificial intelligence can ensure a reduction of product lead time and quality regarding complaints, mainly through the adaptation of the production process. For the transport, AGV's can reduce the time before and after production, while systems and sensors in machines can indicate real-time progress and status of the production, detecting errors or mistakes early on in products. Third, the use of these artificial intelligence systems (i.e. systems used for optimising process data, predictive planning, automatic transportation, and preparing key performance indicators) can facilitate in managing knowledge, leading to a bigger positive effect of proper knowledge management on operational performances. For organisations to implement artificial intelligence systems, the knowledge management processes should be thought of. It needs to be clear in which process the artificial intelligence system is going to facilitate work. According to the open codes from the findings of the qualitative analysis, the storing of knowledge should be done accurately and digitally, so that other systems know where to find relevant data. These systems can all be connected through ERP systems, resulting in one collaborative unit for a system through an organisation. The sharing of knowledge can be promoted through a system as Power BI, that generates, measures and shows indicators. The use of knowledge can be enhanced through the use of digital academies, where trainings, courses and handbooks can be used for new employees or the adoption of new technologies.

Practically speaking, a manufacturing company that uses artificial intelligence systems as tools to enhance data processing will thus be able to manage and transform incoming data into useful knowledge for the organisation itself. The firm will be allowed by this transformed knowledge, circulating within the organisation, to improve its operational performance. However, therefore it needs to give their employees proper training in using the new technology to ensure that it is used to its full potential and to ensure that employees are stimulated in using the technology.

5.2.3 Limitations

The limitations of this research are mainly in the design of the study. A mixed-methods study ensures triangulation of results and therefore well substantiated, valid, and reliable results derived from theory, quantitative analysis, and qualitative analysis. The generalizability of the results is possible for the outcomes of the quantitative analysis. However, this is limited for the qualitative analysis, because these are specific cases and different in every organisation and therefore may not be representative of the larger population. Furthermore, this research only uses a limited number of five interviews, resulting in limited data, limited generalizability, and a potential lack of diversity in the companies, leading to difficulty proving a causal relationship. The use of only five interviews is due to a limited timeframe and the difficulty of finding enough fitting respondents.

Future research could try to expand the quantitative analysis with a larger sample size or the inclusion of other industries or contexts, resulting in a more substantiated, generalisable outcome. In addition, future research could also try to extend the qualitative analysis by disregarding the quantitative findings and focussing more on specific cases by trying to get more respondents for interviews, leading to a more profound, in-depth view of practical situations. Finally, this research has not empirically examined artificial intelligence in the form of self-learning systems. Future research could take this into account by testing what self-learning could do for an organisations operations and in terms of performances as well as work culture, and how that in turn can be integrated in the knowledge management processes.

5.2.4 Ethical reflection

When conducting the analyses in this study, research ethics were kept high to ensure the integrity and credibility of the results. Therefore, articles used and cited have been read and checked for reliability. Furthermore, the rights and confidentiality of the respondents and their firms have been protected by anonymising the interviews and the results. Additionally, agreements and promises made with respondents have always been honoured and kept, and the researcher has remained transparent about his research through the entirety of the research period.

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Appendices

Appendix A: Interview script

Inleiding (5 min)

Allereerst bedankt voor de mogelijkheid van dit interview. Ik ben Len Eising en ik ben op dit moment bezig met mijn masterscriptie aan de Radboud Universiteit in Nijmegen. Voor mijn scriptie ben ik bezig met een onderzoek naar de invloeden van kennismanagement en kunstmatige intelligentie op operationele prestaties. Het interview zal ongeveer een uur duren waarbij u geheel anoniem blijft. Als u wil, kan ik het transcript of eventueel het onderzoek naar u opsturen wanneer het klaar is.

Voordat ik begin, zou ik dit interview mogen opnemen? Na verwerking zal de opname verwijderd worden.

Heeft u nog vragen voordat het interview begint?

Introductie (5 min)

1. Wie bent u en wat is uw rol binnen het bedrijf? (Functie, ervaringen in carrière, ervaringen binnen bedrijf)
2. Hoe groot is dit bedrijf?
3. In welke sector is het bedrijf werkzaam?
4. Wat zijn de kernactiviteiten van dit bedrijf? (Waarmee onderscheidt het zich van andere bedrijven?)
5. Toekomst/strategie: wat probeert dit bedrijf te bereiken in de komende 5 à 10 jaar? (Wat zijn de doelen?)
6. Op welke manier bent u betrokken bij innovatieve activiteiten/ toekomst plannen? (Verschillende afdelingen, welke focus: activiteiten of overkoepelend?)

Kennismanagement (10 min)

Mijn onderzoek gaat over de invloed van onder andere het gebruik van kennis op de prestaties van het bedrijf. Ik zou nu graag verder gaan op de rol van kennis en informatie in uw bedrijf.

7. Wat voor een soort informatie of kennis is van belang voor uw bedrijf?
8. Hoe verzamelt u deze informatie? Hoe blijft u op de hoogte?
9. Op wat voor een manieren wordt kennis gebruikt? (Door werknemers, (digitale) systemen, werkwijzen)
10. Hoe wordt informatie opgeslagen in uw bedrijf? (Systemen, fysiek of digitaal)
11. Is er iemand verantwoordelijk voor de opslag en deling van kennis, zodat alles correct gebeurd? Wordt kennis ook geüpdatet? Worden er **trainingen** gegeven? Zo ja, wat voor een trainingen?
12. Hoe gaat u om met kennis die bij werknemers in het hoofd zitten?

Kunstmatige intelligentie (10 min)

Een ander aspect van het onderzoek is het gebruik van robots en digitale systemen. Bij deze wil ik graag hierop verder gaan hoe dit is geregeld in uw bedrijf.

13. Is er een systeem dat verschillende belangrijke indicatoren zichtbaar maakt? Zo ja, wat voor een systeem? Is er ook een systeem dat reageert op bepaalde waarden van deze indicatoren?
14. Gebruikt u in uw productiemachines of systemen die automatisch (bedrijfs-/operationele) gegevens opslaan? Zo ja, hoe? / waarvoor gebruik data? → Optimaliseren proces, planning onderhoud, planning resources, maken van indicatoren
15. Heeft u industriële robots in uw productieproces? Zo ja, wat voor een soort robots? (Robots die produceren, robots die werkstukken en gereedschap pakken, mobiele robots, cobots)
16. Hoe worden deze robots aangestuurd? (Werknemers, digitale systemen, zelfsturend)

Operationele prestaties (10 min)

Ik zou het nu graag willen hebben over het belang van bedrijfsspecifieke prestaties binnen het bedrijf, met name gefocust op het productieproces.

17. Welke indicatoren of prestaties zijn voor uw bedrijf van belang? Welke worden met name gemonitord?
18. Hoe worden deze prestaties gemeten? (Indicatoren, KPI's)
19. Hoe worden deze prestaties kenbaar gemaakt binnen het bedrijf?
20. Zijn deze prestaties op een bepaalde manier leidend? Zo ja, hoe wordt ernaar gehandeld?

Invloed van kennismanagement op operationele prestaties en de rol van kunstmatige intelligentie (10 min)

Dan nu het laatste onderdeel van het interview. Het laatste aspect van het onderzoek gaat over de relatie tussen kennis en prestaties.

21. Hoe verhoogt bepaalde kennis de besproken prestaties?
22. Hoe dragen bepaalde mensen, systemen of handelingen hieraan bij?
23. Hoe zou bepaalde kennis prestaties juist kunnen beperken?
24. Hoe helpen de besproken digitale systemen en productiemechanismen bij of juist tegen het behalen van hogere prestaties?

Afsluiting (5 min)

We zijn aan het einde gekomen van dit interview. Erg bedankt voor uw tijd en medewerking. Nogmaals, dit interview zal geheel anoniem verwerkt worden en de opname wordt naderhand gewist. Als u het wil, kan ik u het transcript toesturen. Ik kan u ook het definitieve eindverslag toesturen.

Appendix B: Questions from the EMS questionnaire

Here, the relevant questions corresponding with the operationalisation of the concepts for the quantitative analysis are presented.

Knowledge management: question 7 EMS database

❑	←❑	Grafische weergave werkprocessen en-status (Visual Management; dashboard)	❑→	19/20		l	m	h
❑	←❑	Taakverrijking productiemedewerker (integratie van planning, uitvoering of controle)	❑→	19/20		l	m	h
❑	←❑	Kwaliteitsmanagement (bijv. preventieve onderhoud, total quality management/ TQM, Six Sigma)	❑→	19/20		l	m	h
❑	←❑	Training-on-the-job (bijv. Taakroulatie, georganiseerde uitwisseling ervaringen met oudere werknemers	❑→	19/20		l	m	h
❑	←❑	Maatregelen voor het behoud van oudere werknemers of hun kennis voor uw bedrijfsvestiging (bijv. teams met verschillende leeftijdsgroepen, begeleidingsprogramma's, senior-junior tandems)	❑→	19/20		l	m	h
❑	←❑	Maatregelen om werknemers in de productie te laten experimenteren met nieuwe ideeën door beschikbaar stellen van bijv. werktijd, locatie, machines.	❑→	19/20		l	m	h

Artificial intelligence: question 10.1

10.1	**Gebruikt u machines of systemen in uw productieproces die automatisch [zonder menselijke tussenkomst] gegevens opslaan?**					
❑ nee ❑ ja →	Waar worden deze gegevens voor gebruikt?					
	Gebruikt voor:	❑	Optimaliseren van productieprocessen	❑	Plannen van onderhoud en reparaties	❑ Ander gebruik
		❑	Plannen van middelengebruik en -toepassing	❑	Voorbereiden productiviteits- of prestatie-indicatoren	
		❑	Geen gebruik			
	Zijn verzamelde gegevens uit het productieproces ook gebruikt voor risicoanalyse? (identificeren, analyseren, evalueren)?				❑ nee	❑ ja

Operational performance: question 11

11.	**Welke van de volgende kenmerken is het meest van toepassing op uw hoofdproduct(groep)?**					
Wat is de gemiddelde productietijd van uw hoofdproduct(groep)? ► (doorlooptijd vanaf moment dat opdracht binnenkomt bij productie tot product klaar voor levering)	ca		werk-dagen	of		uren
Hoeveel procent van de orders wordt op tijd afgeleverd? ► (Beantwoord op basis van afgesproken levertijd)	ca		%			
Hoeveel procent van uw producten of halfproducten moet na kwaliteitscontrole nabewerking ondergaan of geheel worden afgekeurd?			ca		%	
Welk percentage van de geleverde bestellingen heeft klachten opgeleverd vanwege kwaliteitsproblemen?			ca		%	

Appendix C: Assumptions check and reliability test regression analysis

Assumptions check.

Here, the assumptions for the regression analysis will be discussed. The first assumption is the sample size. For this analysis, there is a minimum of five respondents per included variable. However, the preferred amount is fifteen to twenty-five respondents (Hair, Black, Babin, and Anderson, 2018). This research includes three variables. With a preferred ratio of 15 to 20 respondents per variable, the preferred number of respondents is at least 45 to 60. The dataset used contains around 200 respondents, which means that the assumption of the sample size is broadly met.

Second, the linearity of the relationship with the dependent variable operational performance is tested. In all four scatterplots (four because it was tested on all indicators of operational performance) there was a little linear shape to be seen. Next, the multicollinearity was assessed. The multicollinearity is acceptable if the variance inflation factor (VIF) is lower than ten (Hair et al., 2018). All VIF values were between 1 and 2, meaning that multicollinearity can be accepted, therefore meeting the assumption.

Another assumption is that all variables should be normally distributed. If the skewness is |2|, a normal distribution is achieved (Hair et al., 2018). The results of the control variables showed that 'Size number of employees 2017' has a skewness of 13.537. Therefore, this variable is transformed to 'lnSize number of employees 2017', which has a skewness of 1.038. For the variable operational performance, all four factors Production Lead Time, Not on Time, Scrap Rate, Quality Complaints have a skewness of 5.435, 2.947, 4.104, 6.440 respectively. These factors are all log-transformed, leading to the respective skewness's of 0.471, 0.008, 1.109, 1.316. The indicators of both the variable knowledge management and the variable artificial intelligence are all considered normally distributed.

Furthermore, in Table 9, the correlations between the variables are shown. There are no noteworthy strong correlations between variables, as correlations are considered strong when reaching a value of 0.7.

Table 9: Correlations table

Correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13
1 Product Lead Time	1,000												
2 Not on Time	0,309	1,000											
3 Scrap Rate	0,170	0,299	1,000										
4 Quality Complaints	0,242	0,367	0,526	1,000									
5 Size (log number of employees 2017)	0,078	0,029	0,152	-0,008	1,000								
6 Food	-0,248	-0,333	-0,172	-0,284	0,094	1,000							
7 Textile	-0,051	-0,068	-0,018	-0,080	-0,074	-0,123	1,000						
8 Construction	0,072	-0,103	0,004	0,104	0,030	-0,048	-0,065	1,000					
9 Chemical	-0,107	-0,034	-0,108	-0,109	-0,103	-0,116	-0,156	-0,061	1,000				
10 Machinery	0,341	0,288	0,171	0,277	0,159	-0,147	-0,199	-0,077	-0,187	1,000			
11 Electronic	-0,031	0,001	0,138	0,058	-0,018	-0,166	-0,224	-0,087	-0,210	-0,268	1,000		
12 Knowledge management practices	-0,110	-0,078	0,009	-0,140	0,097	0,065	0,050	0,027	-0,039	-0,172	0,039	1,000	
13 Automatic storage and use of operating data	-0,240	-0,107	0,024	-0,172	0,412	0,084	-0,023	0,103	-0,017	-0,070	-0,003	0,366	1,000

Reliability

A reliability test was carried out for the knowledge management concept, to measure the internal consistency of the items measuring knowledge management. The result of the test was a Cronbach's Alpha of 0.605 (see Table 10), suggesting a lower level of consistency. However, Table 11 shows that removing items does not result in a substantial increase in the Cronbach's Alpha. Therefore, all items are kept measuring knowledge management.

Table 10: Cronbach's Alpha knowledge management

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,605	,602	6

Table 11: Cronbach's Alpha if item deleted

Item-Total Statistics

	Cronbach's Alpha if Item Deleted
Display Boards in production to illustrate work processes and work status	0,619
Integration of tasks	0,536
Quality Measures - Methods of assuring quality in production	0,535
Training on the job	0,483
Experimentation for employees in the production	0,591
Maintain Elderly - Instruments to maintain elderly employees	0,585

Appendix D: Regression analysis SPSS output model fit

In this appendix, the model summaries and the ANOVA tables are being presented which have been used to assess the model fit of each dependent variable.

Output dependent variable Product Lead Time

Table 12: Model Summary of dependent variable Product Lead Time

Model Summary[d]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,413[a]	,171	,141	1,26807	,171	5,727	7	195	<,001	
2	,486[b]	,236	,201	1,22312	,066	8,298	2	193	<,001	
3	,490[c]	,241	,201	1,22282	,004	1,096	1	192	,296	2,163

a. Predictors: (Constant), Electronic, lnSize number of employees 2017 (log), Construction, Food, Chemical, Textile, Machinery

b. Predictors: (Constant), Electronic, lnSize number of employees 2017 (log), Construction, Food, Chemical, Textile, Machinery, KM_practices Employee level knowledgemngt activities, CleanProdData data storage of optimization, maintenance, utilization, productivity

c. Predictors: (Constant), Electronic, lnSize number of employees 2017 (log), Construction, Food, Chemical, Textile, Machinery, KM_practices Employee level knowledgemngt activities, CleanProdData data storage of optimization, maintenance, utilization, productivity, I_KM_CPD

d. Dependent Variable: lnProdLeadTime

Table 13: ANOVA statistics of dependent variable Product Lead Time

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	64,468	7	9,210	5,727	<,001[b]
	Residual	313,561	195	1,608		
	Total	378,029	202			
2	Regression	89,297	9	9,922	6,632	<,001[c]
	Residual	288,733	193	1,496		
	Total	378,029	202			
3	Regression	90,936	10	9,094	6,082	<,001[d]
	Residual	287,093	192	1,495		
	Total	378,029	202			

a. Dependent Variable: lnProdLeadTime

b. Predictors: (Constant), Electronic, lnSize number of employees 2017 (log), Construction, Food, Chemical, Textile, Machinery

c. Predictors: (Constant), Electronic, lnSize number of employees 2017 (log), Construction, Food, Chemical, Textile, Machinery, KM_practices Employee level knowledgemngt activities, CleanProdData data storage of optimization, maintenance, utilization, productivity

d. Predictors: (Constant), Electronic, lnSize number of employees 2017 (log), Construction, Food, Chemical, Textile, Machinery, KM_practices Employee level knowledgemngt activities, CleanProdData data storage of optimization, maintenance, utilization, productivity, I_KM_CPD

Table 14: Coefficients of Product Lead Time

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	2,157	,438		4,925	<,001		
	lnSize number of employees 2017 (log)	,064	,106	,040	,603	,547	,953	1,049
	Food	-1,075	,369	-,218	-2,909	,004	,757	1,321
	Textile	-,100	,309	-,026	-,323	,747	,676	1,479
	Construction	,666	,602	,076	1,106	,270	,909	1,100
	Chemical	-,306	,320	-,075	-,956	,340	,694	1,441
	Machinery	,999	,288	,288	3,464	<,001	,614	1,630
	Electronic	-,013	,273	-,004	-,047	,962	,598	1,673
2	(Constant)	1,667	,457		3,651	<,001		
	lnSize number of employees 2017 (log)	,260	,113	,163	2,293	,023	,781	1,280
	Food	-1,047	,356	-,213	-2,939	,004	,756	1,322
	Textile	-,121	,298	-,031	-,405	,686	,676	1,479
	Construction	,867	,583	,098	1,487	,139	,902	1,108
	Chemical	-,295	,309	-,072	-,954	,341	,691	1,447
	Machinery	,882	,283	,255	3,120	,002	,594	1,684
	Electronic	-,035	,263	-,011	-,134	,894	,597	1,674
	KM_practices Employee level knowledgemngt activities	,031	,056	,038	,551	,582	,838	1,193
	CleanProdData data storage of optimization, maintenance, utilization, productivity	-,354	,089	-,297	-3,981	<,001	,709	1,411
3	(Constant)	1,665	,456		3,649	<,001		
	lnSize number of employees 2017 (log)	,268	,114	,168	2,357	,019	,778	1,285
	Food	-1,054	,356	-,214	-2,957	,003	,756	1,322
	Textile	-,124	,298	-,032	-,416	,678	,676	1,480
	Construction	,857	,583	,097	1,470	,143	,902	1,108
	Chemical	-,312	,309	-,076	-1,008	,315	,689	1,451
	Machinery	,875	,283	,253	3,093	,002	,594	1,685
	Electronic	-,037	,263	-,011	-,139	,890	,597	1,675
	KM_practices Employee level knowledgemngt activities	,029	,056	,035	,515	,607	,837	1,194
	CleanProdData data storage of optimization, maintenance, utilization, productivity	-,333	,091	-,280	-3,658	<,001	,675	1,481
	I_KM_CPD	-,050	,048	-,069	-1,047	,296	,918	1,089

a. Dependent Variable: lnProdLeadTime

Output dependent variable Not on Time

Table 15: Model Summary of dependent variable Not on Time

Model Summary[d]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics R Square Change	Change Statistics F Change	Change Statistics df1	Change Statistics df2	Change Statistics Sig. F Change	Durbin-Watson
1	,434[a]	,189	,159	,89826	,189	6,476	7	195	<,001	
2	,440[b]	,194	,156	,89992	,005	,642	2	193	,528	
3	,441[c]	,194	,152	,90201	,000	,107	1	192	,744	2,080

a. Predictors: (Constant), Electronic, lnSize number of employees 2017 (log), Construction, Food, Chemical, Textile, Machinery

b. Predictors: (Constant), Electronic, lnSize number of employees 2017 (log), Construction, Food, Chemical, Textile, Machinery, KM_practices Employee level knowledgemngt activities, CleanProdData data storage of optimization, maintenance, utilization, productivity

c. Predictors: (Constant), Electronic, lnSize number of employees 2017 (log), Construction, Food, Chemical, Textile, Machinery, KM_practices Employee level knowledgemngt activities, CleanProdData data storage of optimization, maintenance, utilization, productivity, I_KM_CPD

d. Dependent Variable: lnNotOnTime

Table 16: ANOVA statistics of dependent variable Not on Time

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	36,576	7	5,225	6,476	<,001[b]
	Residual	157,341	195	,807		
	Total	193,917	202			
2	Regression	37,615	9	4,179	5,161	<,001[c]
	Residual	156,302	193	,810		
	Total	193,917	202			
3	Regression	37,702	10	3,770	4,634	<,001[d]
	Residual	156,215	192	,814		
	Total	193,917	202			

a. Dependent Variable: lnNotOnTime

b. Predictors: (Constant), Electronic, lnSize number of employees 2017 (log), Construction, Food, Chemical, Textile, Machinery

c. Predictors: (Constant), Electronic, lnSize number of employees 2017 (log), Construction, Food, Chemical, Textile, Machinery, KM_practices Employee level knowledgemngt activities, CleanProdData data storage of optimization, maintenance, utilization, productivity

d. Predictors: (Constant), Electronic, lnSize number of employees 2017 (log), Construction, Food, Chemical, Textile, Machinery, KM_practices Employee level knowledgemngt activities, CleanProdData data storage of optimization, maintenance, utilization, productivity, I_KM_CPD

Table 17: Coefficients of Not on Time

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	2,087	,310		6,731	<,001		
	lnSize number of employees 2017 (log)	,024	,075	,021	,314	,754	,953	1,049
	Food	-1,230	,262	-,349	-4,702	<,001	,757	1,321
	Textile	-,308	,219	-,110	-1,407	,161	,676	1,479
	Construction	-,784	,427	-,124	-1,837	,068	,909	1,100
	Chemical	-,230	,226	-,079	-1,016	,311	,694	1,441
	Machinery	,423	,204	,170	2,069	,040	,614	1,630
	Electronic	-,146	,193	-,063	-,755	,451	,598	1,673
2	(Constant)	1,994	,336		5,937	<,001		
	lnSize number of employees 2017 (log)	,064	,083	,056	,765	,445	,781	1,280
	Food	-1,224	,262	-,347	-4,670	<,001	,756	1,322
	Textile	-,312	,220	-,112	-1,423	,156	,676	1,479
	Construction	-,743	,429	-,118	-1,732	,085	,902	1,108
	Chemical	-,229	,227	-,078	-1,007	,315	,691	1,447
	Machinery	,397	,208	,160	1,907	,058	,594	1,684
	Electronic	-,151	,194	-,065	-,778	,438	,597	1,674
	KM_practices Employee level knowledgemngt activities	,003	,041	,006	,081	,935	,838	1,193
	CleanProdData data storage of optimization, maintenance, utilization, productivity	-,071	,065	-,084	-1,089	,277	,709	1,411
3	(Constant)	1,994	,337		5,924	<,001		
	lnSize number of employees 2017 (log)	,062	,084	,054	,740	,460	,778	1,285
	Food	-1,223	,263	-,347	-4,653	<,001	,756	1,322
	Textile	-,312	,220	-,112	-1,416	,158	,676	1,480
	Construction	-,741	,430	-,117	-1,723	,087	,902	1,108
	Chemical	-,225	,228	-,077	-,986	,326	,689	1,451
	Machinery	,398	,209	,161	1,910	,058	,594	1,685
	Electronic	-,150	,194	-,065	-,775	,440	,597	1,675
	KM_practices Employee level knowledgemngt activities	,004	,041	,007	,092	,927	,837	1,194
	CleanProdData data storage of optimization, maintenance, utilization, productivity	-,076	,067	-,089	-1,132	,259	,675	1,481
	I_KM_CPD	,012	,035	,022	,327	,744	,918	1,089

a. Dependent Variable: lnNotOnTime

Output dependent variable Scrap Rate

Table 18: Model Summary of dependent variable Scrap Rate

Model Summary[d]

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,317[a]	,101	,068	,92040	,101	3,119	7	195	,004	
2	,319[b]	,102	,060	,92459	,001	,118	2	193	,889	
3	,325[c]	,106	,059	,92494	,004	,853	1	192	,357	1,774

a. Predictors: (Constant), Electronic, lnSize number of employees 2017 (log), Construction, Food, Chemical, Textile, Machinery

b. Predictors: (Constant), Electronic, lnSize number of employees 2017 (log), Construction, Food, Chemical, Textile, Machinery, KM_practices Employee level knowledgemngt activities, CleanProdData data storage of optimization, maintenance, utilization, productivity

c. Predictors: (Constant), Electronic, lnSize number of employees 2017 (log), Construction, Food, Chemical, Textile, Machinery, KM_practices Employee level knowledgemngt activities, CleanProdData data storage of optimization, maintenance, utilization, productivity, I_KM_CPD

d. Dependent Variable: lnScrapRate

Table 19: ANOVA statistics of dependent variable Scrap Rate

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	18,496	7	2,642	3,119	,004[b]
	Residual	165,190	195	,847		
	Total	183,687	202			
2	Regression	18,698	9	2,078	2,430	,012[c]
	Residual	164,988	193	,855		
	Total	183,687	202			
3	Regression	19,428	10	1,943	2,271	,016[d]
	Residual	164,259	192	,856		
	Total	183,687	202			

a. Dependent Variable: lnScrapRate

b. Predictors: (Constant), Electronic, lnSize number of employees 2017 (log), Construction, Food, Chemical, Textile, Machinery

c. Predictors: (Constant), Electronic, lnSize number of employees 2017 (log), Construction, Food, Chemical, Textile, Machinery, KM_practices Employee level knowledgemngt activities, CleanProdData data storage of optimization, maintenance, utilization, productivity

d. Predictors: (Constant), Electronic, lnSize number of employees 2017 (log), Construction, Food, Chemical, Textile, Machinery, KM_practices Employee level knowledgemngt activities, CleanProdData data storage of optimization, maintenance, utilization, productivity, I_KM_CPD

Table 20: Coefficients of Scrap Rate

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	,856	,318		2,695	,008		
	lnSize number of employees 2017 (log)	,153	,077	,138	1,983	,049	,953	1,049
	Food	-,426	,268	-,124	-1,588	,114	,757	1,321
	Textile	,140	,224	,051	,623	,534	,676	1,479
	Construction	,154	,437	,025	,352	,725	,909	1,100
	Chemical	-,076	,232	-,027	-,326	,745	,694	1,441
	Machinery	,448	,209	,185	2,138	,034	,614	1,630
	Electronic	,401	,198	,178	2,026	,044	,598	1,673
2	(Constant)	,795	,345		2,303	,022		
	lnSize number of employees 2017 (log)	,161	,086	,145	1,882	,061	,781	1,280
	Food	-,425	,269	-,124	-1,578	,116	,756	1,322
	Textile	,138	,226	,051	,613	,540	,676	1,479
	Construction	,166	,441	,027	,377	,707	,902	1,108
	Chemical	-,069	,234	-,024	-,296	,768	,691	1,447
	Machinery	,456	,214	,189	2,131	,034	,594	1,684
	Electronic	,402	,199	,178	2,018	,045	,597	1,674
	KM_practices Employee level knowledgemngt activities	,019	,042	,034	,450	,653	,838	1,193
	CleanProdData data storage of optimization, maintenance, utilization, productivity	-,022	,067	-,026	-,326	,744	,709	1,411
3	(Constant)	,796	,345		2,305	,022		
	lnSize number of employees 2017 (log)	,156	,086	,141	1,816	,071	,778	1,285
	Food	-,421	,270	-,123	-1,561	,120	,756	1,322
	Textile	,141	,226	,052	,623	,534	,676	1,480
	Construction	,173	,441	,028	,392	,695	,902	1,108
	Chemical	-,058	,234	-,020	-,246	,806	,689	1,451
	Machinery	,460	,214	,191	2,153	,033	,594	1,685
	Electronic	,403	,199	,179	2,021	,045	,597	1,675
	KM_practices Employee level knowledgemngt activities	,020	,042	,036	,481	,631	,837	1,194
	CleanProdData data storage of optimization, maintenance, utilization, productivity	-,036	,069	-,043	-,520	,604	,675	1,481
	I_KM_CPD	,033	,036	,066	,924	,357	,918	1,089

a. Dependent Variable: lnScrapRate

Output dependent variable Quality Complaints

Table 21: Model Summary of dependent variable Quality Complaints

Model Summary[d]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,408[a]	,166	,136	,79981	,166	5,557	7	195	<,001	
2	,435[b]	,189	,152	,79269	,023	2,759	2	193	,066	
3	,436[c]	,190	,148	,79457	,000	,091	1	192	,763	2,068

a. Predictors: (Constant), Electronic, lnSize number of employees 2017 (log), Construction, Food, Chemical, Textile, Machinery

b. Predictors: (Constant), Electronic, lnSize number of employees 2017 (log), Construction, Food, Chemical, Textile, Machinery, KM_practices Employee level knowledgemngt activities, CleanProdData data storage of optimization, maintenance, utilization, productivity

c. Predictors: (Constant), Electronic, lnSize number of employees 2017 (log), Construction, Food, Chemical, Textile, Machinery, KM_practices Employee level knowledgemngt activities, CleanProdData data storage of optimization, maintenance, utilization, productivity, I_KM_CPD

d. Dependent Variable: lnQualityComplaints

Table 22: ANOVA statistics of dependent variable Quality Complaints

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	24,884	7	3,555	5,557	<,001[b]
	Residual	124,742	195	,640		
	Total	149,626	202			
2	Regression	28,351	9	3,150	5,013	<,001[c]
	Residual	121,274	193	,628		
	Total	149,626	202			
3	Regression	28,409	10	2,841	4,500	<,001[d]
	Residual	121,217	192	,631		
	Total	149,626	202			

a. Dependent Variable: lnQualityComplaints

b. Predictors: (Constant), Electronic, lnSize number of employees 2017 (log), Construction, Food, Chemical, Textile, Machinery

c. Predictors: (Constant), Electronic, lnSize number of employees 2017 (log), Construction, Food, Chemical, Textile, Machinery, KM_practices Employee level knowledgemngt activities, CleanProdData data storage of optimization, maintenance, utilization, productivity

d. Predictors: (Constant), Electronic, lnSize number of employees 2017 (log), Construction, Food, Chemical, Textile, Machinery, KM_practices Employee level knowledgemngt activities, CleanProdData data storage of optimization, maintenance, utilization, productivity, I_KM_CPD

Table 23: Coefficients of Quality Complaints

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	1,311	,276		4,749	<,001		
	lnSize number of employees 2017 (log)	-,039	,067	-,039	-,582	,561	,953	1,049
	Food	-,762	,233	-,246	-3,272	,001	,757	1,321
	Textile	-,140	,195	-,057	-,720	,472	,676	1,479
	Construction	,599	,380	,108	1,578	,116	,909	1,100
	Chemical	-,219	,202	-,085	-1,086	,279	,694	1,441
	Machinery	,532	,182	,244	2,924	,004	,614	1,630
	Electronic	,124	,172	,061	,719	,473	,598	1,673
2	(Constant)	1,214	,296		4,105	<,001		
	lnSize number of employees 2017 (log)	,030	,073	,030	,407	,684	,781	1,280
	Food	-,752	,231	-,242	-3,254	,001	,756	1,322
	Textile	-,147	,193	-,060	-,759	,449	,676	1,479
	Construction	,663	,378	,120	1,754	,081	,902	1,108
	Chemical	-,226	,200	-,088	-1,131	,260	,691	1,447
	Machinery	,467	,183	,214	2,551	,012	,594	1,684
	Electronic	,113	,171	,056	,665	,507	,597	1,674
	KM_practices Employee level knowledgemngt activities	-,021	,036	-,042	-,592	,555	,838	1,193
	CleanProdData data storage of optimization, maintenance, utilization, productivity	-,111	,058	-,149	-1,932	,055	,709	1,411
3	(Constant)	1,215	,297		4,096	<,001		
	lnSize number of employees 2017 (log)	,028	,074	,028	,385	,700	,778	1,285
	Food	-,750	,232	-,242	-3,241	,001	,756	1,322
	Textile	-,146	,194	-,060	-,754	,452	,676	1,480
	Construction	,665	,379	,120	1,755	,081	,902	1,108
	Chemical	-,223	,201	-,087	-1,111	,268	,689	1,451
	Machinery	,469	,184	,215	2,551	,012	,594	1,685
	Electronic	,114	,171	,056	,665	,507	,597	1,675
	KM_practices Employee level knowledgemngt activities	-,021	,036	-,041	-,580	,563	,837	1,194
	CleanProdData data storage of optimization, maintenance, utilization, productivity	-,115	,059	-,154	-1,947	,053	,675	1,481
	I_KM_CPD	,009	,031	,020	,302	,763	,918	1,089

a. Dependent Variable: lnQualityComplaints