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The transition to predictive quality in high-knowledge manufacturing industries

A case study of obstacles and facilitators for digital innovations in quality management for lithium-ion battery manufacturing

Master's thesis in Management and Economics of Innovation

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Abstract

The rise of industry 4.0 facilitates many opportunities for the manufacturing industry, turning some into a digitalized, high-knowledge industries and enabling a whole new scale, customization, and optimization. Quality 4.0 captures the same benefits as Industry 4.0 but is still fairly underutilized. The purpose of this thesis is to provide insights on the implementation of predictive quality innovations, which are data-based quality assurance methods that utilize statistical patterns to predict future outcomes, in a high-knowledge manufacturing company. This was done by investigating obstacles to the implementation and how these could be reduced by drawing upon three constructs from innovation implementation literature; management support, information- and knowledge diffusion, and implementation climate. To investigate this, an eight-week, longitudinal single-case study of a European lithium-ion battery manufacturing was performed. Seven predictive quality projects were observed, which spanned from software-based innovations aiming to develop a machine learning algorithm for process optimization, to digital technology innovations, which aimed for enabling quality data analytics. Data collection also included observations of company documents, and 16 interviews with company employees from different departments, such as the Quality department, Digitalization department, and other departments involved in the projects. Four obstacles to the implementation of predictive quality innovations were identified, a technological obstacle, a resistance obstacle, a deliverable obstacle, and a supportive obstacle. Further, all constructs had an impact on each of the obstacles, for instance through bridging new cross-departmental dependencies that emerged from the combined digital- and quality characteristics of predictive quality methods in a complex manufacturing setting. The insights from this thesis contribute to the literature on digital transformation by providing a detailed empirical account of implementing data-driven innovation in a complex context. For practitioners, the findings are useful in providing guidance to mitigate challenges in the transition towards Quality 4.0.

Keywords: Predictive Quality, Predictive Analytics, Data Analytics, Quality Management, Quality 4.0, Industry 4.0, High-knowledge Manufacturing Industry, Lithium-Ion Battery Manufacturing

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Hanna Bergland & Emelie Lundqvist, Gothenburg, May 2022

List of Acronyms

Acronyms list that are used throughout this thesis in alphabetical order:

I4.0	Industry 4.0
IIoT	Industrial Internet of Things
IoT	Internet of Things
KPI	Key Performance Indicator
ML	Machine Learning
QCA	Qualitative Content Analysis

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1
Introduction

The digitalization trend is spanning branch-wide and our surrounding is increasingly filled with digital components and technologies. The high-knowledge manufacturing industries are no exceptions, especially as they demand a large degree of technological- and scientific knowledge in each process step (Powell & Snellman, 2004), throughout a long process chain. The fourth industrial revolution, Industry 4.0, has indeed brought about new and exciting opportunities and challenges.

The recent electrification trend has further resulted in an upswing for the battery market. Not the least of lithium-ion batteries as that technology is considered fit for the electrification of the automotive industry (Curry, 2017). The lithium-ion battery manufacturing is a complex and knowledge-intense process (Li, Lu, Chen, & Amine, 2018; Turetskyy et al., 2020), and thereby one example of a high-knowledge industry. Lithium-ion battery application areas request low cost, but most prevalent high safety and a long life-cycle (Goodenough & Kim, 2010), meaning high-quality requirements.

The new opportunities with Industry 4.0 have been reflected in the quality domain, where optimization and data modeling technologies are applied to keep up the high development pace of the digitalized industrial setting. A paradox in the new, digitalized, quality domain is to improve, assure, and optimize the quality, and do it fast while meeting the uncertainties new innovative technologies bring in a highly complex setting with extensive safety and quality demands. By researching the topic of implementation of innovations for predictive quality methods, which are data-based and statistically modeled quality assurance methods, the paradox may become a little less complex. The findings could provide a tool for accelerating the conversion to electrification by enabling an optimized way of handling quality issues in high-knowledge manufacturing industries, like the lithium-ion battery industry.

This chapter aims to provide a background for the thesis, elaborate on relevant concepts, as well as clarify the research gap and the direction of research.

1.1 Background

One driver of the transition towards Industry 4.0 was the demand for faster innovation (Lasi, Fettke, Kemper, Feld, & Hoffmann, 2014). Innovation is, in its purest form, the creation of a product or a process that is novel and useful (O'Sullivan &

Dooley, 2008). It is also a key driver for a company to reach competitive advantage and stay competitive over the years. Innovation is a strategic choice that a company makes to position itself on the front line of the market to achieve competitiveness. However, it is difficult where many attempts fail due to an innovation strategy that is decoupled from the business strategy (Pisano, 2015).

The digitalized trend has brought new opportunities and challenges to companies' innovation capabilities. A digital innovation could be both the innovation outcome, that was made possible from digital technologies and digitized processes, but also a new, enabling, digital technology being the innovation itself (Ciriello, Richter, & Schwabe, 2018). Meaning that new digital technologies bring innovation opportunities by having the role as both the basis and the result of digital innovation. However, the high speed and fast changes in the digital domains also come with challenges to digital innovations through demanding a high pace and continuously ongoing progress (Yoo, Boland Jr, Lyytinen, & Majchrzak, 2012).

Digital innovations applied to the quality domain are part of Quality 4.0, the quality domains sub-category of Industry 4.0. Historically, quality management has been viewed as its own field, but lately, it has become more evident that *'quality'* permeates everything within a company, which is in line with the increased quality demands and expectations (Hoyle, 2007). Quality management is thereby crucial to ensure competitiveness, not least in the manufacturing industry. However, the development in the quality management field is, by some, seen as stagnated, where few digital, innovative, quality models and technologies have been proposed and adopted (Zonnenshain & Kenett, 2020). This is despite the usability of connected factories is argued to be amongst the highest within the quality field (Hoyle, 2007). There is, hence, an urgent need for quality teams within companies to adapt to digital innovations and apply modern data analytics to utilize correlated benefits and, thereby, accelerate the transition to Quality 4.0. Essential within Quality 4.0 is that quality should be a data-driven and evidence-based disciple (Zonnenshain & Kenett, 2020), and a way to achieve this is through predictive quality.

The use of data analytics and predictive quality holds the promise of generating competitive advantage as it is a way of optimizing costs by fast and statistically supported proving the quality of products and processes (Belhadi, Zkik, Cherrafi, Sha'ri, et al., 2019), in comparison to manually controlling the quality through traditional methods. Traditional quality methods refer to quality improvements or tests performed by applying quality concepts on non-connected data, such as notes, reports, or extracted results, to understand what happened in the process through descriptive analysis or why it happened through diagnostic analysis (Jacob, 2017). Traditional quality is, hence, more time-consuming and risks overlooking important holistic or interlinked relationships, as a consequence of context-bounded data usage. Adopters of predictive analytics, thus, expect economic advantages as it would allow for a decrease in both the time for quality inspections and the number of products required for testing (Schmitt, Bönig, Borggräfe, Beitinger, & Deuse, 2020).

This study will investigate obstacles to the implementation of predictive quality innovations in high-knowledge manufacturing industries. Innovation can be thought of as a multi-stage process, as visualized in figure 1.1. One of the stages is to bring innovation from development into an organizational context, known as the implementation. The implementation of innovation is a head-itching issue for companies which is crucial to understand since it is in that phase where innovations often fail (Klein, Conn, & Sorra, 2001).

The study will contemplate a battery manufacturing company as an empirical context for exemplifying a high-knowledge manufacturing industry. Battery manufacturing includes a long and highly complex process where the companies aim for cost-efficient and high-performing products, but not at the expense of quality because of the risks associated with battery defects. Cost, safety, and battery life are all critical challenges to overcome in this field (Goodenough & Kim, 2010) and are all connected to quality. To ensure competitiveness there is a need for a quick transition to Quality 4.0, which is why battery manufacturing is considered interesting as an empirical context for this study. The past couple of years has exhibited an explosion in the battery market as a response to the electrification trend. Several large battery manufacturers are establishing in Europe, and by 2023 the supply of European-produced batteries is predicted to surpass the European demand (Transport & Environment, 2021).

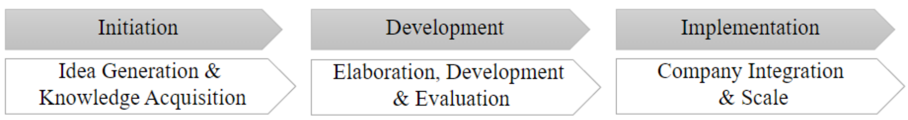

Figure 1.1: A three step innovation process inspired by Garud, Tuertscher, and Van de Ven (2013) and Pichlak (2016).

1.2 Problem identification

Despite the heavy digitization trend of manufacturing processes and the last decade's advancement of concepts like Industry 4.0 (Lasi et al., 2014) and smart factory (Lucke, Constantinescu, & Westkämper, 2008), the area of *digitization in manufacturing* has little scientific research (Brettel, Friederichsen, Keller, & Rosenberg, 2017) and there is still a low degree of connectivity in manufacturing (Khan & Turowski, 2016; Sufian, Abdullah, Ateeq, Wah, & Clements, 2021). Existing research mainly focuses on the overarching concept of Quality 4.0, and some on more detailed topics, such as predictive maintenance. However, a gap has been identified in the research on how organizations implement innovations for predictive quality exclusively. Predictive quality is largely based upon big data analytics where management capability, technical capability, and talent capability are claimed key issues to consider and overcome to capture the related benefits (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016). Moreover, the implementation of quality management tools in a digitized setting is considered to be a complex and uncharted question (Clancy, O'Sullivan, & Bruton, 2021; Zangiacomi, Pessot, Fornasiero, Bertetti, &

Sacco, 2020), which needs to be examined further.

1.2.1 Purpose and research question

The purpose of this thesis is to contribute to the research within the field of data-driven quality management, and specifically on how to enable the implementation of data-driven innovations within predictive quality. This bridges part of the existing gap in quality management's adaptation to, and application in, digitalization. It could further contribute to the knowledge of how to implement predictive analytics innovations in the quality field, something that is identified as lacking. The findings could provide companies in high-knowledge manufacturing industries, like lithium-ion battery manufacturers, with ideas on how to better meet the increasing quality demands, how to adapt to Quality 4.0, and thereby how to be and stay competitive. Two research questions to be answered have been lined out to fulfill the purpose:

RQ1: What obstacles influence the implementation of data-driven innovation for predictive quality in high-knowledge manufacturing?

RQ2: How do management support, information diffusion, and the implementation climate impact these obstacles to enable a successful implementation of predictive quality innovations within a company operating in the high-knowledge manufacturing industry?

1.2.2 An innovation implementation framework

A lack of implementation effectiveness is argued to be one main reason why innovations fail, which itself is impacted by many different factors in an organization. The thesis zooms in to keep a narrow scope and covers three constructs that are identified to impact the implementation success. The basis of the framework is extracted from Klein et al. (2001) well-cited one but adapted to cover the highly critical aspect of information exchange (Van Riel, Lemmink, & Ouwersloot, 2004). Figure 1.2 visualizes the framework used for the thesis.

Management support
The construct 'management support' impacts the implementation of innovations to a large extent. It can, amongst all, influence the use effectiveness (Leonard-Barton & Deschamps, 1988), enable for collective acceptance (Choi & Chang, 2009), and resource allocation (Dewett, Whittier, & Williams, 2007). Management often has a sponsorship role and can further act as gatekeepers. Hence, management support extends to several influential areas for implementation success as they have decision power, can set up strategies, and form the innovation direction.

Information- and knowledge diffusion
Implementation success requires user acceptance, which often can be hampered by various uncertainties. Increased communication (Fidler & Johnson, 1984) and free information flow (Van Riel et al., 2004) help reduce uncertainties and increase the

likelihood of implementation success, meaning that the construct 'information- and knowledge diffusion' thereby impacts the success rate. Sufficient knowledge, relevant to the innovations, must be spread throughout the organization to achieve the change that the innovation brings (Hislop, Newell, Scarbrough, & Swan, 2000), not the least information must be distributed clearly to decision-makers to enable fair decisions for the innovation progress (Van Riel et al., 2004). The construct is highly relevant to the topic of predictive quality as several domains are required to collaborate, who not necessarily has collaborated, nor depended on one another before.

Implementation Climate
The constructs 'management support' and 'information- and knowledge diffusion' both have an effect on the construct 'implementation climate'. Klein and Sorra (1996) argue that a strong implementation climate positively impacts the implementation of innovations, as it (1) assures sufficient skills and resources are available, (2) motivates through incentivising adoption, and (3) eliminates barriers.

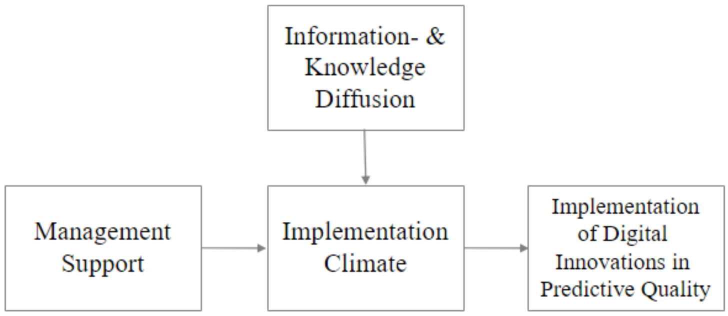

Figure 1.2: A theoretical research framework, based on a implementation effectiveness model by Klein, Conn, and Sorra (2001), and the aspect of information- and knowledge diffusion as discussed by Hislop, Newell, Scarbrough, and Swan (2000) and Van Riel, Lemmink, and Ouwersloot (2004).

2

Literature review

This chapter gives an overview of the literature that underlies the study. Starting by presenting the digitalization of manufacturing and digitalization of the quality domain including the thesis' core concept, namely predictive quality. Then, digital innovations are emphasized, whereafter a framework for implementation of innovations is presented. The framework consists of three constructs; management support, information diffusion, and implementation climate, and have a focus on their influence on the implementation of innovations.

2.1 Digitalization of manufacturing

Over the last couple of decades, European manufacturing has declined as a result of globalization and the trend of locating manufacturing industries in countries with low labor costs (Westkämper & Walter, 2014). However, with the introduction of Industry 4.0 (I4.0), Westkämper and Walter (2014) highlight that there is once again a belief in gaining productivity in Europe with the shift towards digitalized, high-knowledge industries and thereby boosting economic growth. High-knowledge manufacturing industries are, in this study, defined as industries that, to a large extent, are based on knowledge-intense process steps, in which high technological- and scientific knowledge is essential (Powell & Snellman, 2004). Moreover, I4.0 is a broadly defined term that includes automated manufacturing, robotics, digitally integrated-, and data connected processes (Lasi et al., 2014), amongst others, and has indeed brought about a paradigm shift and advanced the world economy.

The technologies relating to I4.0 have enabled smart factories, which are factories having integrated sensors and other data-generating industrial internet of things (IIoT) that enable connectivity throughout the whole process (Lasi et al., 2014; Lucke et al., 2008). These resources generate higher productivity, better quality, a larger degree of flexibility, and lower labor costs. That is since the industry largely depends on smart technologies, intelligent robots, and simulations, to name a few, which are digital tools enabled by the vast amount of data produced (Westkämper & Walter, 2014). Such generated data becomes a resource for optimization, quality improvement, and better company performance (Akter et al., 2016), and thereby, competitiveness.

2.1.1 Digitalization of quality management

Despite all the opportunities I4.0 brings, the quality management profession is lagging in utilizing the related benefits (Zonnenshain & Kenett, 2020). Quality management is a broad concept covering quality activities within an organization with the ultimate goal of improving the quality (Hoyle, 2007). The term *'quality'* is defined as the degree to which certain attributes satisfy expectations, requirements, or needs. Quality 4.0 is a subcategory of the concept of Industry 4.0 and refers to the use of technologies and data to monitor and improve quality performance (Johnson, 2019). Meaning that Quality 4.0 is the digitalization of quality management, building on the same concepts as I4.0 does. The quality management field has a long history with established concepts and well-developed practices which are proclaimed to be unfit for the increased need of shortening time-to-market while assuring high-quality (Mikawa, 2015). Traditional quality methods refer to quality improvements, or tests, performed by applying quality concepts on non-connected data, such as notes, reports, or results, to understand what happened in the process through descriptive analysis, or why it happened through diagnostic analysis (Jacob, 2017). Instead of relying on traditional quality methods with descriptive characteristics, and introducing I4.0 concepts such as data collection, process connectivity, and internet of things (IoT) into the quality management field, the quality management within manufacturing can be advanced (Mikawa, 2015).

In a manufacturing setting, the Quality 4.0 concept is argued to be key to long-term success or even survival of the company (Javaid, Haleem, Singh, & Suman, 2021). Rather than quality methods being utilized as a prevention tool, that instead can be integrated to analyze the consistency of products and processes, i.e. the introduction of traceability, as well as quickly and early find deviations. Both reduce many quality risks and potential disturbances on the line. Further, traditional and manual checks for quality are not suitable or aligned with high-quality demands in a large-scale setting, nor is it flexible enough to meet the modern requirements of mass customization. In these settings, Javaid et al. (2021) argue for an urgent need of applying Quality 4.0 methods to even survive.

2.1.1.1 Predicting quality through predictive analytics

A sub-category of Quality 4.0 is predictive quality. Predictive quality is a concept that includes data-based methods to understand and recognize statistical patterns, which could predict future events in processes or predict product quality outcomes (Nalbach, Linn, Derouet, & Werth, 2018). Hence, predictive quality is, in comparison to traditional, a way of foreseeing and assuring product quality before a product is finalized. Previous research has largely focused on the overall concept of Quality 4.0 with several quality-specific concepts, such as machine- and process maintenance, machine performance, process optimization, and product quality, under the same framework (Jacob, 2017; Johnson, 2019; Zonnenshain & Kenett, 2020). Predictive quality alone is less elaborated upon (Yorulmuş, Bolat, & Bahadır, 2021) but builds on the concepts of predictive analytics applied in a quality management setting. Predictive analytics utilizes a vast amount of data and mathematical modeling to analyze past events to predict future ones (Lustig, Dietrich, Johnson, & Dziekan, 2010). Predictive analytics methods are often applied instantaneously with the process under investigation and include, amongst others, data mining for finding correlations, pattern recognition, forecasting, and predictions of future events (Lustig et al., 2010).

The use of data analytics and predictive quality methods holds the promise of gaining a competitive advantage. It is a way of optimizing costs by fast and statistically supported proving the quality of products and processes (Belhadi et al., 2019) and also reducing recalls or achieving near to zero nonconformities (Yorulmuş et al., 2021), in comparison to manually checking and validating quality through traditional methods. Manual checks are not scalable for today's demands (Javaid et al., 2021), and it is proved that machine learning (ML) algorithms and cloud computing predictive methods can decrease the amount required samples for manual quality inspections, as those instead can be done dynamically throughout the process (Schmitt et al., 2020). Hence, predictive analytics, in a quality setting, can be utilized for assuring quality throughout the production process and early find deviations that otherwise would have been resource-intense (Nalbach et al., 2018).

2.1.1.2 Novel needs and structures with digitalized quality management

Digital innovations come with requirements for new knowledge and skills, which fit the new attributes of the digital technologies, which Nylén and Holmström (2015) argue demands structures for ongoing learning and dynamic teams. Similarly, Javaid et al. (2021) point out that the introduction of Quality 4.0 concepts will require a new baseline for skills and best practices within the quality domain. The new skills required for digital innovations could be borrowed from external consultancy services, but as Nylén and Holmström (2015) highlight, it is wiser to incorporate such skills in-house since digital innovations often indicate fast-moving processes where agility and adaption are critical characteristics.

A key challenge is to merge the new skills with the existing ones. As Nylén and Holmström (2015) point out, the high-quality demands of today require the incorporation of domain expertise into the new digital innovations to not compromise on the quality. Merging different expertise may, however, be challenging. Bechky (2003) argues that one challenging aspect of sharing knowledge across domains is rooted in the various professions contrasting views of the context, and speaks, as the author phrases it, different languages. It can thereby be hard to create a joint foundation, but Bechky (2003) highlights its necessity to overcome the challenge and to gain an even better understanding of the technology or problem due to many merged perspectives.

Worth mentioning is that Quality 4.0 comes with a new knowledge dimension where the perception of quality gets shifted to instead permeate the whole organization, as it aims to connect and integrate quality- and optimization aspects throughout all domains, including both material-, process-, and quality expertise, as well as, analytical- and data expertise (Javaid et al., 2021). Indicating that once sufficient skills and structures are in place, the quality domain transforms into a cornerstone, prevalent in all domains.

2.1.2 An immature digitalized manufacturing setting

The concept of Industry4.0 is only dating back a decade (Lasi et al., 2014), and it is argued that the adoption of digitally equipped processes is progressing faster than the integration of them (Khan & Turowski, 2016; Sufian et al., 2021), i.e., full connectivity and smart factories are still rare and the concepts immature. Despite the many attempts toward I4.0, P. Johansson, Malmsköld, Fast-Berglund, and Moestam (2019) highlight the many challenges remaining before reaching full implementation degree of I4.0 concepts. The lack of full integration and connectivity of data can result in data silos since no standardized data management approach throughout the processes nor from a holistic view is set, which could lead to faulty interpretations of the data and the processes (Khan & Turowski, 2016).

According to Zangiacomi et al. (2020), it is common to disregard opportunities that come with the digitalization of manufacturing, in terms of integrating technologies or models in several levels or steps throughout the manufacturing, as well as fully adapting to the changes required for total utilization. From a quality perspective, there is a need for the smart factory concept to fully emerge in order to see the process as a whole rather than as discrete events throughout the process line and to utilize quality-assuring technologies to their full potential (Powell, Eleftheriadis, & Myklebust, 2021), as the purpose with fully connected Quality 4.0 is to track the products to find deviations as early as possible and in real-time (Javaid et al., 2021).

2.1.2.1 Lithium-ion battery manufacturing as a high-knowledge manufacturing industry

The context of lithium-ion battery manufacturing, as an example of the high-knowledge manufacturing industry, is no exception when it comes to manufacturing digitalization immaturity. Lithium-ion battery manufacturing could be seen as high-knowledge manufacturing as it is a complex process where the different manufacturing steps demand expertise (Li et al., 2018; Turetskyy et al., 2020). Turetskyy et al. (2020) explain how to make the lithium-ion battery manufacturing process data-driven, but conclude that data-driven methods for improving processes and assuring quality are not yet utilized to any large extent. The immaturity in connectivity is further exemplified by the author, elaborating on how to merge different data sources, of both analog and digital types, to gain the insights necessary. Meaning that the holistic picture gets lost.

Despite the immaturity in the connectivity, there is a vast amount of data produced throughout the processes as a consequence of the highly complex manufacturing process, including more than 600 factors which Turetskyy et al. (2020) identified could have an impact on the end result of one type of battery cell. However, the amount of the various data is not sufficient since lithium-ion batteries not yet are manufactured at mass-scale (Westermeier, Reinhart, & Zeilinger, 2013). Meaning that there is a data deficiency from a data science point of view. As a result, the data-driven quality models are often based on small-scale data from pilot lines, which only brings little knowledge and is, hence, challenging to use as the only source to base the quality innovations upon.

2.2 Digital innovations

The digitized world has given new opportunities and challenges considering companies' innovation capabilities. Digital innovation can be defined as both the innovation outcome, that was made possible because of digital technologies and digitized processes, and a new enabling digital technology which is the innovation itself (Ciriello et al., 2018). This implies that new digital technologies have given opportunities for innovation by being both the basis for and the result of digital innovation.

The increased digitalization has impacted the innovation domain, not only in the technology aspect per se but also in the pace at which innovations must proceed. Yoo et al. (2012) argue for this by explaining that digital innovations must adapt to a fast-changing, digitalized, setting where the process must be fast and continuously ongoing. The demand for continuity in innovation refers to competitiveness in a fast-changing environment (Yoo et al., 2012), but also to digital components and technologies being interlinked, meaning that an innovative change within a process or a component often results in a surge in the connected ones (Pershina, Soppe, & Thune, 2019).

The digital resources interlink characteristics means cooperation amongst the technologies (Javaid et al., 2021) and are by Henfridsson, Nandhakumar, Scarbrough, and Panourgias (2018) described as building blocks for a wider scope of applicability of the digital innovation. They argue that digital innovations could be recombined and utilized in additional areas, which increases the value of the innovation and the potential for its generalizability.

An increased speed in digital innovations has caused a struggle in how to prioritize the available resources to optimize the investments (Zangiacomi et al., 2020). An approach for facing this is proposed by Zangiacomi et al. (2020) and relates to putting a large effort into early stages and pilot projects or prototypes to carefully evaluate it before the more resource intense, but still proposed step-wise, scaling phases emerge.

2.3 An innovation implementation framework

A lack of implementation effectiveness is argued to be one main reason why innovations fail. Implementation effectiveness is defined as the systematic use and usability of an innovation in an organization (Klein & Sorra, 1996). The well-cited study from Klein et al. (2001) provide a framework of constructs that influence the implementation effectiveness of an innovation, and hence the innovation's success.

To achieve benefits from a new digital innovation in a company, the employees must accept it and include it in their daily work, i.e., realize its usefulness, according to the Technology Acceptance Model (Davis, 1989). Further, the perceived risks, which come as a result of an innovation's complexity and uncertainties, must be bridged to minimize resistance from employees and achieve implementation success (Fidler & Johnson, 1984). The climate for implementation is defined by Klein and Sorra (1996) as the sum of the shared perceptions the employees have towards the importance of innovation, whereas the perceptions are based upon shared experiences and information about how innovation implementation events and practices are to be conducted. A climate that is favorable for information exchange of innovation increases the probability of innovation success (Van Riel et al., 2004). The role of information- and knowledge diffusion is not existing in Klein et al. (2001)'s model, despite the construct is expected to influence the implementation climate.

The parameter information- and knowledge diffusion, which by Van Riel et al. (2004) is argued to impact the implementation success of digital innovations, is added to the implementation model originally developed by Klein et al. (2001), to gain a deeper understanding of implementation success. The adapted model for this study zooms in specifically on the upper branch of the original model and is, hence, focusing on the management support's and implementation climate's influences on the implementation effectiveness of innovations. The three constructs of interest in the adapted model are *management support*, *information- and knowledge diffusion*, and *Implementation climate*. Figure 2.1 shows a conceptualization of Klein and Sorra (1996)'s implementation effectiveness model, but with the adaption of information- and knowledge diffusion, showing the reasoning for the proposed theoretical framework and how it fits into the original model as well as the focus for the study.

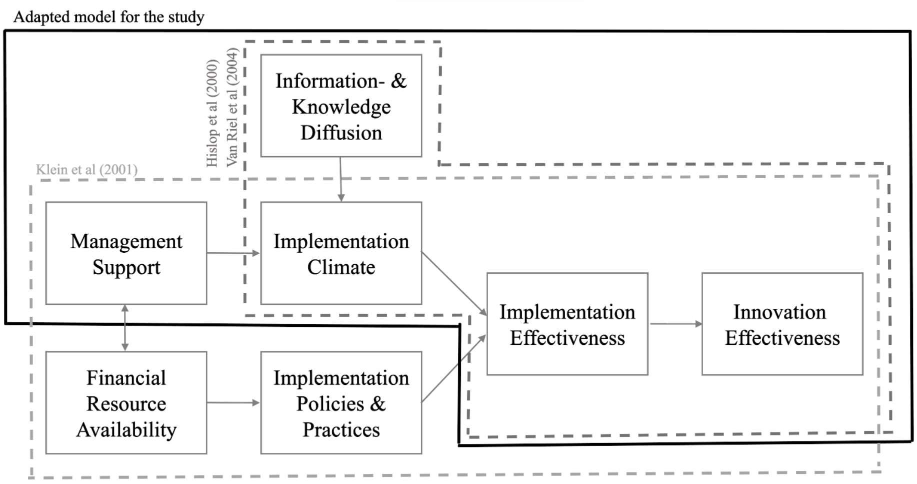

Figure 2.1: Illustration of the innovation implementation framework used in this study. Showing the reasoning behind the chosen constructs from existing literature by Hislop, Newell, Scarbrough, and Swan (2000), Klein, Conn, and Sorra (2001), and Van Riel, Lemmink, and Ouwersloot (2004).

2.3.1 Management support

Klein et al. (2001) find management support to be positively correlated to the innovation implementation climate. Management support is claimed to influence both the individual adoption of an innovation and how effective the innovation is used by the individual (Leonard-Barton & Deschamps, 1988). By supporting an innovation, and by providing a clear vision for the implementation, the management can impact the collective acceptance of the innovation within the organization (Choi & Chang, 2009; Klein et al., 2001).

2.3.1.1 Handling ambidexterity and allocating resources

Finding a balance between exploiting established technologies and methods, and exploring new innovations, i.e. handling ambidexterity, is according to O'Reilly III and Tushman (2008) crucial for the survival of a company. O'Reilly III and Tushman (2008) elaborate on several strategies to reach success in ambidextrous situations, including the necessity of a company to have a clear vision for what they are trying to achieve, and how to allocate resources between exploration and exploitation. This should preferably be decided and elaborated upon by senior managers, and then distributed throughout the company and execute the decisions made (O'Reilly III & Tushman, 2008).

Similarly, Dewett et al. (2007) highlight that senior managers can be seen as sponsors in the implementation process as they can affect the allocation of the resources necessary for success. A sponsor can be defined as someone within the company that provides both formal and informal support to a project through, for instance, providing resources (Markham, Ward, Aiman-Smith, & Kingon, 2010). However, different managers see different values in innovations, as a result of their previous experiences (Kotter et al., 1995), which could affect the way they decide to allocate resources.

2.3.1.2 Decision-making authority and gate keeping control

Managers also function as gatekeepers, as they are being the ones who set criteria and make the decisions for the continuation of a project (Markham et al., 2010). Hence, the importance of management support extends to the forthcoming activities in the implementation process, e.g. the decision making. According to Dewett et al. (2007), complex innovations have to pass through decision-making by managers at several levels of the company. Further, Klein and Sorra (1996) explain that if local managers are excluded from the decision-making process, it tends to negatively impact the managers' interest in creating a strong implementation climate. However, as been pointed out by Dewett et al. (2007), the management, and specifically the top management, might not share the same interest and a common goal. This could lead to conflicting support from management for different projects or innovations, which in turn could lead to rivalry, competition for resources, and the formation of political alliances within the company (Dewett et al., 2007).

Van Riel et al. (2004) describe it as critical to avoid decision-making uncertainties when it comes to innovations, as such decreases the chances for successful implementation of the innovation. According to Van Riel et al. (2004), information diffusion is a way to reduce these uncertainties for decision-making, which is further discussed in 2.3.2. In addition, Zangiacomi et al. (2020) explain that top management must understand the benefits and value of technological innovations and must also be responsive to any changes that come with the digitalization in a manufacturing setting. The authors claim that this can be achieved through ensuring better knowledge sharing within top management.

2.3.1.3 Motivating and creating use incentives

Even if management would share common objectives, and even if these are well distributed in the company, employees are, according to S. Johansson, Kullström, Björk, Karlsson, and Nilsson (2020), often unsure of how they could contribute to these objectives. Moreover, Davis (1989) highlights the need for perceived ease of use from employees, implying that a person is more likely to start using an innovation if it is free of effort. This is strongly linked to both management support and, further, to the implementation climate. Management support could promote use incentives through signaling the importance of change and implementation of an innovation, showing that it is expected and possibly also rewarded (Klein et al., 2001). Furthermore, the management as a decision-making unit could through support, in terms of evidence and rational arguments for the reason behind the innovation, its functionality, and its usefulness, convince employees to voluntarily change their behavior and accept the innovation (Fidler & Johnson, 1984). Thereby, management support gives use incentives that strengthen the implementation climate (Klein & Sorra, 1996), as further described in 2.3.3.

2.3.2 Information- and knowledge diffusion

A free flow of information and an effective strategy of information diffusion increases the likelihood of success of an innovation (Van Riel et al., 2004). Based on Klein et al. (2001)'s model, this would also mean that information diffusion and, not diminishing information in form of knowledge (Van Riel et al., 2004), is crucial for effective implementation of innovations. Knowledge is in this thesis used interchangeably with information since it is believed that knowledge is a kind of information that needs to be communicated and diffused to decrease uncertainty and encourage innovation and change, and hence, strengthen the implementation climate.

2.3.2.1 Vast communication for aligning parties and gain acceptance

To successfully implement an innovation, it needs to be adopted and diffused by its users. Rogers (2003) describes the diffusion of innovations as the process through which innovation over time spreads among people in a social system. One out of four vital elements to consider for successful diffusion of innovations is communication channels (Rogers, 2003). Through communication, different stakeholders can share information and gain a mutual understanding of the innovation (Rogers, 2003). To gain this mutual understanding and avoid misalignments, Van Riel et al. (2004) suggest an open and informal climate for information diffusion, which is further supported by Bechky (2003). In such an open climate, information sharing will be met by a positive attitude, which will enhance the information diffusion even further (Van Riel et al., 2004). Furthermore, Van Riel et al. (2004) argue that even if the climate for information sharing should be open and informal, clear and structured information channels are crucial for successful implementation, as such effectively distribute relevant information.

Moreover, efficient implementation requires employees' acceptance of the innovation. Davis (1989) explains how technology acceptance from users is crucial to getting the users to adopt the innovation. To gain acceptance from users, uncertainty and complexity related to the innovation need to be reduced, something which can be achieved through increased communication (Fidler & Johnson, 1984). Pershina et al. (2019) explain that consistent collaboration between stakeholders and experts, including constant communication, is needed in complex systems where new digital expertise is required.

A condition to convince the employees, and to get their acceptance of the new technology, is a extensive distribution of a clear vision and expected outcome of the change, as well as extensive and credible communication (Kotter et al., 1995). Fidler and Johnson (1984) note that communication costs, which are determined by the resources required to spread specific information, are higher for a complex innovation associated with large risks, than for a simple, low-risk, innovation. Fidler and Johnson (1984) also state that extensive convincing could lead to increased commitment to the innovations which would positively affect the implementation of it.

2.3.2.2 Networks and organizational integration to facilitate spread of information

A new digital innovation equals a change in the organization, its processes, or its products. Hislop et al. (2000) argue that networks throughout the organization are critical to obtaining relevant knowledge for innovations and achieving the required change for implementation success. Tell, Berggren, Brusoni, and Van de Ven (2017) further highlight the importance of a shared understanding of common objectives between different departments. Lawrence and Lorsch (1967) suggest focusing on organizational integration mechanisms to avoid misalignment in a complex organization considering, for instance, the understanding of common objectives. That is, integration of different teams and departments to more efficiently spread information and align on common tasks and objectives.

2.3.2.3 Persuasive individual to drive the innovation vision

Effective persuasion, both to decrease resistance and to get stakeholders committed, is a strategy that increases the likelihood of successful implementation of complex innovations (Fidler & Johnson, 1984). Dewett et al. (2007) describe how individuals, who promote an innovation and spread the vision of the potential value of the innovation throughout the organization, are crucial for the diffusion of innovations within an organization. These driven individuals are claimed to be of greater importance if the innovation is radical or costly (Dewett et al., 2007). Moreover, employees that have an external orientation are more likely to commit and contribute to innovation projects, which increases the chances of success (Aalbers & Dolfsma, 2015). External orientation is described as employees that open up for cross-boundary communication within the firm, e.g. between different goals while focusing on cross-departmental information sharing (Aalbers & Dolfsma, 2015).

2.3.2.4 Context based information sharing limiting progress and facilitating self-interest

Information diffusion is not always utilized in a way that promotes the implementation of an innovation and the common objective of the company. As Hislop et al. (2000) explain, networks for information diffusion and knowledge transfer could be used to instead spread information relating to the own interest of an individual or specific group. Further, groups, teams, or departments might have different thought worlds. A thought world is described as a group of people within a certain domain that share the same understanding about a phenomenon or a situation (Pershina et al., 2019). When groups from different domains collaborate, they might then have conflicting thought worlds and thereby perceive the innovation differently, for instance considering the value of the innovation or how it should be used (Pershina et al., 2019). This could hinder the diffusion of expert knowledge from different domains. However, Pershina et al. (2019) suggest visual tools, such as whiteboards and prototypes, as a way to align goals and bridge different domains of knowledge and, hence, different thought worlds. This strategy is explained to be especially applicable when merging analog and digital knowledge to align all experts.

2.3.3 Implementation climate

As described, both the constructs *management support* and *information- and knowledge diffusion* positively affects the construct *implementation climate* through making it more robust (Klein et al., 2001; Van Riel et al., 2004). For instance, the facilitation of standards and frameworks by the management, and the communication of an innovation's value and contribution to the company's vision, are both claimed to improve the innovation-value fit (Klein & Sorra, 1996). The innovation-value fit is described by Klein and Sorra (1996) as the perception users have of how an innovation is fitting their values or how it might affect them. A strong fit is, by the authors argued to be, a requirement to achieve a strong implementation climate.

According to Klein and Sorra (1996), a robust implementation climate encourages the use of innovation, and thereby the implementation, in three ways. First, it ensures that the employees have, or get, the required skills to use the innovation. Second, it motivates the adoption of the innovation by providing use incentives and avoidance disincentives. For instance, one way to gain acceptance and motivate the adoption of an innovation is to ensure the perceived ease of use from potential users

(Davis, 1989), as mentioned briefly in 2.3.1.3. Third, it eliminates any hindrances to innovation use. A hinder could for instance be that different employees with different roles such as engineers, technicians, and production workers have different views on the same problem, as described by Bechky (2003). However, Bechky (2003) also adds that one of the best ways to merge these different views is by enabling informal interactions, as touched upon when describing an open climate for information diffusion in 2.3.2.1.

A strong implementation climate leads to a more effective and systematic use of innovations, which in turn increases the perceived usefulness and perceived benefits of the innovation (Klein et al., 2001). The perceived usefulness is an individual's feeling that adopting an innovation would boost the person's job performance and the perceived benefit. The benefits could be any which are associated with the adoption of an innovation, e.g. economic benefits, and both increase the adoption of new technology, as shown by Soon, Lee, and Boursier (2016), and increase the chances of successful implementation of an innovation.

2.3.3.1 Establishing a sense of urgency for change and facilitate short-term wins

Innovation is by definition a source for change since it implies that something new, which has not previously been available, is developed or taking form. Change itself is not easy, and Kotter et al. (1995) highlight many reasons why companies fail to transform or adapt to the change. One common error is not establishing enough urgency for the need for change throughout the organization (Kotter et al., 1995), which often results in failure of implementing change in an organization at all. Establishing a sense of urgency is needed to gain the cooperation and contribution to the change throughout the organization (Kotter et al., 1995).

Innovation also impacts the culture in the organization, which restricts the progress of the innovations since people by default are resistant to change, often due to laziness (Barnett, 1953). This is also something where an established sense of urgency can help, as Kotter et al. (1995) describe such an environment can help move people out of their comfort zones and contribute.

Another aspect which, according to Kotter et al. (1995), is crucial to succeeding with change is keeping the pace up and keeping the people motivated. Short-term wins could be utilized in a change process to maintain the sense of urgency and commitment to contributing, even if the whole process is long and the end goal is difficult to see (Kotter et al., 1995).

2.3.3.2 Tolerance of failure to succeed with innovation

In a world of constant change, both successes and failures are natural parts of a company's progress and development (Farson & Keyes, 2003). Farson and Keyes (2003) explain the paradox of allowing both to eventually succeed with innovation, hence, companies need to accept failure as a step towards success. By learning from failures, new opportunities for success are gained which might not have been discovered without the failing (Farson & Keyes, 2003). Further, Holmstrom (1989) describes that innovation projects require an even higher tolerance of failure than other projects, as they always come with uncertainty and risk of failure. Therefore it is a need for changed attitudes when it comes to success and failure, where failure should be seen as a step towards success (Farson & Keyes, 2003).

3
Methods

This chapter outlines the research method of the study, which also includes an introduction to the case company. Further, it covers a methodology discussion considering the reliability, replicability, validity, and risks of the study, and lastly, a section on ethical considerations is provided.

3.1 Research approach and design

The method of choice for the thesis was a qualitative method with an abductive mode of reasoning. The abductive reasoning includes interaction with the social world as an empirical source to develop theoretical ideas and continuous reviews of the existing literature to try to explain these ideas (Bell, Bryman, & Harley, 2019). By utilizing an abductive way of reasoning, the sources of data complemented each other and enabled stronger support for the findings.

The study was a longitudinal case study of one single company. As Bell et al. (2019) suggest, the study was initiated through a literature review to examine what specific research existed in the area of interest and to discover concepts and theories relevant to the topic of predictive quality, predictive analytics, data-driven analytics, and digital innovation. With this background, two research questions were then formulated. The case study lasted for eight weeks and included data collection through observations, interviews, and additional company documents. The data collection and the different sources of data collection are described in 3.2.

The initial literature review indicated that the formulated research questions, covering obstacles in implementing predictive quality innovations and how three selected constructs could impact these to enable implementation success, had not been researched before. By merging insights from the longitudinal case study with existing literature about quality management, digital innovations, and predictive analytics, the thesis contributes to the research area of data-driven innovations for predictive quality.

3.2 Research methodology

The reasoning behind selecting a case study approach was to gain deep and detailed insights through understanding the dynamics and the context (Denscombe, 2017). By allowing the case study to run for eight weeks with daily observations, i.e., adopting a longitudinal approach, a deeper understanding of different processes was achieved, and also decreased the data ambiguity (Bell et al., 2019). This section describes the research methodology and, more specifically, the course of action for the data collection in terms of literature review, case company description, and an explanation of the longitudinal study.

3.2.1 Literature review

The literature review was conducted as a continuous process throughout the whole study. As a start, a literature review was performed to find concepts and theories of interest. The authors thereby got an overview of the topic 'predictive quality' and other topics of relevance such as industry 4.0, digital innovation, and data-driven quality management. During the data collection and data analysis, the literature review pursued to continuously link empirical findings to existing theory and find different perspectives on the research topic. Moreover, when analyzing the results, theory from existing literature was used to support empirical findings and create new insights within the research area.

Throughout this process, there were different literary sources were used, such as academic journals, books, and practitioner publications. However, to ensure the quality of the theory, the main sources used were academic journals and books. Google Scholar was used to searching for literature and quickly validate it based on the number of citations. Another strategy used was to scan the reference list of the relevant literature, as well as scanning literature that cited the presumed relevant literature, i.e., chaining both backward and forwards.

3.2.2 Case company

The case company got selected based upon a few parameters which were relevant to the research topic, as suggested by Denscombe (2017). One parameter was to use a company with a good fit for predictive analytics. A manufacturing company showed high relevance due to the vast amount of possible data to capture through applied Industry 4.0 concepts. Another parameter was to capture the high-knowledge aspect, with a long, highly complex process in which each step is highly knowledge-based. A third parameter was quality relevance. The battery manufacturing setting is a perfect match due to the high demands in safety and lifetime of the products. Further, predictive analytics are highly relevant in a setting where manual methods are not an optimal fit. By choosing a giga-factory operating in the battery industry, all of the considered parameters were ticked.

The case company in this study is a European lithium-ion battery manufacturer that was founded in the last ten years and has, in less than five years, increased its employees by more than 2000%. The company is in its ramp-up phase and will initially mainly produce batteries for automotive manufacturers. As environmental concerns are increasingly growing and electrification are trending, the company is positioning itself in an attractive market intending to become Europe's leading supplier of sustainable, high-quality, and affordable lithium-ion battery cells- and systems. Aligned with this aim and the concept of Industry 4.0 is to achieve fully connected, automated, and smart factories.

The battery of an electric vehicle stands for about 30% of its total cost (Placek, 2021), meaning that the company must keep the costs down as well as enable long life cycles of the batteries. Furthermore, batteries must be safe. Nonconformity or fire risks could be devastating for both the company's brand, its economy, and the customer or extended customer. Both the long life cycles and the high safety aspect are facilitators for the company's vision of becoming a sustainable battery manufacturer, as it, for instance, would allow for fewer resources as a consequence of fewer battery replacements. Hence, the quality aspect is of central concern for the company's growth and survival, as well as, meeting customers' sustainability expectations.

The company works with complete battery manufacturing, from raw materials to cells and later battery packs. However, this study took place in one particular process, namely, the Test & Validation process at the end of the production line, where the quality of the battery cells is tested and validated considering life performance and safety. Since the process is quality-focused, the team which the authors joined was a small Quality team. A few projects for predictive quality were ongoing at the company during the observations, which all concerned battery life cycling and battery safety. By innovating in these processes it is expected that major cost- and time savings can be made. The company further predicts to exceed its existing testing capacity at the end of this year. Hence, it is urgent to understand the prerequisites for innovation implementation to successfully innovate in predictive quality.

The study was, as mentioned, conducted with a small Quality team in the Test & Validation area of the process. Throughout the study, the authors were also involved with other teams and other departments via the observed projects. Thereby, the following description is provided to outline the different stakeholders. The 'Quality department' refers to the whole Quality department, company-wide, whereas the 'Quality team' refers to the specific quality team that the authors observed and who currently are driving the seven predictive quality innovations. The 'Digitalization department' refers to the whole Digitalization department, whereas a 'Digitalization team' describes a smaller team working with a specific digitalization area. These teams are specified to areas of either 'Data', which are focused on data integration and data modeling, 'Automation', which is focused on the enabling digitalization technologies to be integrated, or 'Could', which main focus is on data interface and data structures in the connection to the company could. The internal developers refer to two machine learning developers that during the observation period were employed on a five-month basis to develop an algorithm for the Quality team.

3.2.3 Longitudinal study

A longitudinal research design enabled the authors to collect observation data by following the daily activities and collecting data through daily field notes, all of which related to digital innovation projects for predictive quality in a Quality team at the company. There were seven projects ongoing simultaneously, in different stages, and with different stakeholders. These projects are described in detail in section 3.2.3.1.

Throughout the study, 16 interviews were conducted whereof one was of retrospective characteristic to gain insights of previous events in the seven predictive quality innovation projects. The remaining 15 interviews were performed to gain a deeper understanding of perceptions of digital innovations for predictive quality from different stakeholders in different departments. In addition, unstructured interviews were conducted through spontaneous discussions, resulting in 11 pages of additional field notes. The interviews and their relevance are described in the section 3.2.3.2.

Additional company documents, both project-specific and non-project-specific, were studied. The first type complemented and confirmed the retrospective interview, whereas the second type provided additional insights into the company, its strategy, objectives, and other information, which was of relevance to nuance observations and gaining a holistic picture of processes and dynamics in the company. The data collected thought the study is outlined in table 3.1 below.

Type	Description	Materials
Observation	Participation in internal meetings and workshops considering the active predictive quality projects	Field notes of 29 data-written pages
Observation	Participation in meetings with external partners considering the active predictive quality projects	Field notes of 21 data-written pages
Interview	Semi-structured interviews	10.5 h recording, transcribed. 30 pages of interview notes
Interview	Semi-structured, retrospective interview	4 pages of interview notes
Interview	Un-structured interview. Conducted throughout the observations as informal discussions	Notes of 11 data-written pages
Documents	Project-specific documents relating to the active predictive quality projects	13 documents of various information
Documents	Non project-specific company documents relating to the the company processes and objectives	6 documents

Table 3.1: Overview of the collected data throughout the longitudinal study.

3.2.3.1 Observation study

The observation study consisted of the authors participating in internal meetings and workshops, as well as, external meetings, all relevant to the seven followed projects for predictive quality.

The relevance of the selected projects for observation throughout this study was based on a few parameters. First, they all had to be of relevance to the topic of predictive analytics. Second, all projects were executed in the Quality department, enabling the authors to get a domain-specific understanding of quality and the connection to data analytics. Third, to get a wider knowledge of the innovation process in a limited time frame, the selected projects were in different phases. The different phases was *initiation*, *development calibration*, and *evaluation*, which are further described below.

Furthermore, the projects differed in characteristics. For instance, one project was solely software-based, aiming to create a machine learning (ML) algorithm for improving a process. Another was to provide a physical, digital technology as an enabler for quality data analytics. The third kind of project was a mix of both, digital technology utilizing an ML script to predict the quality of the product. Additional differences in characteristics are whether the projects are executed internally or along with an external part. The projects are outlined in table 3.2. By observing projects with these kinds of differences, a wider and more generalizable understanding of the innovation process was achieved.

Project phase descriptions
Initiation The initiation phase consists of a project idea being generated and necessary knowledge for the idea acquired, involving establishing contact with external stakeholders or finding the right resources internally. The project is being scoped and an initial project plan is elaborated upon.
Development The development phase often includes several phases, for instance, the first being a proof-of-concept of a technology and the second being a small prototype, etc. The development phase, hence, regards the development of the technology or model itself.
Calibration The calibration phase refers to fine-tuning the technology or model toward the process, or product, of application.
Evaluation The evaluation phase consists of testing and validating the technology's or model's performance and also comparing the produced measures or results towards the acceptance levels. If accepted after this stage, the process continues towards implementation or next-step development if it was an evaluation of a prototype.

Project Code	Type of technology	Predictive Quality Application	Improvement Opportunity	Execution	Project Phase
Project A	Digital sensing technology	Predicting battery lifetime performance	States battery life by a fraction of time compared to traditionally cycle a battery	Provided by a start-up	Calibration & Evaluation
Project B	Digital sensing technology	Predicting minor deviations within a battery	Strengthen the product safety case of a battery, fast	Provided by a start-up	Development
Project C	Digital technology using algorithmic modelling	Predict the stability, and hence, the quality of a battery	Measures the stability of a battery in a fraction of time than traditional methods	Provided by an incumbent, customized	Calibration & Evaluation
Project D	Digital sensing technology for battery cycling, produces data	Predicting battery life performance	Optimizing energy efficiency in battery cycling and enables for innovation though data generation	Co-developed with a university	Development & Evaluation
Project E	Machine learning algorithm	Evaluating traditional quality measures and predictive quality measures for battery stability	Validate another predictive quality technology in a faster and cheaper way than traditional measures	Co-developed with a university	Initiation
Project F	Smart monitoring technology, using algorithmic modelling	Monitoring data during battery use to predict potential battery faults	Optimization and quality improvement opportunities of batteries based on prediction of faults	Developed internally	Initiation
Project G	Machine learning algorithm	Enable prediction of battery lifetime	Estimates life through a fraction of cycles than what is traditionally required	Developed internally	Development

Table 3.2: Description of the seven observed predictive quality projects.

3.2.3.2 Interviews

The chosen approach for conducting interviews was to utilize semi-structured ones. Semi-structured interviews include fairly general and open questions, which enables the interviewer to elaborate on the answers to a specific point of interest (Denscombe, 2017). Semi-structured interviews still include a degree of structure, where the interesting and relevant topics are covered but are general enough for the respondent to answer or interpret the question in the way they feel suitable (Bell et al., 2019). The interview method was chosen for a few reasons. First, to assure that the relevant topic for the study was covered, but still not to direct the respondent to a too large extent. This method also opened up for gaining additional insights and knowledge to the study, which was not initially thought of, as is often the case in adaptive research.

A total of 16 interviews were conducted. 15 of them had the purpose of gaining a deeper understanding of the different stakeholders' perceptions of predictive quality innovations. The last one was retrospective, aiming to gain an understanding of the previous progress of the projects which was observed in the study. Representatives from seven different departments contributed to this study, with an emphasis put on the two departments 'Digitalization' and 'Quality'. The relevance of the selected focus was based on the gained understanding, throughout the initial observation, that a new, large, dependency of these two arose with the concept of predictive quality innovations.

The five additional departments were found relevant since they are also involved in predictive quality innovations, despite to a little smaller degree. Meaning that they had a dependent role when it came to digital innovations for predictive quality. For instance, early on in the process, the Legal department was often included to cover IP aspects. The R&D lab got involved to provide data for validation, data to utilize for ML training, or physical cells to validate the technology. Further, Strategy, Blueprint, Controls & Materials often got involved first in the implementation phase.

The sampling of respondents further included various roles with different degrees of decision power and knowledge of specifics, from the 'user' of an innovation to the 'owner' or 'sponsor'. This wide span enabled a nuanced picture of the involved stakeholders, their different perceptions, and the digital innovation context. Table 3.3 outlines a summary of the conducted interviews, including the title of the respondent, their department belonging, how long the interview went for, and whether it was recorded.

Respondent	Department	Time [min]	Recorded
Project Manager	Blueprint	60	Yes
Lead Process Engineer	Controls & Material	60	Yes
Director Cloud	Digitalization	30	Yes
Chief Technology Officer	Digitalization	60	Yes
Manager Data	Digitalization	60	Yes
Senior Manager Automation	Digitalization	60	Yes
Patent Engineer	Legal	60	No
Director Quality	Quality	30	No
Internal Developers	Quality	60	Yes
Process Quality Engineer	Quality	30	No
Senior Project Manager*	Quality	90	No
Test Engineer	Quality	60	Yes
Test Engineer	Quality	60	Yes
Vice President Quality	Quality	60	Yes
Project Manager	R&D Lab	30	No
Strategy Manager	Strategy	60	Yes

**Retrospective interview*

Table 3.3: Summary of the 16 performed interviews.

Notably, the interviews varied in length. The aim was to conduct hour-long interviews, but in the cases where the respondent only could spare 30 minutes, the opportunity of interviewing for a shorter amount of time weighed heavier than to decline. Another aim was to record all interviews to later transcribe them. However, not every respondent allowed this, which meant that these could not be transcribed later on. Field notes from these interviews were considered extra important to carefully work through instantly after the interview to minimize data loss. For the interviews where recording was allowed, notes were also collected and examined as soon as possible afterward, as Denscombe (2017) suggests. The interviews were moderated by one author, while the other took notes. The recorded interviews were transcribed as planned.

Worth noting is that table 3.3 does not include the unstructured interviews, as these were not scheduled but rather spontaneous ones performed during the observations. For these informal interviews, emphasis was put on not tweaking any information or pushing the questions in any direction. The course of action was to be open and curious to understand all processes better.

3.2.3.3 Review of organizational documents

Both *Project-specific* and *Non project-specific* organizational documents were used as a data source in this study. The documents were confidential to the public but shared internally in the company. The project-specific documents consisted of legal agreements as well as a statement of work, which provided a retrospective data source and gave an understanding of the projects. The non-project-specific documents concerned mainly company objectives and organizational structure information. The documents were shared both as an initiative from the case company and by request from the authors.

3.3 Data analysis

Collected data were analyzed both on a weekly basis, during the observation period, and again after completion of the eight-week data collection period. Thereby, the process of data collection and data analysis was iterative and made in parallel with the observations. The reason for that being different stages of the research process are likely to affect each other (Bell et al., 2019).

The data analysis was based on a Qualitative Content Analysis (QCA) method. Schreier (2012) describes QCA as a method that enables systematic illustration of the meaning in qualitative data. As this study included different sources of data, including field notes from observations, interview notes- and transcripts, as well as company documents, QCA was considered suitable as it is useful to apply to several types of data and offers a way to handle detailed data in need of interpretation (Schreier, 2012).

The way of performing the QCA was inspired by the process described by Elo and Kyngäs (2008), including the three main stages preparation, organizing, and reporting. Each of the stages included specific steps of the analysis, which are described below.

3.3.1 Preparation

Step 1: Making sense of the data and whole
To make sense of the data as a whole, it was read through several times after the data collection. At the end of each observation week, the data from that week was read through by each author separately. This procedure was done again at the end of the eight-week observations. When reading through the data, the authors kept questions in mind considering who was telling, what statements were reality-based versus speculations, when did things happen, where did it happen, and why. Both on a weekly basis and at the end of the observation period the read-through was separately performed by the authors.

3.3.2 Organizing

Step 2: Open coding and Coding sheets
After making sense of the data, open coding was done by reading through the data one more time, but simultaneously taking notes in a coding sheet in Excel. The notes written down in the Excel sheet got categorized by adding them to a certain row. One category could include several different notes. The categories were freely created from the open coding and evolved during the open coding. Open coding was done both at the end of each observation week, taking notes from the week past, and at the end of the last observation week, taking new notes based on all data collected. During the first two weeks, the open coding was done by both researchers together to ensure alignment in the coding structure. The next six weeks and during the open coding at the end of the observation period were done individually to avoid biases in the coding. The final run-though was conducted and coded individually on an Excel sheet separated from the weekly notes, to avoid getting influenced by the previous coding. Lastly, the researchers summarized the notes from the open coding in headings together, and also jointly put the headings and categories on post-it notes on a virtual board, using the digital tool provided by Miro.
Step 3: Grouping and Categorization
When all headings and categories were put on post-it notes, the notes were grouped under higher-order categories to find overlaps, get a more complete understanding of a specific phenomenon identified, and reduce the number of categories.

Step 4: Abstraction
The last step of the organizing stage included abstraction where generic descriptions were set on the categories. Sub-categories, in form of headings post-it notes, that described similar situations were grouped as a category. Different categories were then linked together using arrows and formed main categories which were labeled on the virtual board.

3.3.3 Reporting

Step 5: Summarizing and reporting
The reporting stage included summarizing the findings from the categorization process in a table to structure it. After that, the results were outlined, in chapter 4.

3.4 Methodology discussion

The section includes a discussion of the choice of methodology, including a reflection on the study's strengths and potential weaknesses.

3.4.1 Reliability, replicability and validity

To ensure a high quality of the study, contribute the findings to the theory, and make it possible to further build on the research, a certain level of reliability, validity, and generalization was required.

The reliability criteria concerned the repeatability of the results of a study (Bell et al., 2019). As Bell et al. (2019) describes reliability is more complicated to achieve in qualitative research than in quantitative research. To facilitate external reliability the setting of this research has been carefully described. Moreover, the authors performed most of the open coding during the data analysis individually, to increase the internal reliability and make sure they agreed on what had been seen. Further, the study must be possible to replicate to prove its reliability. This requires the study to be transparent and have a well-defined and explained method, which has been considered in this study.

The validity is, according to (Bell et al., 2019), in several ways the most important quality criteria of a study. The longitudinal research in this study contributed to the internal validity as the eight-week long period enabled a high level of agreement between the observations and theoretical ideas. However, as Bell et al. (2019) argues external validity could be difficult to achieve in a single case study. Therefore, the thesis rather enables a detailed understanding of the complexity of the specific case on which the study is based.

3.4.2 Risks

To enable transparency of the research, it is important to highlight the potential risks with the choice of research methodology and which measures have been applied to diminish their impact on the study.

First, as the longitudinal study has been conducted at one single case company, there is the risk of obtained data being non-representative nor the results generalizable for all cases. Second, both authors have previous experience with the case company through internships, which could imply a risk of biased results. Further, the authors of the thesis have a similar academic background, indicating a risk of having similar biases and perceptions of a situation. To mitigate these risks, the authors raised awareness of the fact from the very beginning and throughout the observations, interviews, and when analyzing the data, being careful to not conclude things that were not based on the conducted data throughout the actual study. Through using qualitative content analysis, the lasting potential biases were highlighted and diminished.

3.5 Research ethics

Ethical aspects which could have affected the execution of the study are of great importance to consider. To conduct the research ethically, the authors performed the study with scientific integrity, which aims not to endanger the participants' interest, nor cause them any physiological- or personal harm (Denscombe, 2017). Throughout this study, it was assured and carefully considered to always apply informed consent, confidentiality, voluntariness, and compliance with the law, in all aspects.

The chosen method of qualitative interviewing enabled straightforward surety of informed consent (Bell et al., 2019), whereas the respondents' wish of recording the interview was respected without counter-questions. The interviews were further performed with respect and secured the participants' interests. As part of the interviews, the observations in the field, and the organizational documents included confidential and highly sensitive information, it was of great importance that the information was handled with care and not made available for anyone else unless publishing was mandated. Furthermore, all reviewed literature that contributed to this study was accurately referred to achieve a high ethical standard.

There are further socio-ethical considerations to be made of the choice of industry and company. Battery safety is a critical issue since poor quality could result in societal harm. Further, there is a great emphasis, though an EU directive, on the importance of mine and use the raw material carefully and ethically correct. However, the emphasis put throughout the industry on battery safety, and the company's high standards in its supply chain, while pushing to even greater ones, makes the company and the industry contribute to the green conversion with electrification with reduced ecological footprints. Further, the digitization of factories and its influence on human resources has been considered. A higher digitization degree usually means less need for human labor as manual tasks diminish. On the other hand, more engineers to optimize and secure systems and processes are required as well as the task becomes less harmful to human health.

4
Results

This chapter outlines the empirical results of the findings from the longitudinal study. It is a descriptive compilation of the four most prevalent obstacles identified for the implementation of predictive quality innovations, mixed with illustrative citations from respondents. A summary of the four identified obstacles is illustrated in table 4.1.

Obstacles for the implementation of predictive quality innovations	Specifics

Technological concerns	• Data quality issues
	  – Unclear if sufficient data to base predictive quality models existed.
	  – Some data was unstructured and not integrated to the company's cloud service.
	  – Unclear how to link different data points from the complex production process.
	  – Uncertainty of what data to base predictive quality models on to ensure some level of generalizability.
	• Reliability of predictive quality models
	  – Unclear how and/or difficult to validate predictive quality models.
	  – Uncertainty on the comparability of traditional quality method criteria and predictive quality method outcome.

Resistance to switch from traditional and established quality methods	• High-safety requirements of battery production lead to risk minimizing through avoidance of implementing new technologies. • The complex battery manufacturing required employees with previous experience from the digitally immature industry, resulting in use of 'best practices', e.g. traditional quality methods, by influential individuals.
Differences in focus and deliverables across departments	• Different departments and teams had different prioritization in resource distribution. • The differences in focus indicated differences in perception of the innovation project.
Extensive buy-in required	• Need buy-in from more managers across departments, i.e., a larger amount of buy-ins required. • To get buy-in for the next innovation, there was a need for appreciation of innovative projects, which was difficult due to the novel technology concept. • There was more stakeholders to convince across departments, who all had different perceptions of the innovation.

Table 4.1: Detailed summary of the identified obstacles for implementation of predictive quality innovations.

4.1 Technological concerns of predictive quality

Considering the technological aspects of predictive quality methods, two concerns were prominent; the data quality of data used for the methods and the reliability of predictive quality methods. These concerns created the first obstacle identified, namely a technological obstacle. The empirical findings for the two different parts of the obstacle are outlined below.

4.1.1 Four data quality issues

The data, and specifically the quality of the data, that predictive quality models were to be based on, was a concern for several different reasons. The data, and specifically the quality of the data, on which predictive quality models were to be based was a concern for several reasons. First, it was unclear whether sufficient data existed. There was a captured perception of data missing, with the implied risk of not sufficiently representing all process steps which could affect predictive quality models. However, one respondent from the Digitalization department described how their team used a *"catch it all"* approach when it came to data collection. The reason for this was to ensure that all necessary data for future prediction models existed, but as of now, it was not clear exactly what data that was, nor if the missing-data concern was justifiable.

Second, some data was unstructured and not necessarily integrated into the cloud service that the case company uses as its standard interface for data structuring. Even if a lot of data from different steps of the manufacturing process exists within the case company, the data was not fully utilized and the lack of data structure seemed further to inhibit its ease of use. The structuring of data was considered in the phases of initiating the calibration and also testing of the innovations, where the Quality team reached out to the Data team to jointly sort out a solution for the structuring of data that would be collected from the new technology. The Digitalization department wanted to be involved early in the implementation process of data-driven technologies, to ensure connectivity and a standardized interface. Different parts of the Digitalization department would be involved in different stages of the implementation. For instance, when the technology is installed and connected to the network, the Data team would be involved to make sure that the data is structured properly. The Data team would line out aspects such as *"how to model the data we want to receive, where does it go, how is it structured, how should we search in it"* and to *"create databases and pipelines for analysis"*, as noted by a respondent from that team.

Third, the linking of data points from different production steps, which is required to enable cause-of-problem analyses as well as to give confident predictions, was another concern. The complex battery production includes multiple steps ranging from slurry mixing, which is the mixing and homogenizing of the ingredients that form the active material paste of the anode and cathode, to formation and aging, which is where the batteries are cycled, i.e., charged and discharged to activate them.

All steps from the start to finish of the production process could affect the outcome and thereby there are a lot of data points to link. To build stable predictive quality methods, a causality of the data needs to be captured, as noted by one respondent: *"you need to be able to prove a causality of the data and then have a system or model to pick that up"*. However, such a solution was not established. Machine learning algorithms were mentioned as a solution to handle all data and show correlations, but for the Digitalization department to understand what data could be of interest from each unique step of the complex manufacturing process, input from domain experts within these steps was requested.

Forth, what data to base predictive quality methods on to ensure generalizability was another concern of data quality. There was a prevalent worry that the data would vary depending on if it, for instance, came from different production sites or from the production of different cell types than the one for which the model would be used. The models would then need to be re-validated in the specific process where they would be used. However, if the models would turn out to not be fully generalizable for a process having similar, but not identical, equipment and characteristics or for a process producing a different cell type, the models would most likely only need a smaller rework, according to the internal developers and a respondent from the Digitalization department. Further, a predictive quality model will not be considered complete until it has been tested and validated in the right use setting.

4.1.2 Reliability of predictive quality models

The other part of the technological obstacle is the perception of the reliability of predictive quality models. A risk identified, which came from the low reliability of predictive models, was that it would be very costly if the models did not work as anticipated and, for instance, predicted false negatives. This showed a need for careful validation of the new quality methods to increase the reliability, decrease perceived risks, and gain acceptance for the implementation of predictive quality innovations, as stated by a respondent: *"We are super innovative in quality, but we are very restricted in what different risks we take, but as soon as it is validated, the innovation [from Project C] will fly out into the factories."* However, it was claimed to be unclear how the validation itself should be done, and if it was apparent, it was still considered difficult, as one respondent from the Quality department expressed: *"Do I think things can be predicted? Yes, I do. Validating those models, a little bit harder."*

A specific concern of the validation process was the comparison of the results from traditional methods, that are currently in use, to the results from predictive quality methods. The results themselves were considered comparable, but the concern regarded the Key Performance Indicators (KPIs) used for the validation of predictive quality methods. All KPIs used in the observed projects were extracted from the control plan and were used to determine acceptable results for the traditional quality method. The use of the control plan to determine KPIs was not a widespread strategy in the company, and the criteria, i.e. KPIs, used to evaluate predictive quality innovation could vary between different teams and departments. Moreover, the results might not always be outright comparable, where cross-referencing of results was suggested as an easy and reliable method to enable validation of predictive quality methods by reference to the traditional ones. To understand which data are comparable between traditional- and predictive quality methods, domain knowledge was suggested to be utilized to improve the reliability of the validation.

To limit the risk concerns related to predictive quality innovations, the validation of predictive quality methods was suggested to not be carried out in the main production line as a first step, as that could imply high risks. Rather, the validation and testing of new technologies for predictive quality should take place in parallel with the main production and the traditional quality methods should be used supplementary to predictive quality methods to ensure valid quality methods until the reliability is proved.

4.2 New organizational challenges with predictive quality

The empirical data showed novel needs with adapting traditional quality management to a data-driven approach with predictive analytics, which has implied new challenges to meet. The first was to meet the resistance to switching from the traditional quality methods and technologies to digitalized and connected ones, such as predictive quality. Further, as new skills and knowledge were required in the quality domain, new requirements for cross-departmental collaborations became obvious, which implied two distinct challenges. First was that different teams had different goals and deliverables, and second, more buy-in was required to carry through with the digital innovation.

4.2.1 Resistance to switching from established quality methods

The battery manufacturing industry is considered a high-safety industry where risks connected to quality issues, which could influence the safety of the cells or the production of the cells, cannot be taken. As noted by a respondent: *"Quality is the main prioritization for the batteries, if our cells catch fire because we did something wrong or did not find something... We do not compromise on quality"*. To minimize risks, the use of traditional and established technologies was preferred over switching to predictive quality methods until the latter were considered stable. This created a hesitation towards switching from established quality methods to predictive quality methods, as one respondent stated: *"We very much avoid replacing critical quality inspections"*. Hence, another obstacle identified was the resistance to switching from established quality methods. The high-safety requirements in battery production call for stable processes, but new predictive quality methods were not perceived as such, as expressed by another respondent *"New technologies could be seen as less stable than those that are more traditional"*. In addition to the safety risks and the risks of predicting false negatives, new technologies were perceived to disturb the production process and to rather become a distraction than a tool for improving the process, as a respondent from the Digitalization department described it: *"They are worried that this could be distractions for them or that it could add risks"*.

The high-safety required battery manufacturing setting has influenced the willingness to take on risks associated with the uncertainties in digital innovations for predictive quality. One reasoning behind this was described as; *"You are going to fail to succeed innovating, but people are not programmed to fail"*. To increase the willingness to take on risks, it was requested to clear a standard for failure acceptance of innovative attempts, and also to implement them in a way that could convince skeptics and non-risk takers.

Another aspect to consider was the background experience of employees, as it added to the resistance to switching methods. As several employees in the company came from previous employment at other battery manufacturing companies, they used their previous experiences as a 'best practice' as described in more detail by one respondent:

> *"There are many cell experts in the company that have worked for a long time in other battery manufacturers, and they think 'what equipment did we have then, we had that, that worked, let us buy that again because it worked out well' and that is just how it is. They are sceptical towards new equipment from new suppliers that they did not use in their previous jobs."*

The battery manufacturing industry is immature in its digitalization and connectivity. One respondent stated it as follows: *"You have the whole industrial environment which is in general more traditional, due to many reasons, I think that it has not gone through the development fully yet of making everything more connected and more generalized"*. The employees with previous experience in battery manufacturing thereby encountered a new kind of manufacturing process that they were not familiar with, as it digitalizes and connects to a larger degree. The same employees have been a vital part of the development of the company, as battery manufacturing is a difficult process even without digital integration. Much because of their previous experience, these employees often have key roles in the company and a lot of influence on others. This has spread the use of the 'best practices' from the influential employees' previous jobs, meaning the use of traditional and established quality methods rather than predictive quality methods.

A problematic aspect of this is that traditional methods won't scale. Despite lithium-ion batteries have been around for many years, the industry is immature in its development towards scalability. Further, the methods used previously for quality assurance are not scalable to the giga-scale that the company wants to achieve. This is partly because the traditional methods take up a large amount of storage space due to the long time it takes to validate the quality through such methods. Traditional methods are also more manual, which requires too many resources to adapt to the modern setting of Industry 4.0 and for what is culturally accepted in Europe in terms of salary rate and work tasks. These factors impact the company's competitiveness in both time-to-market and cost. Further, as the company's customers demand more testing to ensure higher safety, predictive quality methods could be a way to scale up the testing to meet customer requirements, as well as a way to meet the company's ambitious digitalization objectives.

The resistance to switching from established quality methods was an apparent obstacle, but it should also be emphasized that if the predictive quality methods are carefully validated, as explained in 4.1.2, the resistance could be reduced. One strategy used by the Digitalization department to overcome the resistance to switching to data-driven methods was to involve the end-user of digital technologies early in the development, both to ensure correct use, but also to make the user feel involved. By showing the future user that the data-driven solution could solve, what seemed like, an impossible problem, they could gain the user's acceptance. This was described by one respondent: *"The best way to get people on board with this is solving one of their problems, that they did not think was possible to solve, through the application and usage of data"*.

4.2.2 New cross-departmental dependencies originating from new skill requirements

Traditional ways of ensuring process quality are known by following certain frameworks and step-wise procedures to ensure performance. The methods used emphasized analyses of risks in the process and how such risks could impact the process, monitoring the process via basic data from the machines, and retrospectively studying the data through root-cause analysis, if deviations were found. With the entering of the predictive quality concept, new skills and knowledge, which have not traditionally been prevalent in the quality domain, were required. For instance, in the evaluation phase of an innovation, the skills required for performing traditional evaluation and digital evaluation differ since you must use different tools and procedures, as one respondent noted: *"For mechanical evaluation, you need mechanical validation test equipment, whereas, for digitalization you need coding, you need databases, you know, a lot of different tools to achieve the same goal at the end"*. Hence, the latter depends on digital skills, from the Digitalization department, as they enable databases and pipelines for modeling in addition to actual data modeling, as mentioned in 4.1.1.

New digital skills and digital know-how were necessary to fully realize the applicability of predictive quality methods but also to maintain, update, and continuously build upon the digital innovation, as described by a respondent: *"These are necessary to have to enable Predictive Quality. Preferably inside of the team, not the least to enable a good handover of the algorithm [of Project G] to skip rework, but the algorithm [of project Project G] also needs to be updated and maintained"*. This would further enable the positive feedback loop which characterizes the connected streams of predictive quality analytics, as the CTO explained, it implies that: *"the cost per unit of digital insight falls"*.

The, for the Quality team, new skills considered necessary were captured as: *"Software engineering is necessary", "Data Science and Machine learning skills to enable analyses in the cloud", "Require more dedicated software know-how", "Big data is the future, we need data scientists", "This kind of data-driven knowledge and applied statistics"*. However, as the manufacturing industry setting, in general, is immature in its digitalization, and especially in the connectivity aspect, the multiple set of skills which was required for predictive quality was not found in one single domain. This implied new cross-departmental dependencies, in the form of assistance of domain expertise, something which also resulted in new challenges because of additional dependencies.

The new cross-departmental dependencies, as a consequence of predictive quality innovations, were mainly between the Digitalization- and Quality departments as Digitalization's skills and resources are necessary to develop the new concepts for Quality in form of data integration, data science skills, and interpretation of results. Another dependency was the Process teams in connection to both Digitalization and Quality, as the Process is the enabler for producing the data upon which the digital predictive quality innovations are built. These dependencies did not only stretch across departments but also across geographically different areas. With the increased dependencies came responsibility and knowledge-sharing challenges, as described by a respondent:

> *"Even if you find a way to collect data, then it still becomes very challenging to consume this data, because there is a lack of understanding of sides who are responsible for making sure we have data collected and of sides that are consuming the data for further applications."*

For instance, in Project G, the process knowledge about how the battery cycler must work and what data points are produced had to be merged with the quality expertise in which data points indicate the life quality, whereas digital expertise enabled the data infrastructure and an algorithm for optimizing the cycler. This knowledge must then be translated back to the operational setting to enable utilization. Another example was Project B which was dependent on the pilot-line production to get hold of a cell with a specific characterization to enable training for the predictive quality algorithm in the technology.

The most reoccurring issues brought up, due to the predictive quality dependencies, were akin to; *"the progress is slow since there is more potential for bottle-necks"*, *"it is like asking others for a favor, outside their main scope"*, *"different departments works and prioritizes differently"*, and that there are *"more complex information flows"*. The most prevalent challenges which resulted from the increased cross-departmental dependencies were categorized as relating to teams and departments having different deliverables, and the increased need for a buy-in of an innovation project, which were both recognized as obstacles to the implementation of predictive quality innovations.

4.2.2.1 Challenge with cross-departmental collaboration 1: Stakeholders having different focus and deliverables

How people within different teams and departments prioritized their resources depended on their expectations of the output of the innovative project. This further depended on their perception of the innovation, and the information they received about it. For instance, the Data team had a scientific approach to predictive quality innovations, requiring details and a clear goal for the project to decide whether to prioritize or not. The Quality team, which drove the observed predictive quality projects had a visionary approach, intending to innovate as much as possible. Further, the Process team mainly wanted the equipment to work and if it was exchanged, they expected it to be better and easier than the previous. These different perceptions, needs, and expectations sometimes led to miscommunication and disappointments.

To minimize the issue, clarity in communication and logical steps for implementation of the predictive quality innovation was important, as described by a respondent:

> *"It is super important to include some kind of end-user early in the design phase, so they can understand how the tool works which they shall interact with...that the users are there and eager to use it and are indulgent with shortcomings because they know it will come a later version"*.

Despite that every department had the same ultimate end objective, they had different visions on how to get there. The differences in priorities could be explained by their deliverables and separate budgets. This complicated the cross-collaborative projects for predictive quality innovations, as described by respondents: *"Main crux is that each department has their own deliverable, definitely budget has a lot to do with it"*.

These tensions in priorities have hampered the progress pace of the observed predictive quality innovation projects. To reach a larger degree of cross-departmental collaboration with fewer tensions in priorities, there must be clearer directives from the management as well as an assigned resource pool for the purpose, as a respondent from the management team framed it: *"we must define an assigned blue-sky budget for specific projects to try stuff"*. In addition, this resource pool requires structure in how they are supposed to be used, a kind of innovation strategy, or as another respondent from the management team explained: *"You really need this long-term investment focus, this kind of patient money behind these projects because there is a lot of ambiguity and uncertainty in how they are gonna run"*.

4.2.2.2 Challenge with cross-departmental collaboration 2: More buy-in required for predictive quality innovations

> *"If you can show that the improvement works and it is valid and has a pay-back period, a return of investment in whatever amount of years, you know, as long as you can make a business case for it to be introduced, it does not really matter what it costs because it pays for itself, either in finding bad cells instead of it goes to a customer. You know, what is the value for a potential recall. If you spend, let's say, 20 million dollars and you remove that, then you gonna save probably a billion dollars in the long run."*

Different kinds of support and sponsorship were required for the innovations, but similar for all was that a benefit-proof which was considered strong enough for the predictive quality innovation would likely meet strong support and be prioritized, as the cite above outlines. As the project structure became more complex with increased dependencies across the domains, there were more stakeholders involved that needed to be convinced. Often, there was a need of getting buy-ins from all departments' managers to proceed with the innovation, as they all were responsible for their resources. For example, Projects A, C, and D required battery cells to be spared for the calibration phase, which, in addition to acceptance from the relevant Quality manager and Digital manager, required the responsible manager of the produced batteries support. Further, Project B required a specific characteristic in the cell, meaning that the ordinary production temporarily had to be interrupted which required strong convincing of the manager to allow such interruption.

Clear convincing, in form of use cases and business cases, were utilized since all of the stakeholders in a project did not have time to get acquainted with it fully. However, as some of the predictive quality innovations lacked reference points, it was difficult to prove the value at an early stage, especially before the demo. In such situations, simple and established tools, like a Value-effort graph, could give an approximate picture, convincing enough. Further, the accepted measures of the control plan to utilize as KPIs could guide persons who had to be convinced without explaining the whole problem domain of the predictive quality innovation. Another strategy to enable buy-ins from multiple domains was to focus on the predictive quality innovation's expected generalizability, i.e., how it could be re-used in various settings.

If an innovator could show a successful innovation project, it was also easier to get the buy-in required for the next one. Such successful innovation was by a respondent explained as a: *"light-house innovation"*. This seemed especially important in the novel area of predictive quality innovations as such methods were not yet widely accepted. This was, however, also problematic since the predictive quality concept is new and there is little to show yet, as another respondent explained: *"There is a need to show successful innovations to get buy-ins, but how do you get the buy-in when there is not much to show in this area yet"*. Predictive quality innovation, hence, called for a strong and dedicated driver of the project to overcome the various opinions of the innovations, as a respondent explained it: *"The drivers need to be someone or a group of people saying 'this is what we wanna do', and they need to go and do that. Screw pocket-veto, screw formal veto, we need to get this done"*.

Not only was the management required to support the projects, but also all people involved or affected by it. This emerged as a struggle since each person involved could, due to the large dependencies of the predictive quality innovations, slow the progress if they were not convinced, that is using their informal veto. A strategy for bridging this issue has been knowledge-sharing in terms of involving stakeholders and clearing the road-map for the innovation and what to expect from each version, as briefly touched upon in 4.2.1, as a respondent explained it:

> *"Much of what we build in-house comes in version 1, version 2, version 3, and what is in version one will never be 'state of the art', but it is probably in the direction which enables version three to be better than alternatives on the market. To enable stakeholders to understand the thought process, the trade-off between level of sophistication vs. speed, is super important to get a buy in from the organization"*.

Dividing the predictive quality innovation project into phases has also been utilized to bridge the various concerns of the stakeholders. For instance, Project D is currently in the second phase of building a demo after the theoretical proof-of-concept in phase 1 was given a green light. This is explained to require less risk-taking in each phase and is more likely to get buy-ins. Another example is Project E, which initially was turned down, but once again brought up when deciding to divide it into many smaller work packages, each requiring less risk-taking and support than the total.

The need for a large buy-in has throughout the projects caused a lot of head-scratching when involving people from different departments with different budgets and deliverables who put in their informal veto against the project. To bypass the issue, the strategy of selective support has been adopted in a few projects. A respondent reasoned like; *"If you go to a 100 people, you will get 20 saying no. The general approach is that you cannot please everyone, so don't"*.

5

Discussion

An overarching barrier to the continued use of traditional quality methods is their limited scalability and, hence, their unfitness in the giga-factory setting. It is, therefore, reasonable to argue for innovations of alternative methods, such as predictive quality methods, for assuring the quality of batteries. The digitalized quality concept is, according to Javaid et al. (2021), crucial for scalability of quality in the manufacturing setting, which is reason enough to elaborate on how the identified obstacles could be reduced. By utilizing a framework constructed for this study, with inspiration from Klein et al. (2001), and adoption of relevant concepts from Hislop et al. (2000) and Van Riel et al. (2004), this chapter will discuss how management support, information diffusion, and implementation climate may impact the identified obstacles for predictive quality innovation within a battery manufacturing setting.

5.1 Obstacles for the implementation of predictive quality innovations

Throughout the observations at the case company, there were several obstacles identified. These obstacles influenced the implementation of data-driven innovations for predictive quality, and answer the first research question:

> *RQ1: What obstacles influence the implementation of data-driven innovation for predictive quality in high-knowledge manufacturing?*

Four obstacles were most prevalent in this study. These were: **(1)** *The technological obstacle*, including data quality concerns as well as hesitancy in the reliability of predictive quality models and how to validate such, **(2)** *The resistance obstacle*, a resistance towards increased digitalization in the quality domain because of the high safety requirements in the industry, high complexity, and people having previous experiences in traditional methods with an established 'best practice', **(3)** *The deliverable obstacle*, which came from cross-departmental dependencies and that different teams had different focus and deliverables, and **(4)** *The supportive obstacle* of requiring larger buy-ins for the projects due to the cross-departmental collaboration.

5.2 Applying the theoretical framework on the identified obstacles

By applying the theoretical framework for implementation of innovations to the identified obstacles of predictive quality innovations, several insights have been identified considering how the constructs of the framework impact the implementation success, and thereby the success of an innovation. The three constructs of impact are: *management support, information- and knowledge diffusion*, and *implementation climate*. This section will elaborate on the second research question:

> *RQ2: How do management support, information diffusion, and the implementation climate impact these obstacles to enable a successful implementation of predictive quality innovations within a company operating in the high-knowledge manufacturing industry?*

5.2.1 Management support

Management support impacts the obstacles in several ways, for example through a resource allocation or setting clear validation criteria. However, as will be discussed in this section, an important prerequisite for management support to positively influence the implementation is that managers are aligned on objectives and how to reach targets, as that sets the vision which will spread within the company. This is elaborated further below.

5.2.1.1 Technological obstacle

The uncertainties of data quality and reliability of predictive quality models could be a consequence of the increased amount of stakeholders from different domains involved in predictive quality projects, due to its combined quality and data characteristics in a high-knowledge manufacturing setting. The increased amount of involved stakeholders implies larger complexity in the projects, which could be a reason for the undesired perceptions of data quality and reliability of models. For instance, there were currently misconceptions on whether or not sufficient data existed and could be used for the intended models, as well as how to accurately validate the predictive quality innovations, as predictive quality methods are novel and have not been used in any larger extent earlier. Overall, the data quality seemed reliable, as the digitalization department was included from an early stage and some parts of the department had data as their main focus. The misconceptions rather seemed to come from employees' occasional experiences. For instance, lacking data quality as a certain data point was missing or complex accessibility.

To decrease the technological concern, such occasional errors and hinders, which create a perception of unreliable data, must be avoided. Undesired data quality perceptions could be decreased through sufficient resource allocation from the management's side, who have the mandate to allocate resources (Dewett et al., 2007). In this case, it would mean distributing human resources from the digitalization department and specific process steps to the quality team. Their expertise would be of help with the predictive quality innovation, as they could help assure the reliability of the predictive quality models and dig down into the data quality to reduce the risks of data errors. Increased management support in terms of human resource allocation is urgent for gaining acceptance from the adopters when implementing predictive quality innovation. This is because predictive quality innovations are a new and uncharted area, where a negative spiral of spreading the uncertainties amongst the many different stakeholders could harm the progress.

For validation of predictive quality methods, there was a concern regarding how to perform the validation and if KPIs for traditional quality methods could be utilized, i.e., if the methods were comparable. As Markham et al. (2010) explain, managers could function as gatekeepers and set criteria for technology acceptance. This study did not investigate the comparability of traditional and predictive quality methods from a technically detailed perspective, but the general perception was that the results were comparable, despite some employees being skeptical. KPIs utilized for evaluation of the observed projects were extracted by the Quality team from the control plan, which was captured as an appreciated go-to method. However, despite those KPIs being perceived as accepted measures in the Quality team, KPIs must be set from a company-wide perspective, as predictive quality projects involve stakeholders from different teams and domains. Having contrasting perceptions amongst the different stakeholders of acceptable KPIs for predictive quality projects, depending on which team initiated the projects, raised uncertainties. Hence, company overarching KPIs should be set by management and used for predictive quality projects to ensure equivalent evaluation and convey reliable and consistent validation methods.

5.2.1.2 Resistance obstacle

The resistance to switching from established quality methods partly depends on employees' background experiences within battery manufacturing companies, an industry that generally has been, and still is, digitally immature (Turetskyy et al., 2020). These skeptical individuals had a large influence on the company due to their previous experience, hence, gaining their acceptance is crucial to enabling a switch. Management support in terms of signaling the importance of the expected change, and related rewards, is according to Klein et al. (2001) a successful way to influence the implementation climate through promoting use incentives. Management support in terms of managers providing evidence and rational arguments for the functionality and usefulness of predictive quality methods could convince influential employees with background experience in a digitally immature setting to voluntarily change their behavior, as supported by Fidler and Johnson (1984). Hence, increased signaling of the importance and the value of predictive quality methods, targeting employees with previous experience in battery manufacturing, is vital since they could spread their slightly negative perception of digital methods through their large influence in the company.

Moreover, failure and risk-taking are part of all innovation projects, and thereby innovation efforts demand high tolerance for failure, as described by Holmstrom (1989). However, the safety concerns of lithium-ion batteries further raised resistance because of risk-minimizing efforts and unwillingness to take on, what was perceived as, unnecessary risks. Management could, in this case, support and decrease the resistance by allowing for a certain degree of failure and risk-taking. That is, increasing the tolerance of failure within the company. A failure acceptance standard should be set explicitly to balance the high-safety requirements in the high-knowledge industry, with an urgency to innovate within the quality domain. The failure balance must be set to not increase critical risks that experimenting may indicate, and the potential that predictive quality methods brings, e.g., enabling increased assurance of product quality in a fast and competitive way. A failure acceptance framework as a communication tool could, further, be vital for predictive quality innovations as the different perceptions from across the domains could be aligned and enable a shared understanding of risk-taking and what failures are accepted in the high-safety setting.

5.2.1.3 Deliverable obstacle

The increased dependencies and cross-departmental collaboration for predictive quality methods were challenged by different focuses and deliverables of different teams. This complexity risks growing more prominent if the top management does not share the same goal (Dewett et al., 2007). Different managers tend to prioritize resources differently depending on the value they see in an innovation, which often depends on their previous experiences (Afuah, 2003). Hence, the different goals and prioritizations within different parts of the company could be caused by higher authorities. As predictive quality projects depended on stakeholders from many departments, it is of great importance that goals are aligned between different parts of the company. To remedy the issue of prioritization- and focus misalignment, the management must reset and make sure to be aligned and share common objectives before distributing the objectives within different parts of the company. As predictive quality methods are moving the case company towards its outlined digitalization objectives, it makes sense for management to support the alignment in prioritization to facilitate predictive quality innovations. A certain amount of knowledge transfer within the top management must, hence, be established to align the benefit perceptions of the technological innovations and their related changes (Zangiacomi et al., 2020).

It was also captured throughout the observations that the company did not seem to have a dedicated budget for innovation projects, i.e., *"patient money"* for long-term investments. This further complicated the alignment of teams' different focus and deliverables, as they had to make their own choices on how much resources to dedicate to the predictive quality innovation projects. In this instance, it could be valuable to bring up the need of finding a balance between exploring new technological innovation, and exploiting existing methods, something which O'Reilly III and Tushman (2008) highlight as critical for company survival. The management should support the teams in balancing this by providing a *"blue-sky budget"* dedicated to innovation projects. However, as there are multiple teams involved in predictive quality innovations, due to its multi-disciplinary characteristics, it is not enough to dedicate different teams' innovation budgets in general terms, as that will not necessarily align the different teams' budgets. This requires some clarity on how to distribute the innovation budget which, in this case, should be done through benchmarking parts of the innovation budget specifically for predictive quality innovations. The clarification would ease the tensions between different teams and support them in the decisions on how to allocate financial resources for cross-functional projects such as predictive quality projects.

5.2.1.4 Supportive obstacle

As Dewett et al. (2007) note, any complex innovation has to pass through decision making at multiple levels of management. The observed projects were no exceptions. Predictive quality innovations' cross-departmental dependencies resulted in increased complexity as each domain had its levels of managers, which led to many decision points in several domains and a strong buy-in and sponsorship were required to proceed with the implementation. As predictive quality combines data and quality characteristics, it could be difficult for a domain-specific manager to get a complete understanding of the new methods, and thereby fully invest in the new quality methods. As touched upon in 5.2.1.1, clear gate criteria could be used to ease the decision-making process for managers at decision points, as it would create a company-wide standard for evaluation of innovations that overlap several domains. Furthermore, such criteria could decrease the dependency on buy-ins by making them predetermined and standardized. The decision of whether an innovation project should continue or not would then be based on the criteria rather than stakeholders' individual opinions. By setting predetermined criteria, management support could thereby both support the other managers' decision-making, e.g. buy-in decisions, and decrease the dependency on buy-ins from specific individuals, i.e., limit informal impacts on the decision-making process. This is considered especially important for predictive quality innovations due to the large number of decision points.

5.2.2 Information- and knowledge diffusion

The concept of Quality 4.0 merges the quality domain with the digital domain, which means new requirements of cooperation of technologies as well as requirements for new skills and a new level for employee skill standard (Javaid et al., 2021). However, as all necessary skills for predictive quality technologies have shown to be difficult, or not justifiable, to incorporate within one specific department, the complexity of information- and knowledge transfer emerged. What is new with predictive quality innovations is the novel cross-departmental dependencies, especially between the Digitalization- and Quality departments, of sharing expertise and information across knowledge domains, which has caused tensions in prioritization and perceptions. To increase the chances for success, it is therefore vital to set up the right conditions to distribute and adapt necessary information across domains and to all involved stakeholders, as described by Van Riel et al. (2004) as an open climate favorable for information exchange. This construct was not captured in Klein et al. (2001)'s original model but emerged as vital during the study as the observed predictive quality innovations required extensive information transfer.

5.2.2.1 Technological obstacle

The identified technological concerns of data quality and reliability are argued justifiably as data existence and data structuring was questioned by several. The prevalent immaturity of digitalization and connectivity in the manufacturing industry (Turetskyy et al., 2020) and the deficiency of mass-production data for lithium-ion cell production (Westermeier et al., 2013) partly caused this. Both aspects are key issues as predictive quality methods are built on the principle that sufficient and enough data are captured and utilized. It, hence, becomes unclear what can be achieved in terms of predictive quality modeling- and innovation. Arguably, to lessen these technological constraints and concerns for predictive quality innovation applicability, it is urgent to achieve vast and effective communication regarding what data is available and what data is required for predictive quality innovations. If all different stakeholders know what they can expect in terms of data to use, the quality of the data, and its potential effect of the models, it is expected to be easier to move around the issue instead of getting stuck at 'what if'.

As predictive quality innovations indicate utilizing data throughout the whole, highly complex, process of lithium-ion batteries which incorporates a large degree of linking points, a wide span of knowledge domains are affected. A key feature of digital innovations is that a change in one component impact other components (Pershina et al., 2019), meaning that not only are the quality domains and the direct stakeholders' knowledge important but also must information from the process domain and the data domain be merged and continuously updated based on changes in the process. As was captured in the study, predictive quality innovations required to be re-validated if applied in an extended use case beyond the initial. An extended use case indicates more stakeholders and a more complex setting, calling for constant communication and collaboration between the various stakeholders and related experts (Pershina et al., 2019). This constant and close communication could thereby impact the generalizability of the technology and generate additional value if only sufficient knowledge and information are spread and captured to optimize its use.

5.2.2.2 Resistance obstacle

One identified cause for the resistance obstacle was employees' previous experiences, generating different perceptions of what is possible and what is 'best practice', than others who more aimed towards full connectivity in the factories. This could be described as them having contrasting thought worlds, something which Pershina et al. (2019) argue hinders necessary communication for sharing domain expertise since they view the same problem differently. If negative perceptions are spread, they may impact the informal vetos of people who trust the experienced employees and then generate a clear split between domains. Hence, networking and knowledge transfer are crucial to getting in place for the implementation of changes but could have the downside of supporting the own interest (Hislop et al., 2000). These differences in the viewing of the situation or innovation are problematic for predictive quality innovations as they require constant overlap across domains. A vital aspect of reducing the resistance is to communicate the message that traditional quality methods will not be able to scale. This fact was not captured as a widespread risk perception at the case company, but nevertheless urgent as the testing capacity is expected to exceed shortly. Hence, predictive quality methods discover a tension, not only across domains but also within as new knowledge from contrasting thought worlds must be incorporated and adopted. With predictive quality, the quality domain, as well as the whole organization, moves towards a change, where urgency must be communicated thoroughly to succeed (Kotter et al., 1995).

5.2.2.3 Deliverable obstacle

The different departments had different expectations of the outputs from predictive quality innovations, which depended on their departmental focus and delivery goals. Hence, they did not necessarily perceive the value of the innovations in a unified way based on overall company objectives. Lawrence and Lorsch (1967) describe how an organizational integration mechanism could help overcome the misalignment in objectives within a complex organization where different departments have specialized knowledge, something which is highly relevant as the new knowledge bridge between different teams must be achieved for predictive quality. Better integration of stakeholders from different teams involved in predictive quality projects, for instance, the Quality team, Digitalization teams, and the different managers could help achieve a unified perspective of the innovations. There is a clear need for structured information- and knowledge diffusion to bridge all these differences and to, as Van Riel et al. (2004) state, minimize misalignment and spread a shared view on objectives through the company. For the observed predictive quality innovations, integration and cross-departmental knowledge exchange were partly captured, but must be utilized to a greater extent through introducing well-defined project teams, integrating both Quality and Digitalization employees, to facilitate the clarity and efficiency in information- and knowledge exchange.

5.2.2.4 Supportive obstacle

It is not surprising that departments with different emergent deliverables focus their resources differently. Clear and communicative information sharing has been discussed throughout this section, however, communication comes with a cost which also affects the implementation success (Fidler & Johnson, 1984). The communication costs for predictive quality innovations in the high-knowledge manufacturing company are presumably high, as these are highly complex and noticeably risky. They also require a large degree of cross-departmental information sharing including merging various thought worlds and aligning schedules and budgets. Predictive quality thereby requires a large amount of persuasion of the stakeholders, as well as many communication channels. It thereby makes sense to apply the proposed strategy of selective inclusion of stakeholders in projects, as it would indicate lower communication costs and less possible resistance. However, a constrained information flow risks overseeing important perspectives which could have made the innovation more successful. This builds on the literature on open and informal communication climate to promote innovation success rate (Bechky, 2003; Van Riel et al., 2004), but from another perspective. For predictive quality innovations, an open and informal climate is difficult to achieve, as informal bridges then must be built across domains that are not necessarily natural nor possible, i.e., the Digitalization department and Quality team are located in different places. Hence, if an open and informal communication climate is not possible, it could be wise to put extra effort into persuasion to achieve a sufficient level of buy-in. This is since such effort could result in high reward as stronger commitment indicated more likely implementation success (Fidler & Johnson, 1984).

The many bridges to build and the many stakeholders to convince for predictive quality innovations clearly required a driver, a convinced person who believed in the possibility of pulling the innovation through. This aligns with Aalbers and Dolfsma (2015), who suggest that a person who orients externally and drives such communication channels more often succeeds with innovations. This phenomenon is highly relevant for predictive quality innovations as they require people with a strong drive towards the goal of bridging resistance while sharing knowledge cross-departmentally, i.e., merging quality, digital, and process expertise. Hence, communicative drivers are of great importance for predictive quality innovations because of the complex setting and the number of people across domains whose buy-ins are required. This, however, implies excessive perseverance of the driving individuals as they need to be able to diffuse the value they see in the innovations to various domains and employees at different levels of the company, and not only throughout the quality domain.

5.2.3 Implementation climate

According to the adapted theoretical framework for this study, the most immediate influence on the implementation of innovations is the implementation climate, including structures, concepts, and processes for promoting and easing the implementation of an innovation. The implementation climate itself is affected by management support factors, according to (Klein et al., 2001) model. Further, Van Riel et al. (2004) highlight factors relating to information gathering and information diffusion to facilitate a successful climate that is favorable for innovation success. Similar has been elaborated upon by Hislop et al. (2000), who argue for networking as well as knowledge distribution and knowledge gathering as factors contributing to implementation success and that these are context-based and tacit. A favorable climate for predictive quality innovations requires a large degree of knowledge adaption, practices, enablers, and structures for enabling the distribution of tacit knowledge, as different domains may see the context differently.

5.2.3.1 Technological obstacle

Davis (1989) highlights the importance of perceived ease of use to gain acceptance of new technology and to motivate users' adoption of those, i.e., to strengthen the implementation climate. A strong implementation climate should, hence, avoid use disincentives (Klein & Sorra, 1996). The technological concerns, which were rooted in the digitalization and technology immaturity as well as cross-departmental dependencies where some parties did not rely on predictive quality methods, could be bridged through inclusion. As observed, the Digitalization department aimed at being included early to ensure data quality but also, the end-users were sometimes involved at an early stage to gain their recognition and provide incentives to use the innovation once implemented. By involving all stakeholders in predictive quality innovations, concerns could be sorted out and sufficient knowledge could be provided to assure adoption and use. By the end-user spelling technical or data-related concerns out, the concern gets handed over whereas the end-user could be assured that others are aware and working on potential issues, something which could decrease use disincentives. The involvement could further increase the perceived ease of use as it would allow for individuals who are not working in the Digitalization department or the Quality team to influence the development of digital technologies and, hence, adapt it properly.

5.2.3.2 Resistance obstacle

Different strategies to overcome the initial resistance were proposed throughout the study, such as parallel testing of batteries or innovation in sub-processes, to minimize risks. These strategies should be fruitful and aligns with Zangiacomi et al. (2020) who suggest aiming toward small explorative projects for new I4.0 technologies and successively exploiting the scalability. By parallel running predictive- and traditional quality methods, skeptics could step-wise test the new methods without compromising on what they perceive as safety risks. This action is, of course, slower than instantly innovating into the main process, but considering the high-knowledge, high-safety environment, it is argued to be the best practice to overcome most risk hurdles. Especially since the quality aspect is critical both from a customer- and a safety point of view. Since, quality cannot be compromised, meaning that predictive quality innovations must be assertive and validated, the proposed strategies should limit the use disincentives which, following Klein and Sorra (1996) reason, would strengthen the implementation climate. This is especially accurate for predictive quality innovations as the problem domain spans wide, meaning the innovations must be use-incentivized for the ones not involved in the development, nor the immediate quality domain.

As discussed, the resistance to switching was often related to a person's perceptions, rooted in their previous experiences. The perceptions of an innovation in terms of its value or benefit is argued to weigh heavy in the implementation climate (Klein et al., 2001) and partly explains the observed resistance. The resistance often originated from a lack of understanding of the predictive quality innovation's value or applicability. To foster the implementation climate, it is hence important to achieve a certain level of perceived value for the innovation itself, which must fit with the persons' beliefs. Motivating the adoption of predictive quality innovations is assumed to be especially complex as it requires high knowledge from several domains, and high enough safety to capture sufficient quality parameters. Through explicitly outlining the value of an innovation and its contribution to the organizational vision, it is reasonable to believe that the innovation-value fit will be improved, which according to Klein and Sorra (1996) is key to an implementation climate promoting innovation success. A baseline perception to spread should, in this case, relate to the significance of predictive quality innovations and how they positively contribute to customer requirements, as well as the consequences of not implementing them. A consequence could be difficulties in meeting customer requirements while being competitive and keeping up the work culture that I4.0 allows, in terms of non-repetitive or non-tiring tasks, or low-salaried labor due to automation.

5.2.3.3 Deliverable obstacle

Predictive quality innovations require new knowledge and skills in the quality domain as well as a larger degree of it being specialized, due to the digitalized aspect merged with quality in specific high-knowledge processes. As a major part of the implementation climate refers to assuring the necessary knowledge and skills are available to facilitate the implementation and use of an innovation, the cross-departmental dependencies must not be overlooked.

Adopting knowledge and information from across departments is, however, a complex task. As Bechky (2003) highlights, engineers, technicians, and production workers often have different views on the problem based on their professional context, which explains the differences in prioritization. The best way of merging the different understandings of the problem is via informal interactions (Bechky, 2003) in an open communication climate (Van Riel et al., 2004), which may increase the success rate of predictive quality innovations. As discussed, this might turn out difficult for predictive quality innovations but it should be emphasized that a deeper understanding and a wider context view of the problem, could ease the prioritization issue as it enables cleared expectations of the innovation solving a pinpointed problem. Despite the difficulty, informal interactions and knowledge exchange should be endeavored. This could limit the perception of teams only are *"asking others for a favor, outside their main scope"*, but rather involving all stakeholders in the process and making them feel like they are contributing to a mutual goal.

A frequent aspect brought up in the study was the differences in long-term versus short-term focus. As the observed innovative projects had a long-term aspect, aiming to solve problems which are about to arrive, while most departments' deliverables were short-term, the two sides clashed. One reason could be the perceptions of predictive quality innovations and their necessity. Also, it could be difficult to grasp the long-term value as the methods are still fairly unexplored. An important aspect to include to promote the change which innovations bring could be to assure short-term victories (Kotter et al., 1995). The proposed parallel testing could be a step on the track, as it allows for smaller milestones and assures the momentum to proceed, as part of the goal can be visualized, but also the predictive quality innovations have time to step-wise prove their value.

5.2.3.4 Supportive obstacle

It is necessary to discuss how to best convince the different parties with different perceptions to support a predictive quality innovation. As multiple departments, with multiple levels of managers within each, are involved, it is reasonable to argue for taking the innovation technological specification down to a general level to reach a clarity of the message that fits multiple knowledge domains. This could facilitate use incentives and eliminate hinders such as vetos against the innovation. Visual tools like prototypes and whiteboard drawings can be essential tools to bridge knowledge domains, both those who are digitally driven and those who are more comfortable with traditional, analog methods (Pershina et al., 2019). Hence, predictive quality innovations could be pitched to all stakeholders, by narrowing the problem space down to an understandable level, despite its high complexity.

The novelty characteristic of predictive quality technologies with few technologies developed fit for the manufacturing setting, indicates a vague application area. Indicating potential applicability outside the originally planned area of use, phrased by Henfridsson et al. (2018) as an 'open-ended value landscape'. Despite the increased value, this implies that more buy-in is required from additional parts of the production processes. This further complicates the implementation of predictive quality innovations, as each application area requires the incorporation of additional knowledge, in terms of data science or quality, to utilize the innovation's full potential. Nevertheless, this emphasizes a requirement for a clear framework for the implementation, sorting all complexities and dependencies out, to increase the probability of success.

An innovation with extended use-cases may, however, have a direct impact on the implementation climate as a specific predictive quality innovation may be the facilitator for the next one. Hence, it does not only generate a stronger business case, but it also increases the possibility of buy-in for the next innovative attempt, i.e., *"a light-house innovation"*. This refers to the *"positive feedback loop"* of digital innovations, where it will become easier to get the increased amount of necessary buy-in as the predictive quality innovations value is showing. Handling the identified obstacles with easy and visible measures in a step-wise manner will, in the long run, bridge the issue of the digitalization immaturity in manufacturing and the novelty-related issues of predictive quality innovations in a high-knowledge, high-safety setting. Needless to say, predictive quality innovations are indeed adding another complex dimension on top of the usual digital innovation complexities and struggles.

5.2.4 Summary of the constructs influence on the identified obstacles for predictive quality

In table 5.1 below the findings on how the three different constructs in the theoretical framework of the study influences each of the four identified obstacles, as discussed previously in this section.

Obstacles	Management Support	Information Diffusion	Implementation Climate
Technological obstacle	Resource allocation to avoid misconceptions and ensure reliability in predictive quality methods. Set company overarching criteria for validation of predictive quality methods.	Vast communication and effective information sharing to lessen uncertainties, achieve clarity in project requirements and expectations, and assure generalizability.	Include end-users in the innovation process to lessen concerns and increase ease of use.
Resistance obstacle	Signal importance and value of predictive quality methods, especially targeting influential individuals to gain their acceptance. Set standard for tolerance of failure to balance safety requirements with innovativeness and risk-taking.	Spread of a joint vision to tackle the backsides of information diffusion, e.g., contrasting thought worlds.	Parallel testing and small scale explorative projects to minimize perceived risks and avoid use disincentives. Clear message of the innovation-value fit towards the organizational vision.
Deliverable obstacle	Conflicting objective priority in top management causes a spread of inconsistent perceptions of the company objectives in different departments, complicating cross-collaboration. Assign budget dedicated to innovation projects and clarify how these should be utilized in cross-collaborative projects.	Integrate teams to enable information diffusion and an aligned view of objectives.	Informal interactions to gain deeper understanding of the problem domain and improve use incentives. Facilitate short-term wins to not lose momentum.
Supportive obstacle	Clear gate criteria to ease managers buy-in decision. Clear gate criteria to decrease dependency on buy-ins.	Enable an open and informal communication climate to promote innovation success rate. Persuasion to be used to gain buy-in from different stakeholders in case an open and informal communication climate is not possible. Need for convincing individuals who effectively drive the communication across the departments.	Narrow problem space by utilizing physical and visual tools to bridge knowledge domains. Set a framework for sorting out dependencies for innovation implementation, including outlining potential extended use cases.

Table 5.1: Summary of how management support, information diffusion, and implementation climate impact the identified obstacles for implementation of predictive quality innovations.

6
Conclusion

This study investigated the concept of implementation of predictive quality innovations in a high-knowledge manufacturing industry. Implementation of innovations has some research behind it but is identified as lacking in some aspects, especially when adding the dimensions of digitalization in manufacturing industries and data-driven quality. The digitalization of manufacturing and the concept of predictive quality have limited scientific research as well as few best practices on how to enable the transition. This brought the opportunity of contributing to literature by bridging part of the gap in digitalized quality management. The following section brings insights on the topic and provides different ways of working to succeed with the implementation of predictive quality innovations.

6.1 Obstacles for implementation of predictive quality innovations and the constructs influence on those

Four obstacles were found to influence the implementation of innovations for predictive quality, these were *(1) the technological obstacle*, *(2) the resistance obstacle*, *(3) the deliverable obstacle*, and *(4) the supportive obstacle*. The obstacles originated from the manufacturing industry, as well as the data-driven quality methods, being digitally immature and in need of new skills, new cross-functional dependencies, and new ways of thinking about the quality domain.

The utilized theoretical framework, which was inspired by Klein et al. (2001), Van Riel et al. (2004) Hislop et al. (2000), contained the three constructs *Management support*, *Information- and knowledge diffusion*, and *Implementation climate*, which all were found to impact each of the four identified obstacles. Management support impacts the obstacles by allocating human resources, including facilitation of specialized knowledge needed, as well as dedicating innovation budgets and clarifying the utilization of such in cross-collaborative projects. It further streamlines collaborative innovation projects by allowing for failure and setting company overarching gate criteria for validation of innovations. The information- and knowledge diffusion construct, in terms of extensive communication and driving individuals, aligns visions and expectations across teams in different domains. In addition, an open and informal communication climate increases the probability of successful implementation as it facilitates frequent information sharing. However, if such a communication climate is not possible, persuasion is an efficient way of gaining buy-in. Lastly, the implementation climate reduces the obstacles by minimizing risks through parallel testing. It also provides use incentives by involving end-users and facilitating short-term wins. In addition, sufficient skills are ensured by utilizing physical and visual tools to bridge knowledge domains.

The understanding of how the constructs impact and reduce the prevalent obstacles is of great importance to succeed with the transition to Quality 4.0 in high-knowledge industries. The transition is crucial to capture a competitive advantage in this high-paced environment, but also to be able to meet the increasing quality demands from the customers. Predictive quality innovations are one part of the digital transition of the quality domain. However, the insights from the implementation of predictive quality innovations in this study could be used for other digital quality innovations in a high-knowledge manufacturing setting as well. That is because the prevalent characteristics of digital immaturity of manufacturing systems in the quality domain as well as the new cross-functional dependencies are assumed to be similar as for predictive quality innovations.

6.2 Future research

This study outlined prevalent obstacles to the implementation of predictive quality innovation and how the selected constructs could impact those. However, it would be interesting to complement this study by conducting a comparative study with multiple cases, where different degrees of the constructs could be compared in how they impact the obstacles and to what significance. This could provide additional insights into the research area and managerial implications on where it is most urgent to put in resources to increase the success rate of the transition to Quality 4.0 in high-knowledge manufacturing companies.

It is further worth pointing out that this study was conducted at a single company, i.e., a one case study. To make the research findings more generalizable and the predictive quality research area richer in content, it is proposed to conduct a similar study on other high-knowledge companies than the one subject for this study. That is, to add to these study's insights by looking at other than the lithium-ion battery manufacturing industry. Such findings could, for instance, bring about additional obstacles and how the constructs impact them, as other high-knowledge industries might slightly vary in characteristics of their quality management. For instance, in the lithium-ion battery manufacturing industry, the quality management focus is on stability and safety as it produces high-risk products. Other high-knowledge industries may have other characteristics which are less risk-concerned.

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A

Appendix

Two different types of semi-structured interviews were performed. One with the purpose of understanding different stakeholders' perspectives of digital innovations for predictive quality. The other type to understand the progress of the observed projects before the point of observation initiation. This was, hence, of retrospective type. This resulted in the use of two different templates.

A.1 Semi-structured interview questions

The following template was used once for each of the 15 interviews that was conducted aiming to understand the different stakeholders perception of predictive quality innovations.

Respondent Background and Topic Context

1. What is your role in the company? What are the specific tasks? For how long have you been a part of the company?
2. How do you consider your role connection to digital innovation?
3. How would you describe the way this company is approaching digital innovations?
4. What is your relation to quality management and predictive quality? How would you say your team is connected to predictive quality?

Innovations for Predictive Quality

5. What parameters do you/your team find important to consider when creating an opinion of a new digital innovation for predictive quality?
6. What happens next? Who makes the final decisions?
7. How do you experience different business objectives currently weighed against each other? Do you see any differences in priorities when it comes to data-driven quality compared to traditional quality?
8. How do you weigh long-term versus short-term pros and cons against each other?
9. How are the priorities communicated throughout the organization/team?
10. Do you experience different managers share the same objectives, or does it differ in some way? Why?
11. What knowledge and skills do you believe are necessary in the area of Predictive Quality? How does it compare to traditional quality?
12. How do you experience the specialization trend, which comes with digitalization, impacts the organization/organizational structure?

13. We have found that there are differences in how important people believe data-analytics based quality methods and a connected factory are. Why do you think that is?
14. What are your thoughts about the data which the company are building the predictive quality models on?
15. Which factors do you believe are the driving forces for using data-driven analytics in quality management? And what are the largest obstacles?

A.2 Semi-structured, retrospective, interview questions

The following template was used once for each of the seven projects which was observed.

Initiation of predictive quality project

1. How was the project initiated? How was the search process? Who identified the problem/need for the innovation?
2. Who, at this company, was required as support for initiating this project? Why?
3. What was your position to initiate the new project? What criteria do you need to consider before initiating the possible adoption?

Development of predictive quality project

4. What did you need to start the development?
5. Briefly, how has the development process looked like so far and how does that compare to what you believe is a usual development process?
6. Who has been involved in the stop/go decisions?
7. What identified bottlenecks have you met in the process? What have been the largest obstacles in this project?

Future implementation of predictive quality project

8. When, do you believe, is the optimal point for handing over?
9. Who, do you believe, will you hand the project over to?
10. How do you think a handover process should look like?

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