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The Impact of Visualizing Operational Deviations on Quality

A Case Study at a Manufacturing Company

Master's Thesis in Quality and Operations Management

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Abstract

In today's fierce market conditions and within an industry heavy influenced by quality- and lean management, continuous improvement is almost a necessity for success. In addition, the ever-increasing digitalization presents both challenges and opportunities for organizations worldwide. This thesis departs from these opportunities by investigating how the visualization of operational deviations may impact the quality for a global truck manufacturer. The overall purpose of the thesis was to explore the potential impact that visualization may have on quality, as well as to create a framework for how data collection and visualization should be structured.

To answer this, the methodology guiding this thesis is that of an inductive, qualitative, case-study. The study is structured in two parts, one creating a theoretical linkage between how visualization impacts quality and complementing this with the study's findings, the other part is developing a framework for the data collection process and visualization. In total, 18 interviews were conducted with both managers and team leaders, which acted as input for the theoretical linkage and as a foundation for the developed frameworks.

This thesis is underpinned by theory that cover areas such as quality management, data quality, data-driven decision-making, and data visualization. The results from this case study show that Plant Y has a rigorous emphasis on both data collection and visualization of quality deviations, however, both these processes have significant improvement opportunities where digitalization efforts and restructuring of information systems can prove beneficial.

Concludingly, visualization of operational deficiencies has the potential to increase quality at a manufacturing company. To increase the possibility of beneficial results, the data collection methods and procedures should be structured in a way to enable data analysis, and visualizations must be easily understood in order for it to guide decision-making.

Keywords: visualization, quality deviations, quality management, business intelligence, data driven decision making, data quality.

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1. Introduction

Already in 1994, Dean and Bowen (1994) proposed that total quality is best achieved through consistent customer focus, where continuous improvement and teamwork form the basis for said consistency. Bergman and Klefsjö (2010) somewhat build upon this framework and present the cornerstone model, which also includes the areas of "Focusing on processes" and "Base decisions on facts". Although the authors explain different means and areas of importance for arriving at the destination, the destination is nonetheless the same, namely, to achieve customer focus. Moreover, Grönroos (1984) explains the distinction between perceived quality and expected quality, where a discrepancy between the two can create dissatisfaction. It is thus possible to argue that acknowledging the cornerstones and framework presented by Bergman and Klefsjö (2010) and Dean and Bowen (1994) may yield in a greater customer focus, which in turn, could increase customer satisfaction by decreasing the discrepancy between perceived and expected quality. In this thesis, the concept of quality is viewed both as Bergman and Klefsjö's (2010, p. 23) definition "*a product's or service's ability to satisfy, or preferably exceed, the needs and expectations of the customers*" and "*fitness for use*" that De Feo (2017) argues is a common definition.

Moving into the third decade of the 21st century sets increased requirements for manufacturing companies' ability to adapt to their digitized environment. A fierce market competition, along with increased customer expectations and customized requests, forces manufacturing companies to implement new technologies in their manufacturing systems (Shivajee, Singh, and Rastologi, 2019). Furthermore, as illustrated by Shivajee et al. (2019), there is the possibility of reducing costs by utilizing real-time data visualization. Digitalization acts as an enabler for this improvement and one way for manufacturing companies to reap its benefits is through data analytics platforms (Fahmideh & Beydoun, 2019), where operational data can be integrated and visualized in an intuitive way to facilitate fact-based decision-making and to focus problem-solving efforts.

As argued above, one core dimension to accomplish customer satisfaction is to base decisions on facts. Furthermore, Tao, Liu, and Kusaika (2018) suggest that data is a key enabler for increasing operational competitiveness through prioritized, and well-informed, decision making. In addition, the increasing degree of digitalization has created a new means for collecting high quality data (Parviainen, Tihinen, Kääriäinen, and Teppola, 2017). Altogether, digitalization acts as an enabler for collecting the data, which may prove useful in the attempt to increase operational quality through visualization and prioritized decision-making, which in turn increases the possibility of achieving customer satisfaction and operational efficiency.

1.1 Background

This chapter first offers a brief description of the company under investigation and the market in which it operates. Further, the current state of their quality efforts will be presented as well as a synthesis of how clean data and visualization may enable quality improvement.

1.1.1 Company Description

Company X is part of a large and global group, in this thesis referred to as Group Z. Group Z is primarily active within the business areas of trucks, busses, construction equipment, and marine manufacturing. In 2019, the company accumulated a revenue of approximately 430 billion SEK and a net profit of around 49 billion SEK. Company X, which is located under the business area of trucks, accounted for approximately 110 billion SEK in revenue and 0.9 billion SEK in net profit. Group Z has its headquarters in Sweden and employs more than 90 000 people around the globe. Altogether, the group is active in more than 190 markets and is generally considered to be one of the big players within many of their industries. Group Z's long-term vision is to be in the forefront of providing transport and infrastructure solutions to the world and being the customer's first choice when requesting such solutions.

Within the industry, as well as in society in general, there are major trends towards digitalization, autonomous drive, and electrification. These trends put immense pressure on the organization both in terms of achieving its vision, but also for maintaining its market position. First and foremost, autonomous drive and electrification have the potential of disrupting the market and, in that case, be classified as major product innovation, according to the classifications proposed by Granstrand (2007). Further, depending on the context of application, digitalization may not only pose as a means for major product innovation from a product perspective, but also as a major process innovation for manufacturing companies. Additionally, Granstrand (2007) depicts the concept of the S-curve and how innovations can make flourishing businesses diminish. It is thus safe to say that the industry is potentially on the verge of disruption, which puts tremendous emphasis on reaping the benefits that these opportunities bring forth.

The focus of this thesis will be on one of Company X's manufacturing plants in Sweden, in this thesis referred to as Plant Y. This plant produces medium and heavy-duty trucks, using a line production factory setup and all trucks are assembled from scratch. In the next subchapter, a further explanation of the factory layout will be provided.

1.1.1.1 Factory Layout

The current production layout and organizational structure are visualized in Figure 1 and 2, where the manufacturing plant consists of six different production departments. There is a main line, represented by the blue line in Figure 1, which consists of three of said departments; base module (BM), final assembly 1 (FA1), and final assembly 2 (FA2). Furthermore, the main line is supported by three feeding lines that deliver axes, engines, and cabins in a fishbone structure. The structure of each department is broken down into parts, which are responsible for specific processes. In addition, each part has several teams performing various tasks divided up into workstations (WS) which are handled by an individual operator, all of this is visualized in Figure 2. Furthermore, all parts have a main quality gate, however, the most important ones from Plant Y's perspective are the quality gates Q6, Q7, and Q8. Quality gate 6, Q6, is located at the end of the main line, Q7 is close by Q6, but after adjustments have been made. Lastly, Q8 is the final quality gate and occurs after further adjustments and final testing, and after Q8, the truck is ready to be delivered to the customer.

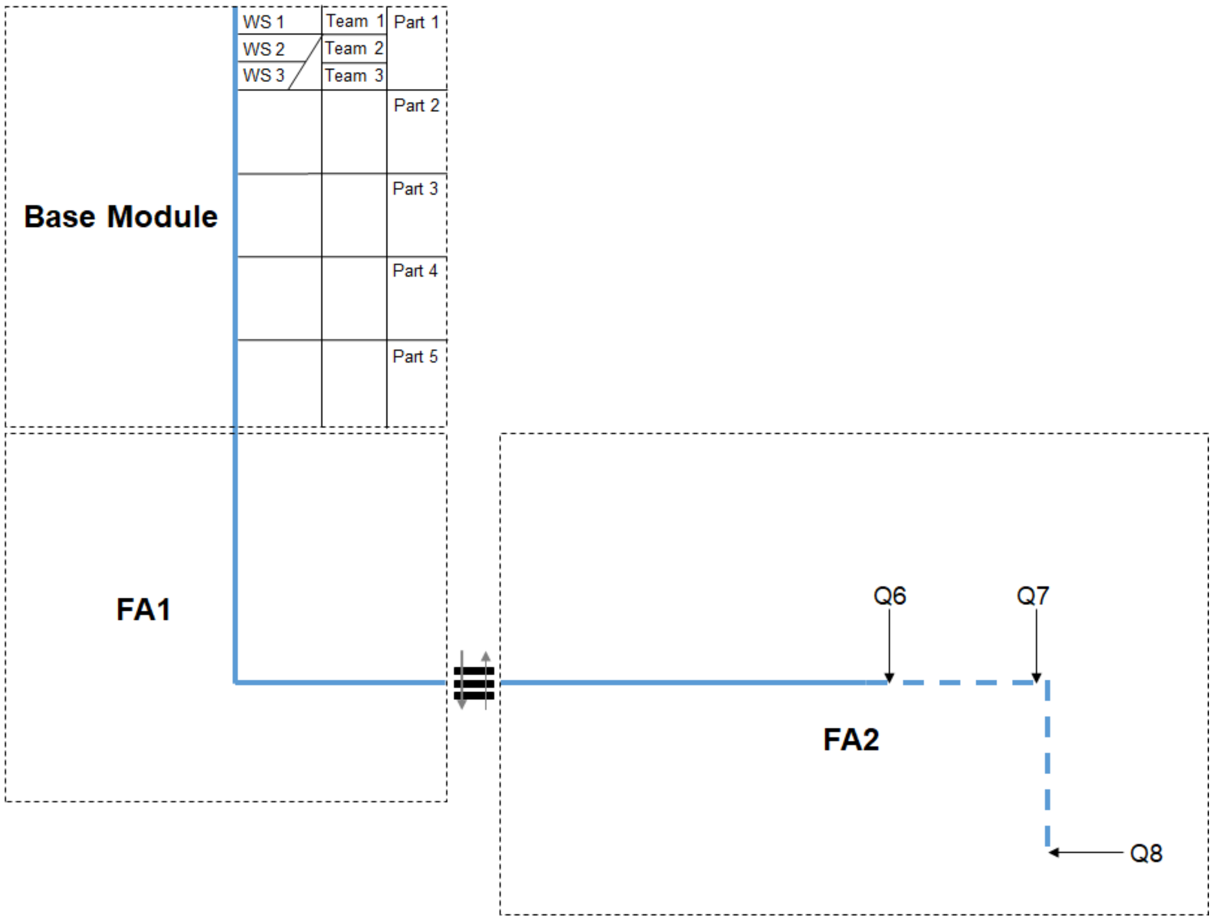

Figure 1 - Graphical visualization of the main production line at Plant Y

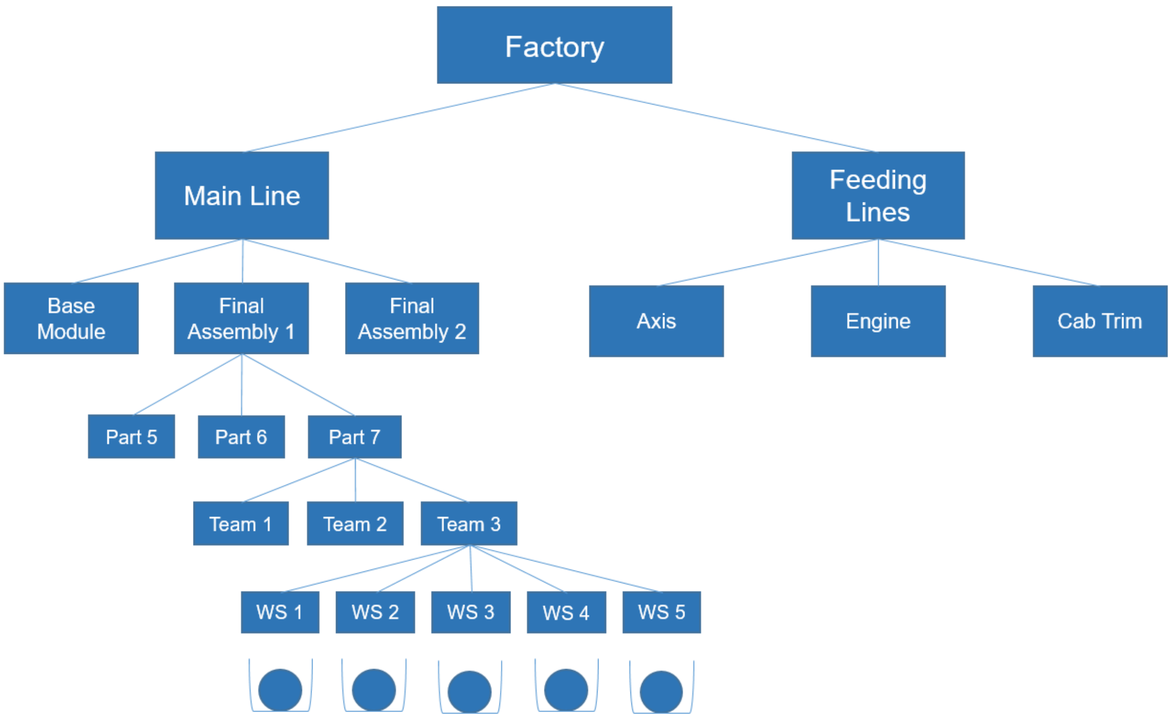

Figure 2 - Visualization of the production's organizational structure at Plant Y

1.1.1.2 Current State

Regarding Plant Y's quality management, it is continuously under development and its production system is influenced by Toyota's lean philosophy. The digitalization era has catalyzed several technological improvement projects at Plant Y, where quality is a common denominator in many of the projects. Considering quality data collection and visualization procedures, previous efforts and implementation have been conducted in all global plants, however, there does not exist a global standard. One plant has recently implemented a new platform for collecting and visualizing deviations related to manufacturing issues, which act as a facilitator for decision-making and prioritization of problem solving at the plant. This knowledge and structure will thus serve as an input for improving the current structure of Plant Y's standard of collecting, visualizing, and making decisions in the attempt to improve the quality of their products. Today, Company X is using the KPI *first time through,* hereinafter referred to as FTT, to measure quality, which is calculated as the number of products that runs error-free through the control stations at the production line.

Currently, the plant has a quality information system which collects information about occurrence of quality issues during the production line. This information is collected on a physical product specific paper, called a travel card, which at the end of the line consists of quality information from the different workstations. Additionally, there are several control points during the production line, where the product is checked for deviations, and this information is then added to the quality information system. Regarding the information from the travel cards, this is added to the system at specific control points on the production line, as well as archived when the product is finished. Despite Plant Y's up and running quality information system, it lacks a standardized procedure for error logging on a workstation level, making it difficult to search and find the root cause of problems. This has resulted in inefficient problem-solving processes, where sometimes symptoms of problems are solved rather than the root cause. Recently a quality initiative called "Why not 100" was initiated at Plant Y, which focuses on reaching 100% FTT in the plant. There is thus a need to standardize the way of collecting quality data, as well as how to visualize this in order to facilitate Plant Y's decision-making and prioritization process, which may result in improved quality of the production plant and one step further to reach the goals of the "Why not 100" initiative.

Concludingly, the market is changing and the industry is facing severe challenges due to the potential paradigm shift within transportation; where sustainability, electrification, and autonomous drive forces organizations to improve and transform their operations to cope with the new demands (Tongur & Engwall, 2014). However, with challenges comes opportunities, and reaping the benefits that digitalization has brought forth could potentially pave the way for excellence at Plant Y. Although Company X is succeeding in today's marketplace, there is a need to update and standardize their processes for data collection and visualization of quality deviations. As depicted in Figure 3 and argued above, clean data and visualization may enable more informed and prioritized decisions, and in turns, potentially an improved quality. This thesis thus seeks to create the foundation for quality improvement through visualization and, inevitably, acts as a part within the "Why not 100" initiative and a step forward towards Group Z's overall vision. More specifically, the thesis will focus on the bottom of the pyramid, namely, clean data and data visualization.

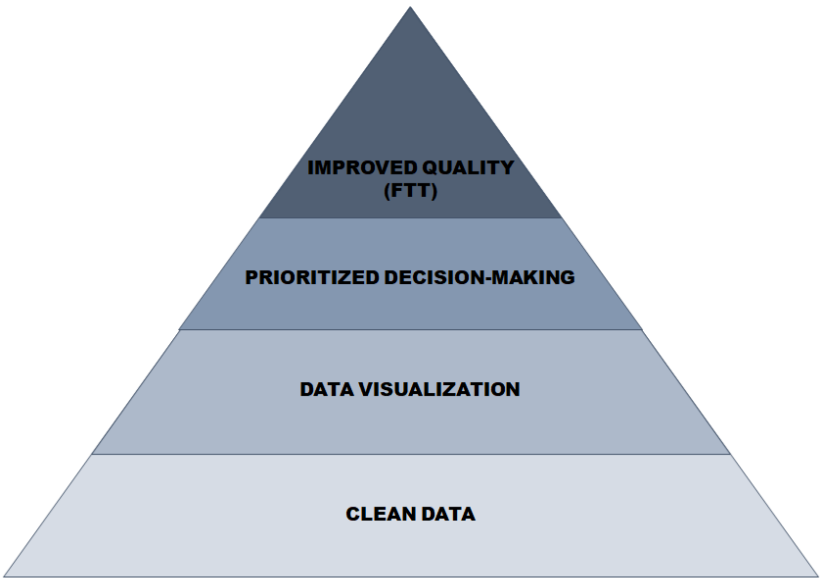

Figure 3 - Visual representation of how data and visualization may impact quality

1.2 Purpose

The purpose of this master thesis is to create a framework for data collection and visualization of operational deviations and explore its potential impact on the quality for a manufacturing company.

1.3 Delimitations

Due to time limitation and the current COVID-19 situation, the data collection will primarily be conducted at one plant located in Sweden. Furthermore, the validity of the frameworks will not be quantitatively assessed. Lastly, the frameworks will merely focus on production deviations.

1.4 Specification of Issue under Investigation

The iceberg metaphor, first depicted by Harrington (1987), clearly illuminates the cost of poor quality, hereinafter referred to as CoPC. Operational deviations are primarily visible on the top of the iceberg, in terms of defects and rework, however, as Harrington (1987) argues, there are severe costs involved at the bottom. It is thus shown that operational deviations are directly related to cost for a company. Furthermore, Sörqvist (1997) and Oakland (2003) strengthens this metaphor by arguing over the importance for companies to acknowledge these costs. This acknowledgment is also visible in the quality movement, where focus has gone from quality inspection and control to the rise of quality management (Dahlgaard-Park, 2006). To enhance and achieve customer satisfaction, it is of importance to continuously improve processes (Bergman & Klefsjö, 2010; Dean & Bowen, 1994). It is thus prominent that there is a need to continuously improve for companies in order to increase the quality and reduce costs.

Visualization is a way to graphically present data in order to make it easier communicated. Data can be visualized in several different ways, for example in the form of histograms, time series, and pie charts. These graphical representations of data can be utilized in order to identify patterns and ease decision-making (Meyer, Höllerer, Jancsary, and Van Leeuwen, 2013).

As argued above, there is a need for companies to continuously improve quality, where operational deviations are inevitably a factor influencing said quality. As digitalization has enabled powerful computer processing tools, visualization has become increasingly popular due to its ability to shed light on problems hidden from the plain eye. Combining the need for quality improvement, with the enabling means of visualization, forms the foundation for the first research question, namely:

- *RQ1: How does visualization of operational deviations impact the quality of a manufacturing company?*

Digitalization, and all new technologies that evolves with it, has generated new possibilities of collecting operational data. However, with possibilities there are often risks, and in terms of collecting data, these new technologies can result in great amounts of unsorted data that are impossible to draw conclusions from. Nagle, Redman, and Sammon (2020) present in their data quality assessment study, that averagely 47 % of the investigated samples consists of at least one severe error. Even though this is just an example from one research study, it is important not to neglect the takeaways from these authors. Furthermore, the rise of big data, poses several challenges necessary to overcome in order to reap the benefits it offers. As explained by Tole (2013), the large variety of the obtained data poses integration, sorting, and interpreting issues.

It is thus prominent that the availability of data is present, however, there seems to be a need to evaluate how this data should be structured for it to be useful. Starting from the bottom, it is of interest to further investigate how the data-collection should be structured in order to ease the use of the obtained data, which provides grounds for the second research question:

- *RQ2: How should data collection methods and procedures of operational deviations be structured in order to ease visualization?*

Following, according to Meyer et al. (2013), the benefits of visualization have been thoroughly covered in academia. Furthermore, the authors argue that there is a remarkable rise in adoption of tools for visualization. On the contrary, Bresciani & Eppler (2015) depicts a framework of common pitfalls when visualizing data and argue that it is crucial to acknowledge these pitfalls for achieving effective visualization. As for everything, there is no silver bullet, and it is thus of interest to investigate how visualization within the given context should be structured in an effective way, which forms the basis for the last research question:

- *RQ3: How should visualization of operational deviations be structured in order to ease decision-making?*

2. Theoretical Framework

This chapter outlines the theoretical framework that supports answering the research questions of this thesis. Including areas are quality management, data quality, data-driven decision-making, data visualization, lean management, and change management.

2.1 Quality Management

In this subchapter definitions of both quality and quality management are provided.

2.1.1 Definition of Quality

Quality can be defined in several ways, where various views and perceptions are suitable in different contexts. On an overall level, Bergman and Klefsjö (2010, p. 23) defines quality as "*a product's or service's ability to satisfy, or preferably exceed, the needs and expectations of the customers*". Further, "fitness for use" has been a common definition, however, this definition is not suitable in the service economy (De Feo, 2017). In the Harvard Business Review, Garvin (1987) presents a more detailed view with his eight dimensions of quality; performance, features, reliability, conformance, durability, serviceability, aesthetics, and perceived quality. Performance relates to the main attributes of a product or service, for example the acceleration of a truck. Features are connected to performance but rather refers to complementing functions, such as a parking sensor on a car. The third dimension, reliability, focuses on the functionality of a product during a specific time frame, where a typical measure could be mean time to first failure. The conformance dimension refers to the degree a product is corresponding with its established standards. Durability measures the product's lifetime, i.e. how long it lasts. The dimension of serviceability is connected towards the services provided in relation to the product, for example how fast a repair is completed in case of a machine break down. When it comes to the dimension of aesthetics, it consists of more subjective aspects since it covers areas of how a product looks or feels. Finally, perceived quality also has a subjective nature since different consumers have different knowledge about a product's characteristics, where the product's quality is based on indirect measures. Considering these eight dimensions, it is important to understand their strategic implications. Due to tradeoffs between different dimensions, companies have to prioritize what to focus on, preferably on dimensions that are most important to the customers (Garvin, 1987).

2.1.2 Quality Management

One prominent characteristic of Total Quality Management, hereinafter referred to as TQM, is a strong emphasis on customer needs and understanding their demands (Alänge, 1994). According to Alänge (1994), the customer should be the starting point, guiding the company's strategy and efforts, towards what their customer values. However, as argued by Hellman and Klefsjö (2000), the true definition of TQM is rather vague and undefined. Although there is a lack of a clear definition, the concept of TQM is described as a management approach that rests on certain principles, dimensions, elements, and cornerstones (Hellman & Klefsjö, 2000). The concept is further illustrated by Bergman and Klefsjö's (2010) cornerstone model, which consists of the principles: Focus on customers, base decisions on facts, focus on processes, improve continuously, and let everybody be committed. In addition to these five dimensions, Bergman and Klefsjö (2010) also emphasizes on the importance of top management commitment. Dean and Bowen (1994) takes a similar approach and proposes that customer focus is the key aspect to consider for companies and that continuous improvements and teamwork paves the way for achieving customer focus.

Continuous improvement, teamwork, and base decision on facts are central in quality management theories. Dean and Bowen (1994) further break down the former two into principles, practices, and techniques. The authors explain the principle of continuous improvement as *"consistent customer satisfaction can be attained only through relentless improvement of processes that create products and services"* (p. 395). To facilitate this practices and techniques such as process analysis, problem solving, plan/do/check/act cycles, flowcharts, and fishbone diagrams are useful (Dean and Bowen, 1994). To establish a successful continuous improvement culture, teamwork and collaboration both internally within the organization as well as with customers and suppliers is essential (Dean and Bowen, 1994). In practice, this can be supported by agreements that involve and benefit all interested parts, forming different teams, and carry out team building activities. Regarding base decisions on facts, this highly connected to data-driven decision-making, which further developed under section 2.3.

Alänge (1994, p. 2) describes the components of TQM through the characteristics of "*customer focus, leadership, total approach, continuous learning, process orientation, and standardization for creativity"*. Although the components differ to some extent between different authors, the common denominator is arguably the emphasis on customer focus. Moreover, it is possible to divide the concept of a customer further into internal customer and external customer. Juran and De Feo (2010, p. 96) define internal customer and external customer as whether they are inside or outside the *"... producing organization"*. Although most academic research has focused on external customers (Marshall et al., 1998), Sörqvist (2001) proclaims that internal customer satisfaction may yield benefits in form of higher employee motivation and job satisfaction. Furthermore, Gilbert (2000) proposes that there is a discrepancy between internal customers' perception of the prior team's effectiveness versus how the prior team believes that the internal customer rates their effectiveness, and takes form in an overestimate of the own team's effectiveness. There is thus a bias towards the own team's performance, versus how their internal customers rates their performance. Combining this bias with Sörqvist (2001) claims of internal customer satisfaction benefits, there might be a possibility for increasing employee motivation and job satisfaction by illuminating the actual performance of each team, disregarding potential biases and presenting the hard facts of each team's performance.

2.2 Data Quality

In order to store and utilize operational data, companies create information systems that can help them improve performance in different areas of their operation (Parvari, A., Anvari, Mansor, Jafarpoor, and Parvari, M., 2015). To stay competitive in today's fierce market, it is more important than ever to base decisions on data, however, Heinrich, Klier, Schiller, and Wagner (2018) point out that companies are struggling because of poor data quality. Orr (1998, p. 67) defines data quality as the "agreement between the data views presented by an information system and the same data in the real world." Further, the most common mistakes that impinge this agreement are inaccuracy, incompleteness, and mismembership (Parssian, Sarkar, and Jacob, 2004; Dey, Kumar, 2013). Becoming a data-driven organization hence pose a risk if decisions are based on false data, resulting in monetary loss and operational inefficiencies (Bai, 2012). Redman (1998) further highlights the impact of poor data quality that leads to dissatisfied customers, increased operational cost, ineffective decision-making, and inaccurate strategies.

To improve the quality of the available data in information systems and mitigate the risks of introducing data errors, Bai, Nunez, and Kalagnanam (2012) suggest the development and implementation of control strategies at a level where data are collected. This could be complemented with the mistake-proofing lean concept of Poka-Yoke, which Singh and Kumar (2020, p. 1157) as a way in *"... reducing the mistake at the origin, rather than taking a mitigation plan after encountering the risk."* According to Liu, Feng, Zhao, and Wang (2020), the improvement strategies of data quality in information systems could be divided into two areas: data-driven improvement strategies and process-driven improvement strategies. Data-driven improvement strategies use different methods or procedures in order to improve data quality. For example, Xu, Lei, and Li's (2019) method for detection and cleaning of poor data values. On the other hand, process-driven improvement strategies focus on controlling and enhancing the process of data usage (Liu et al., 2020). Examples of this are information maps that facilitate the management of data quality, methods for handling data quality risks, etcetera.

2.3 Data-driven decision-making

The establishment and continuous development of information technologies have enhanced the process of data-driven decision-making (Hyers, 2020), hereinafter referred to as DDDM. Troisi, Maione, Grimaldi, and Loia (2020, p. 541) defines DDDM as: *"…a real ideology that conceives data as strategic resources, rather than on intuition and experience and requires the active role of leadership in fostering an innovation-oriented culture and the careful attention to data management in each step of decision-making."* Dodman, Swalwell, DeMulder, and Stribling (2020) further describe that the usual steps of DDDM consist of: identifying the problem through the collected data, find and implement a solution, and follow up the consequences of the decision in order to plan the next steps. This modern way of working results in opportunities for companies to improve operational performance. Brynjolfsson and McElheran (2016) discuss in their paper how new digital technologies have provided companies with possibilities to collect increased amounts of data, and improved data can generate better decision-making. Rejikumar, Aswathy Asokan, and Sreedharan (2018) concretize this by discussing how data-driven work procedures can facilitate managers in understanding and finding emerging trends connected to specific business units, hence creating a foundation for competitive strategies and decisions. Opportunities with data-driven approaches are further explained by Sadati, Chinnam, Nezhad (2018), who states that operational data collected in production can be used to model, control, and improve the performance of processes.

In order to achieve all the benefits provided by DDDM, organizations must face and prevail several challenges. Hume and West (2020) present seven challenges in becoming a DDDM organization; choosing the right data, identifying the right tools, building experience using data, dealing with decentralized data, ensuring data integrity, creating a culture shift, and taking action. First, the challenge of choosing the right data is not only associated with sorting and finding in the large amounts of data that is often collected, but also a question of whether you have the data needed for drawing conclusions. Second, identifying the right tools could be difficult due to excessively many providers of data analytics software that are suitable in different contexts. Third, as with all changes in organizations, building experience of working with data is essential to be able to analyze and draw conclusions from data. Fourth, regarding decentralized data, organizations often have different departments which may consist of several different systems and databases. In that case, one has to know how to deal with those systems and how to integrate them with each other. Fifth, ensuring data integrity is crucial in order to trust the data, because if it is inaccurate or inconsistent it will only guide you in the wrong direction. It is thus important to establish standards of how data should be collected and who is responsible for it. Sixth, all of the previous challenges are in some sense related to culture, hence, in order to transform into a data-driven organization, the culture has to transform as well. Seventh, a DDDM organization is not only about collecting the right data and presenting it in a fancy way, one also has to base your decisions on it and take fact-based actions. Concludingly, even though Hume and West (2020) discuss this in the context of non-profit organizations, those challenges are still arguably applicable in a profit-seeking context as well.

2.4 Data Visualization

As emphasized by Jaca, Viles, Jurburg, and Tanco (2014), companies rarely suffer from lack of data but rather the capabilities for analyzing and drawing conclusions from this data. For this purpose, there seems to be a common ground within the literature that visualization may serve as a mean for facilitating these capabilities. This thesis departs from the definition of visuals provided by Maire and Liarte (2018, p. 1405), namely that visuals are *"...paintings, drawings, charts, diagrams and photography, including their component colours, perspectives, layouts or typography"*. This definition coincides with the definition provided by Davison (2015, p. 122) who describes visuals as *"...pictures and photographs to film, architecture, logos, fonts, diagrams, advertisements, schematic faces and web pages"*. Davison (2015) further describes that visualization can take form both in two- and three-dimensions as well as being static and moving in regard to the dimension of time. Synthesizing the above definitions, this thesis defines the concept of visualization as *"graphical representation of reality"*.

According to Chen, Härdle, and Unwin (2007), visualization can be considered as a double-edged sword due to its ability to be both very effective, and non-effective for communicating information. The reason for this ambiguity is the easiness of producing visual representations without any further thoughts on the including components of the visual (Chen et al., 2007; Knaflic, 2015). However, on the contrary, studies show that there are advantages associated with visualization in the context of information spreading, in comparison to transferring it by text (Davison, 2015; Goransson & Fagerholm, 2017; Proskurina, 2018). In addition, Aigner (2013) claims that the use of visualizations can enable fast decision making among executives. Similarly, Sadiku et al. (2016) propose that visualization is a mean to facilitate decision-making and creative thinking.

Moreover, according to Aigner (2013), there are several challenges when implementing visualization in an organization. In addition to the lack of quality data, Aigner (2013) mentions that the respondents in his study had a lower level of trust towards visuals created in a business intelligence program than one created through Microsoft Excel or static data. Furthermore, the company culture and not knowing the benefits of dynamic visualization may create a reluctance to incorporating visual aids (Aigner, 2013). Furthermore, Brodlie, Oorio, and Lopes (2012) discuss the uncertainty of data and that this poses a challenge when trying to visualize said data. Often, the underlying data is considered to be exact and a visual tool may further strengthen this assumption, which may yield in inaccurate decision making caused by the uncertainty of the collected data (Brodlie et al., 2012). In addition to above mentioned challenges and pitfalls, Walny et al. (2019) mention the importance of communication between the designers and users of visual tools. Some of the challenges mentioned by Walny et al. (2019) includes; adapting the design to changing data, data edge cases, and interaction and dependencies of the design.

Bilalis et al. (2002) argue over the importance of clarity, visibility, and simplicity of information, in order for it to be effectively communicated. This importance paves the way for the need to further investigate the field of visual management, hereinafter referred to as VM. This thesis will follow the definition of VM provided by Liff and Posey (2004, p. 4), namely that VM is a: "*... a system for organizational improvement that can be used in almost any type of organization to focus attention on what is important and to improve performance across the* *board".* Furthermore, Liff and Posey (2004) propose that VM increases the focus on performance by adding the dimension of visualization to the underlying system. Moreover, according to Galsworth (2017) and Murata and Katayama (2010), VM can facilitate decision-making by visualizing the information in proximity to the intended recipient. Similarly, Kattman, Corbin, Moore, and Walsh (2012) mention that VM has the potential to increase performance due to faster information absorption of the visuals, which in turn facilitates faster decision-making. Typical tools within VM are pictures, charts, and diagrams among few (Jaca et al., 2014). Jaca et al. (2014) further argue that the benefits obtainable from VM are not only greater transparency of results and increased visibility of deviations, but also enhanced employee involvement.

There are several existing books and papers on how to visualize data in an effective manner. Two examples are *"Visualize this: the Flowing Data guide to design, visualization, and statistics"* and *"Effective Data Storytelling - How to Drive Change with Data Narrative and Visuals"* by Nathan Yau and Brent Dykes respectively, who, in a rigorous manner, provides a step-by-step guide for how to build effective visualizations. Another example is Cole Nussbaumer Knaflic's book *"Storytelling with Data: A Data Visualization Guide for Business Professionals"*, which also provides an extensive and practical guide. Although all these books are unique to some extent, there are prominent similarities between them. To reduce the redundancy of information in this thesis, the framework provided by Knaflic (2015), were deemed most suitable due to its extensiveness, simplicity, and close connection to business practice. However, other frameworks would most likely yield similar outcomes due to the prominent similarities between them, and the decision to base the visualization efforts on Knaflic's (2015) guide should not impact the validity of results.

2.4.1 Knaflic's (2015) Visualization Framework

As emphasized by Knaflic (2015), the use of insufficient visualizations can yield a complete lack of information transfer. Knaflic (2015) further argues that due to the increasing amount of available data, as well as the growing attention of data driven decision making, it is of great importance to visualize information in an effective manner. There is thus a need to investigate the area further to acknowledge how visualization should be structured in order to facilitate effective communication of information. According to Knaflic (2015), one of the reasons for the ineffective use of visuals is the lack of knowledge. Data analysts generally have a technical background with expertise of how to collect and analyze the data. However, they lack knowledge within the area of designing and communicating the results (Knaflic, 2015). To effectively communicating data through visuals, Knaflic (2015) presents a framework based on six pillars, which will be further explained below:

Table 1 - The six pillars of Knaflic's (2015, p. 28) visualization framework

1. *Understand the context*
2. *Choose an appropriate visual display*
3. *Eliminate clutter*
4. *Focus attention where you want it*
5. *Think like a designer*
6. *Tell a story*

2.4.1.1 Understanding the Context

The first distinction mentioned by Knaflic (2015) is between exploratory and explanatory. Exploratory concerns the steps towards arriving at the result, e.g. analyzing through testing different visuals to identify trends. Explanatory on the other hand, includes the communication of the results, not how one arrived at it. According to Knaflic (2015), it is of paramount importance to resist visualizing the exploratory effort and rather focus on the explanatory one, since it is there the message lays. Continuing, in order to fully comprehend the context, it is important to acknowledge the *Who, What,* and *How* (Knaflic, 2015). **Who** is the stakeholder and recipients of the visual? **What** is the key-message that should be delivered through the visual? **How** will this visual earn credibility?

According to Knaflic (2015), the "Who" should be as explicit and concrete as possible. If the visual seeks to satisfy a diverse group of people, it may yield ineffective for everyone, quite similar to Arrow's Impossibility theorem. Furthermore, Knaflic (2015) proposes that the relationship between the recipients and transmitter should be acknowledged, on the premise that different information may be needed to build credibility, depending on the relationship. Moreover, it is of utter importance to have a clear perception of the key-message that the visual seeks to communicate. Lastly, Knaflic (2015) expresses the need for earning credibility of the visual and that only showing promoting data may increase doubt from a meticulous recipient.

2.4.1.2 Choosing an Appropriate Visual

Depending on the type of data and message to be visualized, different tools can be utilized. One of the core principles, frequently mentioned by Knaflic (2015), is to maintain simplicity and facilitate intuitive comprehension of the used visual. For example, if the message is easily interpreted through simple text, do not include unnecessary visuals. Furthermore, Knaflic (2015) suggests that the following tools should be sufficient for visualizing the majority of possible needs: *Simple text, Scatterplot, Table, Line, Heatmap, Slopegraph, Vertical and Horizontal bar charts, Stacked Vertical and Horizontal bar charts, Waterfall, and Square area.*

One important thing to bear in mind when creating a table is to make the borders as transparent as possible, otherwise it draws the recipient's attention towards the borders rather than towards the data (Knaflic, 2015). Moreover, Knaflic (2015) proposes that, in some cases, heatmaps can be more effective than tables by utilizing color saturation to highlight the differences. In this way, the visual becomes more intuitive and easier to comprehend. Continuing, a scatterplot is suitable for plotting relationships between two variables, while a line graph is suitable for showing trends (Knaflic, 2015). Furthermore, a slopegraph, with or without highlighting, can be utilized to visualize how several factors changed over a period of time.

The usefulness of bar charts should not be underestimated on the premise that it is a common chart (Knaflic, 2015). According to Knaflic (2015), bar charts are superior to pie- and donut charts due to their ability to show relative differences in a more intuitive way. However, Knaflic (2015) stresses the importance of having a zero baseline to avoid deception, even if it strengthens the message. Furthermore, a horizontal bar chart is useful to increase the readability in comparison to vertical bar charts (Knaflic, 2015). In addition, Knaflic (2015) proposes that stacked bar chart can be utilized to easier show relative size, in comparison to using a multiple series bar chart. Similar to the bar chart, the waterfall chart can prove beneficial when wanting to visualize a change step by step. Lastly, Knaflic (2015) argues that there is rarely any use for two-dimensional visuals e.g. area graphs, due to the limited capabilities of the human eye to interpret such information. However, it could prove beneficial if the factor to be visualized has significantly different magnitude (Knaflic, 2015). In that case, an aerial representation further depicts the differences between the factors.

Regarding visuals to avoid, Knaflic (2015) express severe concern of using pie- and donut chart. This concern is derived from the difficulty of distinguishing between the relative sizes of different pieces and, as argued above, bar charts are in most cases superior. One defense to the pie chart is its ability to capture to show the entirety of the data, however, Knaflic (2015) suggests that serious thought should be put before using a pie or donut chart due to the downsides it possesses. Moreover, Knaflic (2015) suggests to not use three-dimensional visuals unless utterly necessary since it, in most cases, makes the information harder to interpret. Even if the information requires three-dimensions, it should be performed with caution due to the immense increase in complexity that three-dimensions bring. Lastly, Knaflic (2015) raises concerns using a secondary y-axis on the premise that it becomes harder to understand. One countermeasure for this issue is to plot the specific numbers instead of having it as an additional axis.

2.4.1.3 Eliminating Clutter

The primary reason for eliminating clutter is to decrease the cognitive load of the visual (Knaflic, 2015). The more information and components a visual possess, the more cognitive load it takes to interpret. For this reason, Knaflic (2015) stresses the importance of eliminating unnecessary components and non-value adding elements of a visual. Knaflic (2015) further presents six principles that strongly influence the human perception of a visual. The principles are: *proximity, similarity, enclosure, closure, continuity, and connection*. Further explanation of these principles can be found on page 76 in the book *"Storytelling with data: A data visualization guide for business professionals"* by Cole Nussbaumer Knaflic.

Knaflic (2015) further mentions the importance of visual order, and how the lack of it inhibits intuitive interpretation. To increase the visual order, Knaflic (2015) proposes alignment of components, space between and within graphs, use of contrast to highlight, and elimination of unnecessary information and elements.

2.4.1.4 Focus Attention

Knaflic (2015, p. 99) describes that if preattentive attributes are used wisely, they can *"enable our audience to see what we want them to see before they even know they're seeing it!"* Preattentive attributes can be used in texts, where different colors, size, font, etcetera is useful to focus the user's attention. This can further be combined with graphs where one can, for example, highlight parts of graphs in the same color as the describing text. However, it is important to remember that highlighting one part of a graph will make other things harder to see, hence, think twice before deciding what to highlight.

2.4.1.5 Think like a Designer

When working with visualizations it could be useful to think like a designer, meaning that one first considers what one wants the viewer to do with the visuals before creating them (Knaflic, 2015). In relation to this, Knaflic (2015) discusses affordances, accessibility, and aesthetics. In design terms, affordances consider the degree of how obvious it is how something should be used. For example, connecting this to visuals could mean how obvious is it for the user to know what to do or how to interpret the graphs and tables. To help the user, it is important to highlight the important things, eliminate distractions, and provide a clear visual hierarchy of information. Accessibility refers to how usable the visual is to different people with different levels of competence. In order to create visuals with a high degree of accessibility, one should not overcomplicate things. For example, using consistent and easy to read font type and use straight forward language to avoid misinterpretations. Lastly, when visualizing data, it could prove beneficial to put some effort into the aesthetics since this can make the users more accepting and patient working with the visuals. However, not all designs suit everyone and Knaflic (2015) points out three important considerations. First, one must use colors in a strategic and intuitive way, in order to highlight important parts of the visual. Second, it is important to consider alignment, where visuals aligned in a horizontal and vertical way provide coherency. Lastly, leverage the space between your graphics to create intuitive and clean visuals.

2.4.1.6 Tell a Story

Knaflic (2015) draws parallels to telling a story when it comes to communicating information, more specifically meaning that communication should consist of a beginning, middle, and end. The beginning of a report or dashboard should provide the users with introducing content that shows the context of the matter. In this way, everyone looking at the visuals will build a common foundation to guide them to interpret the following data similarly. Considering the middle, one needs to maintain the audience attention and convince them that there is a need for action. This could for example be highlighting problems and suggest solutions of how to solve them. Lastly, the end refers to the need of call to action, where it should be totally clear what the user should do with the information provided to them.

2.6 Lean Management

Liker and Convis (2012) describe five core values that are the foundation of Toyota's lean management and leadership philosophy: spirit of challenge, kaizen, genchi genbutsu, teamwork, and respect. Spirit of challenge provides leaders the energy and drive that is required to achieve the ultimate goal: perfection. This core value is well described by Liker and Convis (2012, p. 54) as: *"... accept challenges with a creative spirit and the courage to realize our own dreams without losing drive or energy."* The Japanese concept of kaizen, in the western world referred to continuous improvement, incrementally provides improvements to a system (Criscione-Naylor, 2020). Liker and Convis (2012) further develop this concept and refer to a kaizen mindset, which has its foundation in that no process is perfect and improving performance is always possible. Genchi genbutsu, or "go and see, to deeply understand", emphasize the importance for leaders to really understand the value-adding work in order to base their decisions on facts (Liker and Convis, 2012). Another fundamental core value in lean management is teamwork, unfortunately, practicing teamwork within a company is often easier said than done. Liker and Convis (2012, p. 56), describe that Toyota's view on teamwork is that *"... individual success can happen only within the team and that teams benefit from the personal growth of individuals is constantly reinforced and lived up and down the chain of command."* Further, teamwork is closely connected to the final core value, namely respect. This core value is based on that Toyota wants to produce products and services that contribute to the society and in order to achieve this, employees, customers, and all business partners need to be respected (Liker and Convis, 2012).

Apart from the philosophical pillars, lean management covers several methods and tools that facilitate waste elimination in a production setting. Waste elimination is fundamental in lean production (Slack and Lewis, 2014), and in Japan waste is referred to as *muda*. The seven wastes originates from Taiichi Ochno, and Nicholas (2018) describe them as; waste from producing defects, waste in transportation, waste from inventory, waste from overproduction, waste of waiting time, waste in processing, and waste of motion. For a more detailed explanation of the seven wastes, see Nicholas (2018). Those seven wastes are sometimes complemented by an eighth, namely unused creativity (Sörqvist, 2013).

2.7 Change management

One of the parts of this thesis concerns the implementation of new practices and procedures for data collection and visualization. It is thus of interest to investigate how this implementation process should be structured and planned, in order for it to yield results, and hence, there is a need to further explore the area of change management.

Within the area of change management, there are several factors to acknowledge when constructing a change strategy. Dunphy and Stace (1993) present a framework that concretizes the different levels of change, where the changes proposed by this thesis can be classified as a level 1 change, i.e., Fine Tuning. According to Dunphy and Stace (1993) fine tuning is characterized by improving the strategic fit for processes and people within the organization e.g., through the development of operating procedures and continuous improvement. This definition somewhat coincides with the definition of “Tuning” provided by Nadler and Tushman (1989) who classify tuning as an incremental and proactive approach where the changes are minor adjustments and improvements internally. Moreover, Schein (1992) lifts the dimension of organizational culture and decomposes it into artifacts, values, and assumptions. The artifacts of organizational culture involve visible objects and elements, such as organizational structure, jargon, and physical characteristics of interiors (Schein, 1992). The values and beliefs are not completely visible, and to some extent intangible, and resolves around espoused values, tacit assumptions, and informal rules within the organization (Schein, 1992). Lastly, Schein (1992) mentions the basic assumptions underpinning and inherent in the organizational culture, which is described as tacit and intangible perceptions and thought that are taken for granted, which influences the prior two dimensions and shapes the organization.

An important element that strongly influences the success of a change initiative is stakeholder acceptance. For analyzing the affected stakeholders, Hayes (2018) proposes to distinguish them regarding their attitude towards the change and the power they possess to affect the change. By mapping out and classifying the different stakeholders, it is possible to direct attention and action towards where it is needed. Moreover, Battilana and Casciaro (2013) explain the importance of acknowledging the informal networks in an organization. Although a person might have more hierarchical authority, their informal network might be smaller than someone without formal authority. It is thus important to identify people with large informal networks and gaining their acceptance as they are major influencers (Battilana & Casciaro, 2013).

Battilana and Casciaro (2013) further discuss how to handle resistance and “fence-sitters”, where it is suggested to put efforts in winning the fence-sitter’s acceptance. For resistors, it is largely case-dependent on how to handle it, but Battilana and Casciaro (2013) propose that if the change initiative is not highly divergent, there may be benefits from keeping resistors close by.

3. Method

This chapter provides the methodology for this thesis where the chosen research design, data collection, data analysis, quality criteria, and ethics are elaborated. The research process consisted of three subsequent steps. In the beginning, the emphasis was on investigating the context and formulating the problem. Later, data collection was conducted over 12 weeks, and in parallel, mock-up visualization models were developed and iterated. After the data-collection process, the results were analyzed and a final framework for the data-collection process and a model for the visualization of quality deviations was developed.

3.1 Research Strategy

The research strategy of this master thesis is an inductive case study, where a single manufacturing plant's data collection and visualization process of operational deviations is evaluated. Since there is no universal framework for how to collect data in the specific setting, nor is there any standard for how to visualize quality deviations, an inductive study was deemed more appropriate in order to develop this. Yin (2014) explains that a case study is suitable for answering questions of "*How?"* and *"Why?"* when there is no control of behavioral events and where the focus is on contemporary events. Furthermore, due to that the study aims at exploring and developing a framework and model for data collection and visualization of quality deviations, a qualitative study was undertaken. As emphasized by Azungah (2018) and Bell et al. (2019), qualitative research has the benefit of capturing details and has a humanistic approach, and a qualitative study was thus deemed appropriate for this thesis.

3.2 Research Design

To improve Plant Y's data collection and visualization of quality deviations, the authors performed interviews and observations, as well as searched for best practices in other plants of the organization. Furthermore, the collected information and knowledge were analyzed, which resulted in a framework for how the data-collection process of quality deviations can be improved as well as a model for visualizing these. More specifics of how data collection and analysis for this thesis was conducted are provided later in subchapter 3.2.1 and 3.2.2 respectively.

3.2.1 Data Collection

This subchapter provides information on how data was collected during the thesis, which lays as a foundation for the development of the framework and model, and which ultimately acts as means to answers the research questions. In addition to the below mentioned data collection methods, organizational data from different information systems at Plant Y has been used as input for the data collection framework as well as for the visualization models.

3.2.1.1 Interviews

In order to get a complete view of Plant Y's current state, as well as the problem, the interviews conducted in this thesis were both of structured and semi-structured nature. 18 interviews were performed in a top-down approach, started with semi-structured interviews with five managers to better grasp the problem. Conducting interviews in a semi-structured way allows for more flexibility to ask follow-up questions (Lantz, 2013), hence this was deemed appropriate in the initial phase of the thesis to understand the plant's situation. The first interviews were conducted as pilot interviews, in order to continuously improve the interview questions to cover relevant information. During the pilot interviews, more holistic questions were asked in order to better grasp the situation. These questions were then adjusted to target and get more detailed information of the area investigated in this thesis. For example, a question such as "*Could you describe how the data collection process of quality deviations takes place today?"* asked during the pilot interviews, was later adjusted to focus on certain process steps instead.

The initial interviews were followed up by interviewing three data analysts and three quality engineers to get more detailed information about the subject under investigation. Moreover, information and knowledge gathered from the semi-structured interviews were then guiding the authors in the right direction of where and with whom to conduct more detailed structured interviews on a team level. A total of seven team leaders from all the different departments were then interviewed. Further, all interviews with officials ranged between 45 to 60 minutes and, if given consent, was recorded. Due to time constraints from the team leaders, their interviews were limited to 20-30 minutes and recorded if consent was given. The recordings were later used to summarize the results of the interviews. Additionally, recording is important since it will enable the interviewers to put more focus on listening and understanding the answers, as well as asking essential follow up questions instead of taking notes (Bell et al., 2019). For detailed information about the questions asked during the interviews, see the interview templates in Appendix A and B.

3.2.1.2 Observations

To further deepen and complement the knowledge obtained from the interviews, observations were performed. The observations served as a mean to contrast the interview data, as well as to create a more holistic understanding of the operational practices and procedures. The observations covered different departments of the production line, mainly focused on how operators, team leaders, and control stations are collecting data of deviations.

3.2.1.3 Sampling

The sampling method used for the interviews and observations in this thesis was snowball sampling. Since the project was initiated by a management group within the company, it was convenient and necessary to start the discussion with those to understand whom to interview next. The snowball sampling method means that following interviewees will provide a future direction and establish connections with people who can give more information (Bell et al., 2019). The sampling size was not definitely determined but depended on the number of interviews needed for fully grasping the situation and developing the frameworks. A total of 18 interviews were conducted, distributed over: five managers at Plant Y, four data analysts, three quality engineers, five team leaders, and three quality managers at another plant of Group Z.

3.2.1.4 Literature Review

The literature review for this thesis consists of two parts. One part aims at establishing a theoretical link between how visualization can aid data-driven decision-making, as well as linking data-driven decision-making to the improvement of quality. The other part focuses on how to obtain clean data and effectively visualize this data, which forms the foundation for the creation the frameworks that are presented later in this thesis. Moreover, the literature review also included topics of interest for understanding and strengthening the conducted work, which was included in both parts.

Literature was primarily found through Google Scholar and Chalmers Library using both keywords and utilizing a snowball approach. For the initial phase of the project, keywords were “data driven decision making” and “visualization” combined with secondary words, such as “benefits”, “quality”, and “quality improvement”. For the later phase, the keywords shifted toward “clean data”, “data collection”, and “visualization of data”. To increase the trustworthiness of the thesis, peer-reviewed sources, as well as articles published by large and well-known organizations was prioritized. Furthermore, triangulation was utilized to a large extent to ensure that the information is valid.

3.2.2 Data Analysis

Similar to the literature review, the analysis consists of two parts. The first part aims at synthesizing and discussing the investigated literature with the emphasis on establishing a potential link between visualization and data-driven decision-making as well as whether data-driven decision-making can improve quality. This part of the analysis primarily takes the form of a discussion, trying to lift different perspectives of the matter.

The second part of the analysis was conducted through comparing the empirical data that were collected through the interviews and observations of the company, with literature. Based on this comparison, discrepancies were identified, both between the current state and literature; between best-practices and literature; between the current state and best practices. These discrepancies were further discussed and analyzed to identify the underlying premise for these. Through applying and combining best practices and literature to the investigated context, a framework was created on how Plant Y should collect data and visualize this in an effective and efficient manner.

3.2.3 Quality Criteria

It is questionable if the quality criteria of reliability and validity are appropriate for qualitative research due to its focus on measurements (Bell et al., 2019), hence, this thesis is evaluated on the criteria of trustworthiness. Bell et al. (2019) divide trustworthiness into four sub criteria; credibility, transferability, dependability, and confirmability. Firstly, credibility evaluates the level of similarity between the researchers’ view of the world in relation to others’ view. Secondly, transferability assesses whether the research is applicable in other contexts. Thirdly, dependability deals with what methods and procedures used during the thesis, focusing if these have been carried out in an appropriate way. Lastly, the quality criteria of confirmability is used in an objective assessment of the thesis, meaning that it evaluates whether personal values have influenced the results. To ensure quality of this thesis, activities related to the mentioned criteria are explained in Table 2 below.

Table 2 - Activities related to quality criteria to ensure research quality

Quality Criteria	**Activities to ensure the quality of this research**
Credibility	Collected data from interviews, observations from multiple departments and hierarchy levels at Plant Y.
Transferability	Provided a clear description of the study and the context along with its limitations.
Dependability	Stored recordings from all planned interviews.
Confirmability	The framework for visualization and data collection was developed by both authors.

3.3 Ethics

As emphasized by Bell et al. (2019), there are four main ethical considerations that must be acknowledged when performing research, namely: harm to participants, lack of informed consent, invasion of privacy, and deception. These areas were acknowledged and considered during the entirety of the project to ensure the ethicality of the work. First, avoidance of harm is both in regard to physical and psychological harm, as well as harm to one's career or self-esteem (Bell et al., 2019). This principle was identified as a potential problem during the thesis due to the purpose of focusing on quality improvement, which may yield new practices and systems for the company. For example, visualizing data may be done differently as a result of the suggested improvements, yielding in current competencies being obsolete. This risk is hard to diminish entirely, but efforts were made to spread knowledge of new systems and practices to entities affected by the change to try enhancing their expertise and perhaps even their careers, rather than diminishing them.

Second, to avoid transgression of informed consent, all interviews and observations were initiated with a presentation of the project in order for the participants to make an informed decision. Furthermore, recording of interviews as well as conducting observations were only performed if informed consent has been given by all the participants. It was also explained during the presentation of the project that the participants have the opportunity to withdraw their statements at any time, as well as ending the interview or observation prematurely. Third, one way to avoid invasion of privacy is to have informed consent (Bell et al., 2019), thus, the above-mentioned considerations were taken into concern as well as granting all participants with anonymity during the project and thesis to avoid any invasion of privacy. On a higher level, the company is also granted anonymity in the thesis to avoid leakage and spread of sensitive information. However, it is worth noting that the anonymity of the company is somewhat compromised by the company description due to the limited number of truck manufacturers operating within the country. To counteract this, sensitive information and numbers are figured in the thesis. Due to the qualitative nature of the thesis, the figured information is unlikely to affect the replicability of the results. Fourth, since the focus in this thesis is to aid and support all interviewees, the risk for deception is low.

Lastly, due to the COVID-19 situation, special precautions were undertaken to ensure that the data-collection did not pose any significant risk of further spread of the virus. More specifically, interviews were held in rooms allowing a minimum distance of 1.5 meters from the respondent. Moreover, as per request from the company, the thesis authors participated in weekly COVID-19 testing to facilitate a safe work environment for everyone involved.

4. Results

This section will present the result of the 18 interviews conducted with managers, analysts, quality engineers, and team leaders at Plant Y. Additionally, this is complemented with the interviews conducted in other parts of Group Z, along with insights collected during the master thesis work at Plant Y. The result is divided into two sections, one focusing on data collection procedures and the other on data visualization, both in relation to quality deviations.

4.1 Data Collection

Data collection of quality deviations is well integrated and widespread over the different plants of Company X. The main system used for collecting quality deviations over the plants is an information system called QULIS. QULIS is extremely comprehensive, with possibilities for things such as collecting detailed information about quality deviations, adding pictures of the problem, and performing common analyses, to mention a few. However, as Manager A points out, "*QULIS consists of standardized fields, but the data is not always entered in the same way*", leading to a lot of miss-logged data. Manager D follows up on this subject and states that *"It is the same scroll menus no matter what selections you make in the system, which open up to the possibility to remark an issue that is not even possible on a particular truck"*. Further, Quality Engineer B express the concern that *"it takes a lot of time to clean the data"*. Due to QULIS's comprehensiveness, it requires training to understand and be able to enter data as well as to use its features. This is related to a critical time lag in Plant Y, between finding a problem and reporting it into QULIS, and Manager D describes that *"It is very seldom that the person who finds the problem is the one reporting it into the QULIS"*. A bit simplified, today's procedure starts with an operator or team leader documenting a deviation on a paper, called a travel card, which is later reviewed by the closest quality gate that enters the information into QULIS. Manager D believes that the reason for not reporting the issues directly into QULIS is because it is too time-consuming and that not everyone has the competence in using the system. In order to deal with this time lag, there is an ongoing initiative at Plant Y of digitizing the travel card by providing tablets to operators and team leaders. This would enable the one finding the problem to also report it directly into QULIS in an easier and more accessible way. However, Plant Y has a tendency of struggling with digitalization initiatives and decisions, as well as resource allocation to those take a lot of time. For example, when telling a colleague that something was requested in November, the response was "*Which year?*". Even though this is said with humor in mind, the statement is still based on the truth.

Since reporting quality deviations is a time-consuming task, the collected data does not always speak the entire truth. Like Quality Engineer A mentions: "*It is faster to fix a problem than to report it, which results in a black hole with inaccessible information*". Additionally, the team maturity varies, and at most of the interviewed teams, it is only the team leader that knows and/or has the time to fill in the travel card. What also deviates from Plant Y from another plant in Company X, is what details of the quality deviations that are entered into QULIS. For example, QULIS has the possibility to enter the part number that is related to the remark, however, in Plant Y, this field is only mandatory to enter information into if the part is missing. Related to this, Analyst B, who works in another plant, states that *"including part number opens up possibilities for better follow-up and analysis of quality deviations".*

Regarding the flexibility of QULIS, restructuring is quite complex and time-consuming. According to Quality Engineer B, major layout adjustment in QULIS can only be performed by requesting it from IT services in India. During a majority of the interviews with managers and quality engineers it was mentioned that there is an ongoing project to restructure the QULIS system to enable better flexibility, however, it is uncertain exactly when and what this update will include. Worth mentioning is that the changes to the QULIS system will be done in a strict top-down manner, and the individual key-users at Plant Y have gotten none, or close to none, say in the project. Manager B expressed certain frustration on this matter, namely, that the people who actually work with the system on a daily basis were never asked about what features they would like to be developed or changed.

Apart from QULIS, Plant Y uses several other different systems that are connected to the quality area. PI is a system that collects and presents data of the main quality KPI, namely FTT. Another system is called PRODIFY, which handles all data related to stops on the line. For example, if a sensor detects an issue on the line, this is automatically reported into PRODIFY with alarm codes, time, duration, etcetera. However, this still requires some manual reporting from team leaders to add comments about the different stops. Furthermore, regarding electronic control units, a system called PROSIT is used to find detailed information about particular error codes. One issue with all these systems, which several interviewees have mentioned, is that the systems do not speak very well with each other. For example, a system called PRAUDIT is used for collecting data about audit points, even though this is reported into QULIS as well. As Analyst A said: *"There are a lot of isolated systems that do not integrate well with each other, and also systems that are doing similar things such as QULIS and PRAUDIT"*. There also exists an overarching control system, named FCS, that contains general and specific information of all the trucks currently on the line. Once the trucks are complete, this system transfers the data to storage and is accessible through the system FCHS.

One problem that several of the interviewees brought up is that quality deviations that are reported into QULIS are sometimes moved by team leaders since they do not agree that the problem occurred within their workstations. As Manager A says "*there is a lot of focus on maximizing own KPIs by moving points and excluding potential edge cases",* Manager A also continues by saying that "*instead of finding the root cause for the false reporting, the point is just moved, which means that the miss-logging will continue"*.

Concludingly, the data collection at Plant Y is comprehensive, and a lot of the data related to quality are gathered on a daily basis. The process includes a time lag between finding and reporting a problem into QULIS, even though the information is entered directly on the travel card. Some systems are quite outdated and inflexible, and there is no clear communication between them. QULIS has standardized fields and collects relevant and useful information about quality deviations, however, its selection process consists of miss-logging risks.

4.2 Visualization

From the data-collection process, several important findings were obtained regarding the visualization of quality deviations at Plant Y. In general, the plant follows the production system's rigorous emphasis on visualization. Throughout the plant, there are whiteboards and screens used for visualizing short- and long-term activities and results. Furthermore, some of the information systems used in the organization provide the possibility to visualize the data. For example, each team has their own whiteboard, which is to be filled each consecutive day, with information of previous day's quality outcome, line stop-time, safety incidents, responsibilities and progress of short- and long-term initiatives, etcetera. However, much of these visualizations take form in analog and physical shape, rather than digital. From the interviews with team leaders and managers, it was possible to deduce that much of the information traveled from whiteboard to whiteboard every day. Due to the size and complexity of the organization, as well as the use of analog visualization, the information often travels to at least three different whiteboards. On this specific matter, Manager C expressed concerns by saying *"It is quite easy for numbers to be rounded and tweaked in a wrong way, not intentionally, but due to people forgetting the correct number"*. On the contrary, Manager A, suggested that *"when you have to write a number down, you remember it better and you give it a thought if it seems to be wrong"*.

On a manager level, the use of digital tools is more prominent but certainly not prevalent. In general, at a manager level, whiteboards are still widely used for tracking the short- and long-term outcomes, but on a more holistic level than the ones used by the team leaders. The information provided by the team leaders is synthesized for each step in the hierarchy, but the analog visualization is more or less the same. As for the quality technicians and engineers, the analysis and visualization are solely done in Microsoft Excel. Some individual efforts have been put into visualizing the data through Microsoft Power BI, however, there exists no expertise within this area at the quality department of Plant Y. For the entire plant, Analyst C describes that there exist some visualization solutions based on Microsoft Power BI, however, these are holistic and high-level visualizations of overall daily performance, and not on a detailed and team leader level. During the entirety of the data-collection process, several managers have expressed the need for real-time visualizations of the quality outcome, which they believe could aid them in making more informed and faster decisions. As for today, due to all visualizations being developed in Microsoft Excel, real-time observations are not possible and manual development is needed to create each visual.

During Gemba walks and day-to-day observations, as well as during the preliminary interviews, the team leaders expressed that the daily preparations for reporting was a rather time-consuming activity. All of the team leaders who were interviewed claimed that they spend between 10-20 minutes every morning, gathering and synthesizing the information from the different data sources as well as calculating specific KPIs that are to be visualized on the whiteboards. A majority of the team leaders further expressed that they often feel stressed and anxious about this task, and Team Leader D, E, and F pointed out that it is hard to prioritize which problems to focus on as well as keeping track of trends when it comes to quality deviations. Team Leader A explicitly said that *"I usually come in to work 15 min ahead, just to make sure that I have enough time to prepare everything"*. Additionally, Team Leader B and C expressed enthusiasm for having all the relevant information in one place rather than checking and gather data manually from several different systems. Furthermore, the daily preparations are expressed to be complex, and not all team leaders have the knowledge of how to conduct it. Team Leader G was frustrated in relation to this and stated that *"It is very cumbersome to switch between different systems that is often complex to deal with. Luckily, I have a support number that I use frequently"*. This results in that some team leaders are responsible for preparations for several teams, hence making this process vulnerable.

When asked about how the short- and long-term prioritization of improvement efforts take place, it often comes from the managers and/or through an analog tracking visual named Built in Quality (BIQ). The BIQ can most easily be described as a tool for the tracking of recurring and critical quality deviations, which is visualized on whiteboards. However, Team Leader D, E and, F said that the process of picking a certain quality deviation to focus efforts on can be rather tedious and ambiguous. As mentioned before, there are limited use of sophisticated visualization and analysis tools by the officials, and for the team leaders, Microsoft Excel is the only tool that is used. The process of picking the top three quality deviations to resolve thus consists of downloading all the quality remarks from QULIS over a given time period, often a couple of weeks, copying these to a Microsoft Excel worksheet and then trying to make sense of the data. Due to its complexity, many team leaders mentioned that they often pick issues based on gut feeling and know-how.

For visualization of trends and day-to-day performance on a team leader level, a total of seven team leaders were interviewed. From these interviews, it was identified that the following data and KPIs from the previous day needed to be included to ease day-to-day reporting: (1) number of quality remarks and detailed information about them, (2) total number of produced trucks, (3) audit remarks and customer claims with detailed information, (4) quality remarks that were not resolved before a quality gate, (5) quality remarks that were resolved before a quality gate, (6) line stop-time and detailed information about the different stops, (7) whether a quality remark was detected within the team or later on, (8) the difference between the planned number of produced trucks and the outcome, and (9) the previous day's FTT. To visualize trends in order to aid prioritization of problem solving efforts, the following information and/ or graphs was requested: (1) most common deviation part, (2) quality deviations placement on the truck, (3) most common type of problem, (4) which part the deficient part was attached on, and (5) time-period selection. One frequently mentioned need, expressed during the interviews, was to have all information in one place and that it should be easily accessible.

"As for today, you first have to log into QULIS, which is not very user-friendly, search for your team and copy down the results. Then you have to log into PRODIFY and get the information of the stop-time. After that, you have to log into PI to get the FTT and after that, you can start calculate the results of the previous day." – Team leader A

Concludingly, Plant Y has a rigorous emphasis on visualization, however, the majority of the visualization work is done in an analog way in terms of whiteboards, where often the same number travels from board to board. The team leaders' preparations for daily morning meetings are expressed to be time-consuming, and the process for prioritizing which problems to focus on is stated to be ambiguous.

5. Discussion

The purpose of this thesis was to create a framework for data collection and visualization of operational deviations and explore its potential impact on the quality for a manufacturing company. In order to concretize this purpose, this chapter will include a discussion aiming at answering the three research questions, covering how visualizations impact quality and how data collection and visualization should be structured. Lastly, this chapter will include short- and long-term recommendations for how Plant Y can move forward with the findings from this thesis.

5.1 Quality Impact of Visualization

The first research question, RQ1, targets the area of how visualization of operational deviations impacts the quality of a manufacturing company. From the literature review, it is possible to deduce that the use of visualization has both significant benefits and challenges/ risks. While Davison (2015), Goransson and Fagerholm, (2017) and Proskurina, (2018) all claim that visualization is better than plain text for information spreading, Chen et al. (2007) proposes that it can be both very effective and non-effective for said purpose. It is thus of importance to acknowledge the aspect of how the visualization seeks to transfer information. As emphasized by Bilalis et al (2002), for information to be effectively communicated, there is a need for clarity, visibility, and simplicity of the information. Strengthening this, Kattman et al. (2012) mention that it is possible to obtain an increased performance of visualization due to faster absorption of information. It is thus important that the information that is visualized is structured and presented in a way which is clear and simple to interpret, in order for it to be effectively communicated. Furthermore, presenting information in a clear and simple way may increase the absorption of the presented information, and in turn, increase the performance.

During the interviews, several team leaders expressed that the daily reporting preparations were time consuming, and one explicitly said that they came to work earlier, to have sufficient time for the daily preparations. Streamlining this activity could thus yield a direct efficiency increase. As emphasized in both lean management by Liker and Convis (2012) and in quality management by Bergman and Klefsjö (2010); Dean and Bowen (1994), no process is perfect and there is always room for improvement. Slack and Lewis (2014) further strengthens the premise of streamlining such an activity, as it can be viewed as waste i.e., muda. Given that the company culture is strongly influenced by the lean philosophy and quality management in general, there seem to be a need to streamline this activity.

Furthermore, from the interviews, it was brought to air that the prioritization and selection of deviations to put efforts on resolving was a complicated and ambiguous task; for example, one team leader said that they often decide on gut feeling due to this. This is somewhat similar to what Jaca et al. (2014) mention, namely that there is rarely a lack of data within an organization, but more often a lack of means to visualize this data. Connecting this to quality management, both Bergman and Klefsjö (2010) and Dean and Bowen (1994), strongly emphasize basing decisions on facts rather than intuition for increased customer satisfaction. Brynjolfsson and McElheran (2016) further strengthen the claims of Jaca et al. (2014) by explaining that the use of digital technologies has enabled companies to gather an increased amount of data than previously possible, adding that this increase presents the opportunity to generate better decision-making. Furthermore, according to Galsworth (2017) and Murata and Katayama (2010), it is possible to facilitate decision-making by visualizing information in proximity to the recipient. In addition, Dodman et al. (2020) emphasize that it is possible to improve operational performance through DDDM. Utilizing visualization to aid the quest of prioritization and selection of quality deviation resolving efforts could thus serve both as a mean for DDDM as well as to increase customer satisfaction.

On a more holistic level, visualization can increase transparency and visibility, both on the quality of the available data, but also on team performance. As argued by Gilbert (2000), there is often an overestimate of the own team’s performance in comparison to how their internal customers perceive them. By utilizing visualization, it may be possible to diminish this overestimate, or at least, make the results transparent and rooted in the actual performance of each team. To some extent, it is possible to argue that this could in turn lead to higher employee motivation, since Sörqvist (2001) proclaims that internal customer satisfaction has the potential for increasing employee motivation and job satisfaction. By increasing the transparency, visualization could thus potentially increase employee motivation by giving a more objective representation of reality; diminishing and reducing the occurrence of “blame games”. In addition, visualization has the possibility to improve the data quality of quality deviations by making it more visible for everyone that is currently reporting these. This may create a more holistic understanding of the importance of making sure that the quality remarks are logged with greater detail, since this data will be used by the team leader themselves to prioritize improvement efforts. Furthermore, as mentioned by a manager during a meeting, initial visualization efforts can act as a catalyst of the possibilities with visualization tools and business intelligence. This is an important possibility to bear in mind since Sörqvist (2013) argues that *"unused creativity"* can be considered as a waste.

On the contrary, there are also several challenges and pitfalls that must be acknowledged when using visualization to aid decision making processes. One challenge for Plant Y, identified from the interviews and observations, were the lack of knowledge of more sophisticated visualization software. This may pose a challenge during the hand-over process, due to limited capabilities for maintenance and troubleshooting of the developed visualization models. These challenges are somewhat similar to the challenges proposed by Aigner (2013) regarding dynamic business intelligence tools, such as Microsoft Power BI over more static tools, such as Microsoft Excel, for visualizing. These challenges take form in a general lower trust towards the results. Aigner (2013) further adds that company culture and/or not fully comprehending the benefit of dynamic visualization tools may create a reluctancy to incorporate such tools. Furthermore, as mentioned above, Chen et al. (2007) argue over the duality of visualization and that it has the risk of being a non-effective way of communicating information. Moreover, Brodlie et al. (2012) explain the importance of having accurate data as a foundation for the visual, since data in general has the inherent characteristics of being perceived as exact, and a visual representation further strengthens this. These claims are further strengthened by Bai (2012), who discusses the dangers of becoming data driven without sufficient and accurate data. Redman (1998) further adds that bad quality data draws the risk of causing dissatisfied customers, increased operational costs, and ineffective decision making. Similarly, Hume and West (2020) mention several challenges, such as the cruciality of ensuring data integrity in order to be able to trust the data. These challenges may imply that the company must put efforts into expanding their knowledge of visualization tools, both to enable maintenance and troubleshooting, but also to acknowledge the potential pitfalls of visualization in general.

Perhaps it comes as no surprise that the short answer to whether visualization impacts the quality for a manufacturing company is yes, however, depending on the circumstances, it could be both in a good and bad way. As argued above, it is of utmost importance to ensure that the data, which creates the foundation for the visualizations, are accurate. In addition, it is also important that the visualization is validated and constructed in the right way, with valid measures and calculations, to decrease the risk of drawing conclusions on false grounds. On the bright side, the findings of Aigner (2013) may suggest that the potential skepticism of dynamic visualization tools may lead to a more thorough investigation of the underlying data before trusting it. Furthermore, the literature findings suggest that, in order for visualization to aid and convey the message intended, it must be structured in a simple and clear way. To some extent, it is also possible to argue that the digital maturity of the organization must be sufficiently high in order for them to reap the benefits from visualization. The potential reluctancy mentioned by Aigner (2013) can, in this perspective, be counteractive for the use of visual tools. Furthermore, while Brynjolfsson and McElheran (2016) argue that the availability of data has increased, Bai (2012) mentions the dangers of becoming data-driven without ensuring the quality of the data. It is possible to argue that this is to some extent linked with the digital maturity of the company and that this plays a vital role before deciding to move forward with visualization initiatives.

Altogether, it is possible to deduce some key prerequisites and necessities for the possibility of yielding positive results from visualization. First and foremost, the underlying data must be of sufficient quality. Secondly, the visualization must be valid. Thirdly, the company should have a sufficient level of digital maturity to, in a safe way, reap benefits from visualization. Fourthly, the visualization needs to be clear and simple for it to convey the intended message.

Once these prerequisites are in place, there are higher possibilities for a company to become data driven. The benefits of being data driven is widespread within quality management literature and it is prominent that this is a key enabler for improved quality and, in turn, customer satisfaction. The possibilities of streamlining activities and reducing waste using visualization further illuminate how visualization may impact quality for a company. Furthermore, the increased transparency and visibility of results may impact the quality by achieving higher employee motivation and job satisfaction. It may further increase quality by increasing the awareness of the current quality of the data, which could create an incentive for more detailed error loggings. Lastly, preliminary visualization efforts can act as a catalyst for the possibilities with sophisticated business intelligence software, and new areas of applications can be identified once seeing these possibilities. However, to some extent, there is an inherent catch 22 situation presented with preliminary visualization efforts. By seeing possibilities, visualization can also reveal that the underlying data is not sufficient and that the company is not digitally mature and reaching these conclusions may require preliminary visualization efforts.

To summarize and answer RQ1, visualization of operational deviations has the possibility to increase the quality of a manufacturing company due to the possibility of making decisions based on data. It further increases quality by offering possibilities of reducing waste and increasing transparency of information. Although the danger, visualization can also improve quality by revealing the underlying data quality and preliminary efforts may act as a catalyst for creativity. However, to yield these benefits, it is important to bear in mind the prerequisites needed. Ensuring data quality, valid visualizations, digital maturity of the company, and clear and simple visualization, greatly increases the possibilities for achieving a higher quality for a manufacturing company.

5.2 Data Collection Framework

The second research question, RQ2, focus on how data collection methods and procedures of operational deviations should be structured in order to ease visualization. In the context of Plant Y, and as mentioned briefly in Chapter 4.1, there exists a prominent time lag between both the occurrence of a quality deviation and its discovery as well as between its discovery and its reporting into QULIS. These time lags are visualized in Figure 4, where the red arrow represents the potential occurrence of a deviation, the green arrow represents the finding of said deviation, and the yellow arrow represents where this deviation is reported into QULIS.

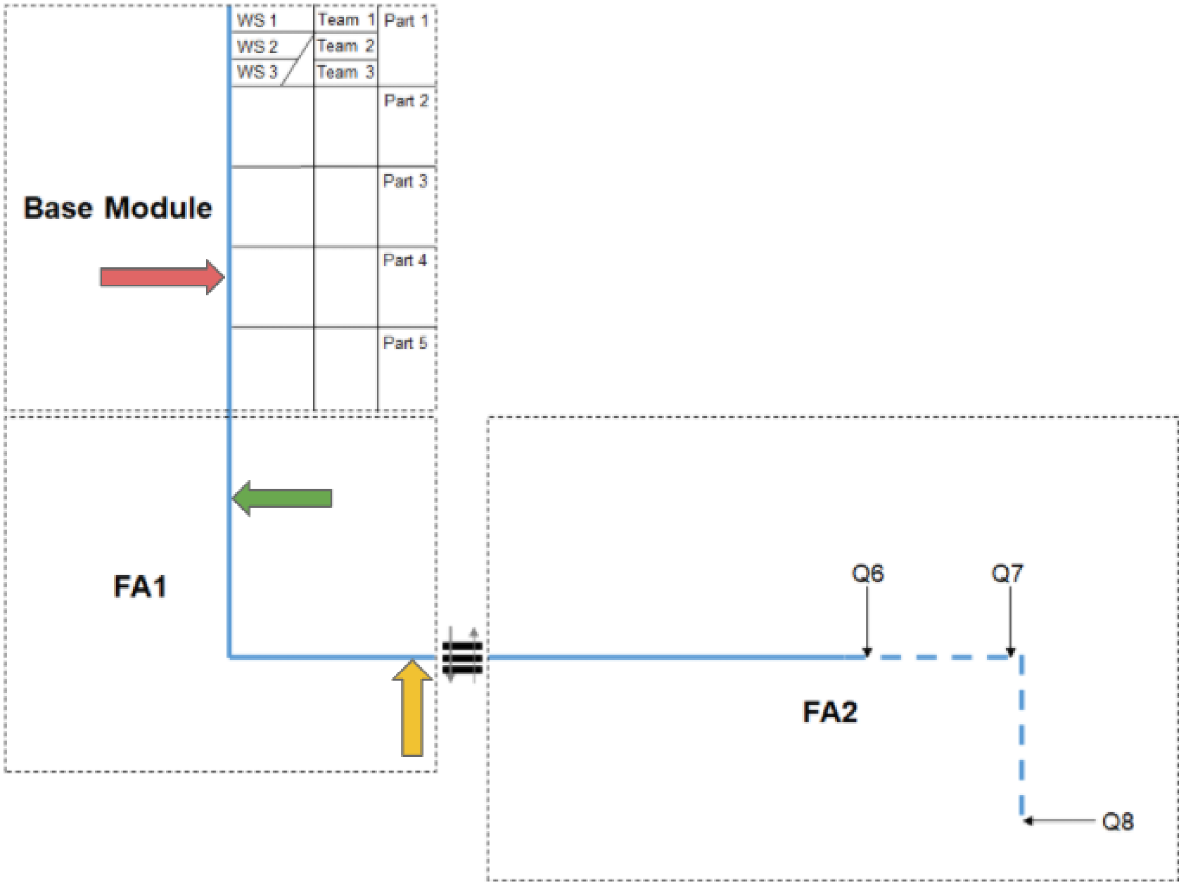

Figure 4 - Visual representation of the time lags inherent in the quality reporting process

As for today, duplicate work is being conducted at the green and yellow arrows, with the only difference that the green logs the quality deviation on the travel card, while the yellow logs it into QULIS. There thus exists significant room for misinterpretation due to loosely handwriting and general misinterpretation of the wording used to describe a quality deviation. In addition, the control personnel rarely have time to investigate the deviations logged on the travel card any further and often just copy the information into QULIS. As mentioned before, to counteract the time lag between finding and reporting, there is an ongoing initiative with digitizing the reporting process, however, this initiative is still in its cradle and has a long way to go before a potential implementation. According to Slack and Lewis (2014), waste elimination is fundamental in lean production, which further strengthens the importance of eliminating these time lags. In addition, Heinrich et al. (2018) point out that it is common for companies to suffer from bad quality data. Furthermore, Parssian et al. (2004) and Dey and Kumar (2013) argues that the most common causes of bad quality data is inaccuracy, incompleteness, and mismembership. Removing this time lag could thus increase the overall resource efficiency by lessening the workload for the control personnel, the ones represented by the yellow arrow, and it will also be in line with Plant Y's lean emphasis. Furthermore, it will diminish the need for interpretation of loosely handwriting and, by that, potentially increase the quality of the data. Additionally, digital reporting into QULIS could further enhance quality by making the reporting closer to where the knowledge of the problem is possessed. Doing so, could potentially decrease the risks of inaccuracy, incompleteness, and mismembership, and yield better data quality.

In order to obtain clean and an increased quality of the data, it could prove beneficial to rearrange the reporting structure on the travel cards, if they were to still be used, as well as in QULIS. The detailed information necessary to distinguish one defect from another currently resides in a free text box, which inhibits the possibility for analysis. Efforts should thus be put into making the free text description categorical, without losing the amount of detail required for distinguishing, but also without becoming too time-consuming. This will mitigate the risks of the most common mistakes related to data quality, namely inaccuracy, incompleteness, and mismembership (Parssian, Sarkar, and Jacob, 2004; Dey, Kumar, 2013). One possible way, that will allow for more detailed information, without becoming too time-consuming, is changing the graphical user interface for error logging into a user-friendly and app-like interface. For example, instead of categorical scroll downs, ranging up to 100+ options, a search function accompanied with touch buttons could be utilized for faster input. The interface should further be designed in a way where previous inputs act as guidance for later loggings. For example, when logging a quality deviation on a team, the most frequently occurring options for the rest of the inputs should be shown first, to allow for faster and more accurate input, resulting in a more Poka-Yoka way of working, hence reducing the number of mistakes (Singh & Kumar, 2020). Furthermore, it is recommended to include the specific part number of the faulty component when logging the error, or at least complete this information in a later stage, to allow for more specific follow-up and analysis. Although Manager A expressed concerns about whether this would have a significant impact, Analyst B, and other plants, have implemented this to allow for more detailed follow-up on faulty components.

Moreover, it was discovered that some information is continuously entered wrong in the system, for example, the case number that is to be logged when a quality controller discovers a critical fault. This number is supposed to be logged in a field called "Case Number", but the standard practice is to log them in the free text description. It is thus recommended to continuously evaluate and control whether the information is logged in the right way and at the right place to identify discrepancies and potential causes for these. Conducting continuous improvement efforts, as mentioned both Bergman and Klefsjö (2010) and Liker and Convis (2012), within the field of data collection procedures is a prerequisite for Plant Y to become a data-driven organization and minimize the risks of base decisions on false data, which results in operational inefficiencies (Bai, 2012). Furthermore, as mentioned in the interviews, there is a prominent emphasis on moving quality remarks between teams to improve their own team's KPIs. Additionally, sometimes remarks are moved to other teams because the team, which the remark is logged on, does not know where it might have occurred, often resulting in an endless loop. The problem with moving quality remarks is that the team leaders rarely check the data more than in the morning. There is thus the risk that frequently miss-logged quality remarks fall between the cracks, and the problem never truly surfaces. A possible remedy for this issue is to highly restrict the use of moving quality remarks which will create an incentive for fixing the root cause of the problem, namely, to inform the person that logged the remark wrong and start asking why this is the case.

To summarize and answer RQ2, the data collection process should be structured in the following way:

1. Digitize the reporting process to avoid time- and knowledge gaps
2. Restructure the digital interface of QULIS to allow for faster and more accurate reporting
3. Remove or down-prioritize the use of free text description and use categorical options instead
4. Include the specific part-number for all faulty components
5. Continuously control that the data is entered in the right way and at the right place
6. Prohibit moving remarks, or restrict it by only allowing for it intra-day, to eliminate the root cause of the miss-logging

5.3 Visualization model

To discuss and answer the third research question, RQ3, of how visualization of operational deviations should be structured in order to ease decision-making, this section presents Microsoft Power BI models for both visualizing day-to-day performance as well as short and long-term trends of quality deviations. Departing from the importance of simplicity and clarity, argued by Bilalis et al. (2002), the models have been developed with a strong emphasis on being user-friendly and with clear connection to what was requested by the team leaders, as they are ought to be the lead users of it. One of the prerequisites identified in Chapter 5.1 was the importance of valid visualization. To ensure this, the development process of the model and its measures consisted of three steps; prototyping using static data and continuous verification and validation with team leaders, developing a model using dynamic data and piloting this alongside the regular daily reporting routines, and a factory-wide implementation once validity can be guaranteed. In addition, Knaflic (2015) explains the importance of acknowledging **Who** the stakeholder and recipients is, **What** is the key message to convey, and **How** will the visual earn credibility. By having close connections to the intended users and iterating the developed model, the Who and What can be adhered to. To reduce the impact of Arrow's Impossibility theorem, all dashboards are built in a way that allows for customization. For example, since the teams in cab trim measure FTT against a different control checkpoint than base module, the model must allow for easily changing this. To ensure that the model earns credibility, it has been thoroughly validated during the development process, both through piloting and rigorous testing. The emphasis on the models being user-friendly further enhances the possibilities for earning credibility, and the reluctancy to incorporate, argued by Aigner (2013) can be decreased. Furthermore, the underlying model which forms the foundation for the visuals has been thoroughly and continuously tested for potential edge-cases of input data, to ensure uptime and validity.

5.3.1 Day-to-day Dashboard

The developed day-to-day dashboards were developed on premise to ease the daily preparation process by synthesizing all the information needed as well as to eliminate the risks of miscalculations due to human error. Succeeding with this, creates the potential to increase quality through streamlining and reducing waste, as argued in Chapter 5.1. Close to all the different metrics and visuals shown in Figure 5, Figure 6, and Figure 7 were directly requested by the team leaders during the interviews. As argued by Chen et al. (2007), visualization can be both an effective and non-effective way of communicating information, and it is thus of utter importance that the right information is visualized. These metrics were then further validated through overseeing the daily reports and current, analog, visuals used. The main dashboard, Figure 5, contains the most important KPIs needed for the daily reporting, such as FTT, stop time, and audit points (Gårdagens Poäng). The metric "ÖP" describes how many of quality remarks that passes a quality gate without being resolved, where "Stängda" is quality remarks that has been closed before the quality gate. For the calculation of “FTT”, only the “ÖP” impacts the metric. Furthermore, the metric “Egenrapporterat” displays the number of quality remarks that is reported by the causer of the remark, for example, in Figure 5, “Egenrapporterat” refers to quality remarks caused and reported by “Cab trim grupp 6 A”. On the opposite, “Kundrapporterat” refers to quality remarks reported by another team later on the line. “Andel Egenrapporterat” is the only metric not directly requested by the team leaders but is developed by the thesis authors. This was done on the premise to increase the incentive for finding the own team’s errors and thus, decreasing the time lag between occurrence and finding of a quality deviation. For more detailed information about previous day’s quality remarks, it is possible to navigate to another tab, Figure 6, where the remarks are ordered by their criticality and severe faults are highlighted. This tab includes all the relevant information about the remarks that are available from QULIS. Lastly, Figure 7 contains more detailed information about previous day’s stop time, for example, which workstation responsible, during what times, and a chart showing the stop-time distribution.

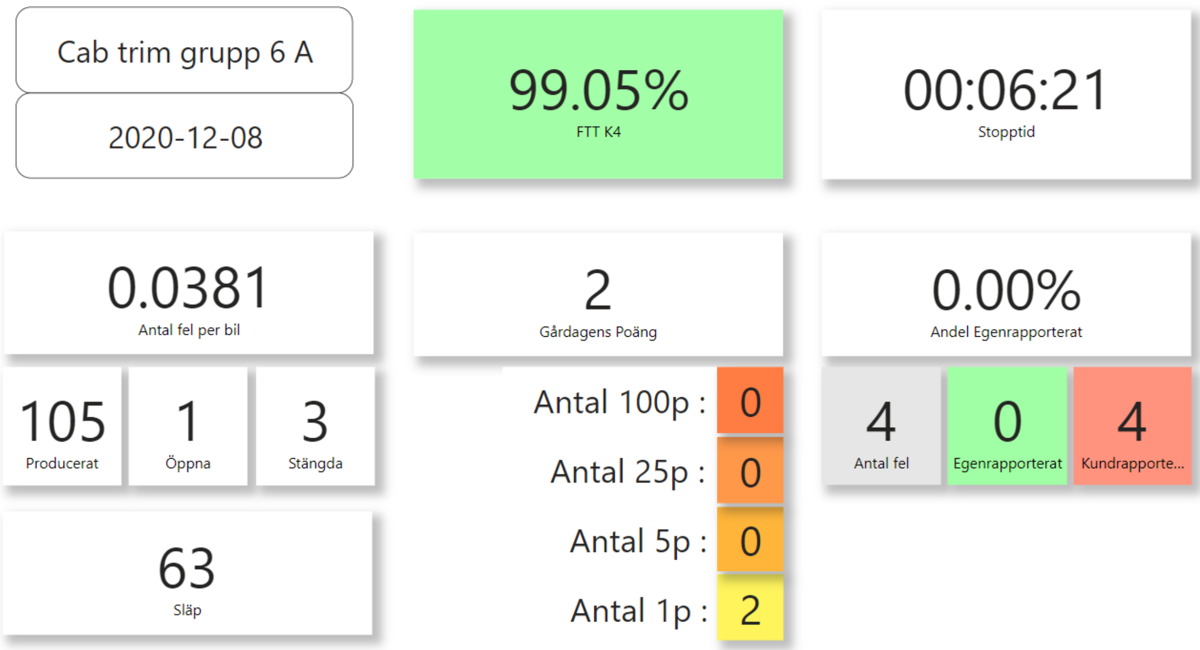

Figure 5 - Visualization of the main dashboard used for daily reporting

Qulispunkter

Chassinr	Problemdetalj	Hjälpobjekt	Problemtyp	Placering	Rapporterande	Felbeskrivning	Öppen punkt	Poäng
	glas för främre sidodörr		smutsig		BE35700 Kvalitet	Kladd på sidoruta hö/vä sida.		1
	ledningsmatta, komplett	sidodörr, komplett	böjd, vriden		BE35700 Kvalitet	Kablage gummi vriden till hö dörr.		1
873006	kontaktstycke	hytt	monterad inte	ca01	Flöde del 7	gråa kontakten	ÖP 9	
873099	styrenhet	dörr	monterad fel	hin	Cab trim grupp 8	visp styrenheter i dörrarna shiftade	ÖP/CT K-pos 4	

Figure 6 - Tab 2 in the day-to-day dashboard with detailed information of quality remarks

Cab trim grupp 6 A

2020-12-08

Stopptid

Station	Occurance	Stopptid
29	11:05:48	00:05:39
29	14:06:21	00:00:23
33	14:14:06	00:00:09
34	08:59:10	00:00:10
Total		**00:06:21**

Stopptid per Station

Station	Stopptid
29	00:06:02
34	00:00:10
33	00:00:09

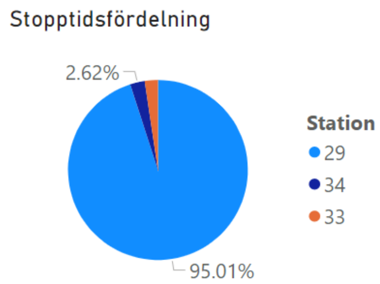

Figure 7 - Tab 3 in the day-to-day dashboard with detailed information about stop time

To some extent it is possible to argue that the developed dashboards may not spread information better than plain text, which was an argued benefit of visualization by Davison (2015) Goransson and Fagerholm (2017) and Proskurina (2018). The reason for these argues is that the dashboards primarily consist of plain text, rather than graphs or sophisticated visualizations. However, as emphasized by Knaflic (2015), the goal of visualization is to transfer knowledge and convey a message. In addition, Knaflic (2015) explicitly states that if the information is best communicated through plain text, the visualization should be kept simple and preferably expressed by a text box or similar. Bilalis et al. (2002) further strengthens this by proclaiming that information is effectively communicated when it is clear, visible, and simple to understand.

Knaflic (2015) argues the importance of considering appropriate visuals during the entire development period. For example, the table in Figure 6 has no significant borders, it highlights the paramount data, and utilizes transparency of colors. To decrease the cognitive load of the visual, efforts have been made to eliminate clutter and only include what is requested by the team leaders, thus adding value to the visual. Furthermore, Knaflic (2015) mentions the importance of focusing attention to the most important attributes. To do so, the visuals are structured by showing the most important KPIs, FTT and Stop time, at the top, as well as making them fairly larger than the less important ones. In addition, dynamic color coding has been utilized to strengthen the intended message of the visual. To some extent, it is possible to argue, with the support of Knaflic (2015), over the use of pie charts, which is used in Figure 5.4. The reason for the use of this visual tool is its ability to capture the entirety of the data and showing the proportional distribution in a good way. It was thus deemed that these benefits outweigh the drawbacks associated with pie charts and therefore, it was used.

5.3.2 Trends Dashboard

The underlying premise for the development of the trend dashboards was to both aid team leaders in their prioritizing and selection process. As discussed in Subchapter 5.1, there is the possibility for companies to achieve higher quality by basing decisions on fact and becoming more data-driven. Today, many team leaders find the prioritization and selection process complicated and ambiguous, resulting in basing decisions on gut feeling. To counteract this, the below dashboards aim at easing this selection process by visualizing both short- and long-term trends of different quality deviations. The dashboard for trends that is visualized in Figure 8, Figure 9, Figure 10, Figure 11, and Figure 12 is team-specific, but compared to the day-to-day dashboard, the user has the possibility to look at trends in a specific time period that suits their needs. As seen in Figure 8, this is visualized as buttons in the top left corner, where the time periods can be customized. Furthermore, the dashboard in Figure 8 shows histograms of the most common problem types, problem details, and heatmaps of the most common locations of the deviations. Figure 8 shows the results from normal remarks, while Figure 9 shows the results from critical remarks. All of these visuals are filtering each other, meaning that the results dynamically change if you choose a different time period or pressing a particular problem type or detail. This enables analysis of particular problems, where one can choose an appropriate time period and filter down on specific problem types and problem details to see where on the truck most deviations occur. Additionally, as illustrated in Figure 10, one can hover over the problem details to see the distribution of which parts this detail is most commonly placed on.

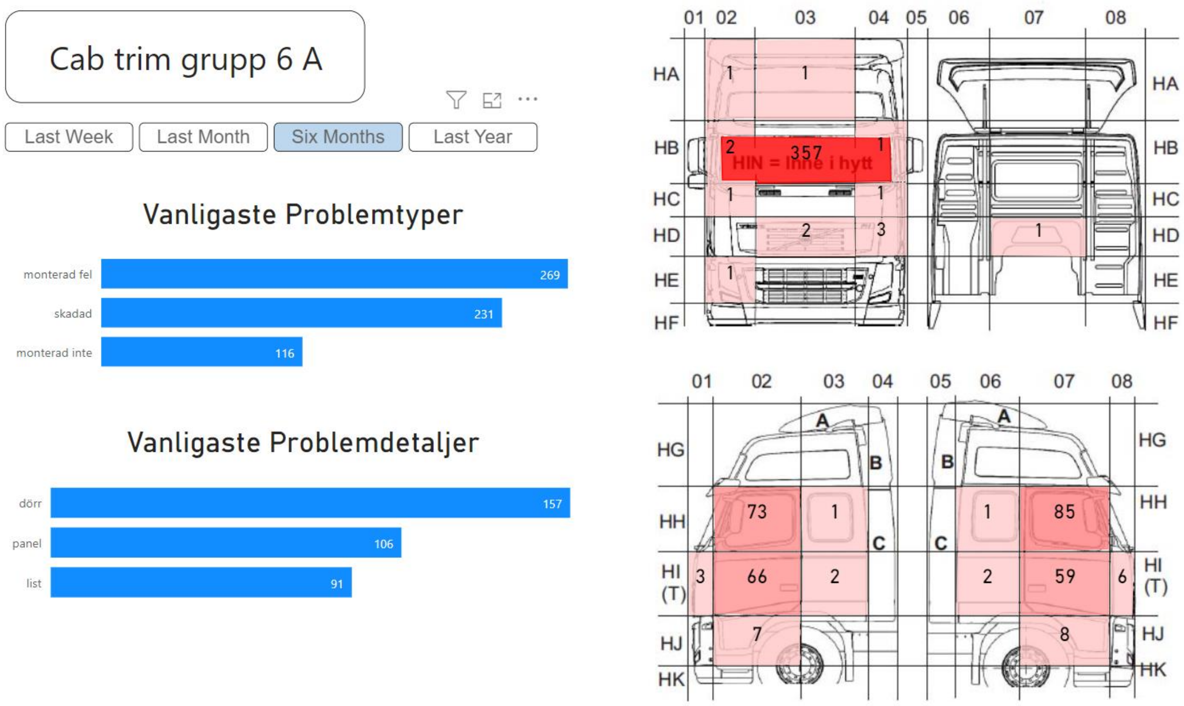

Figure 8 - Visualization of the trend dashboard of most common problems

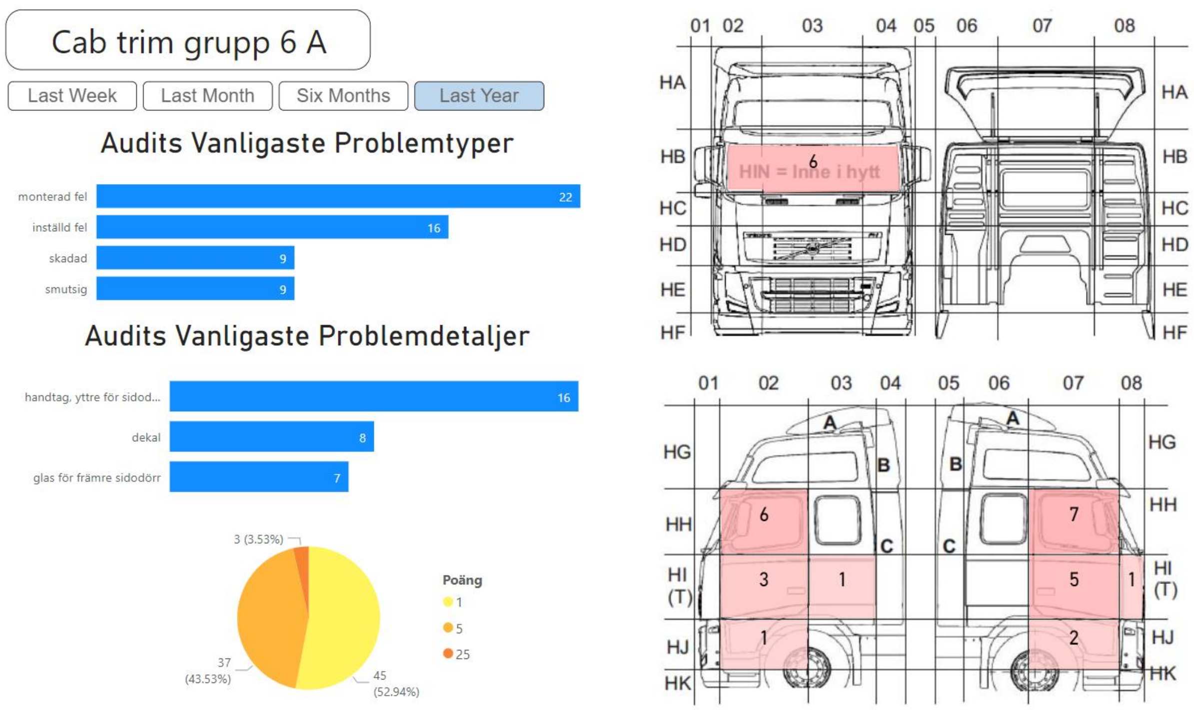

Figure 9 - Visualization of the trend dashboard of critical remarks

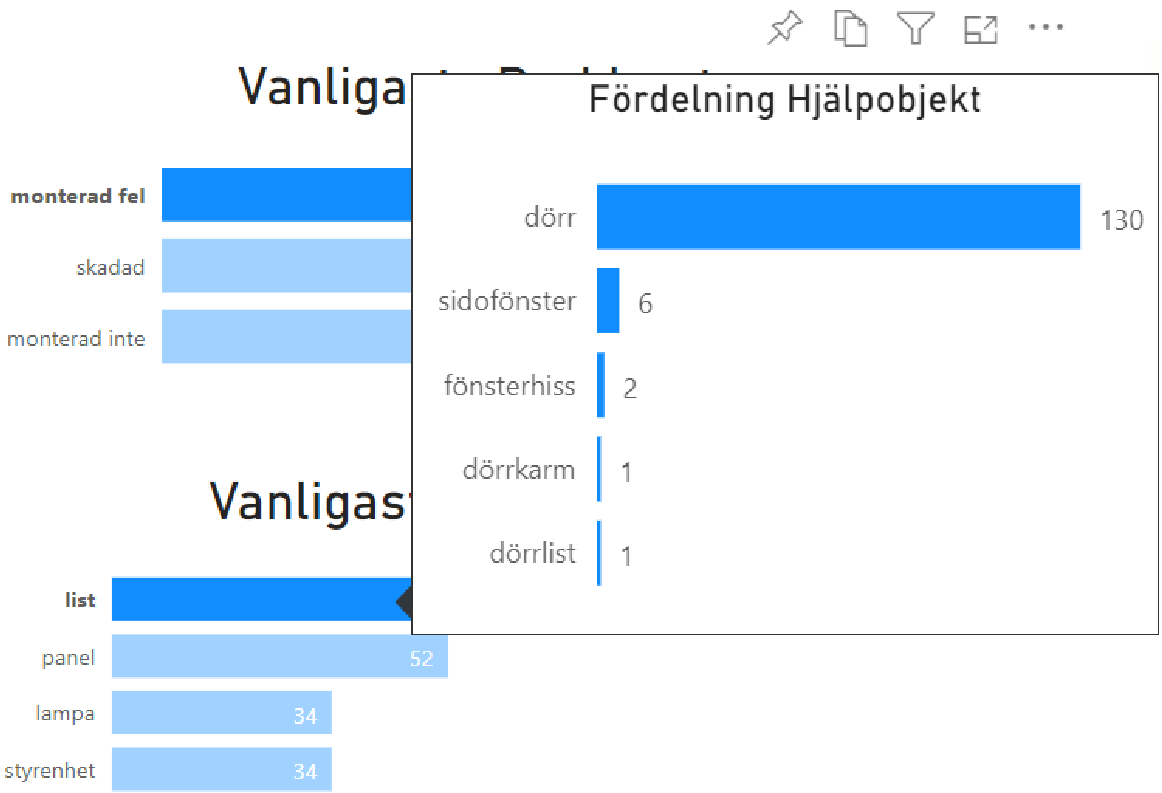

Figure 10 - Visualization of the hoover tooltip

Figure 11 presents the trend of the number of remarks on a particular team, where the green color represents that the team found the problem themselves and the red color represents if the problem was found somewhere else on the line. Figure 12 visualizes the trend in stop time for a specific team.

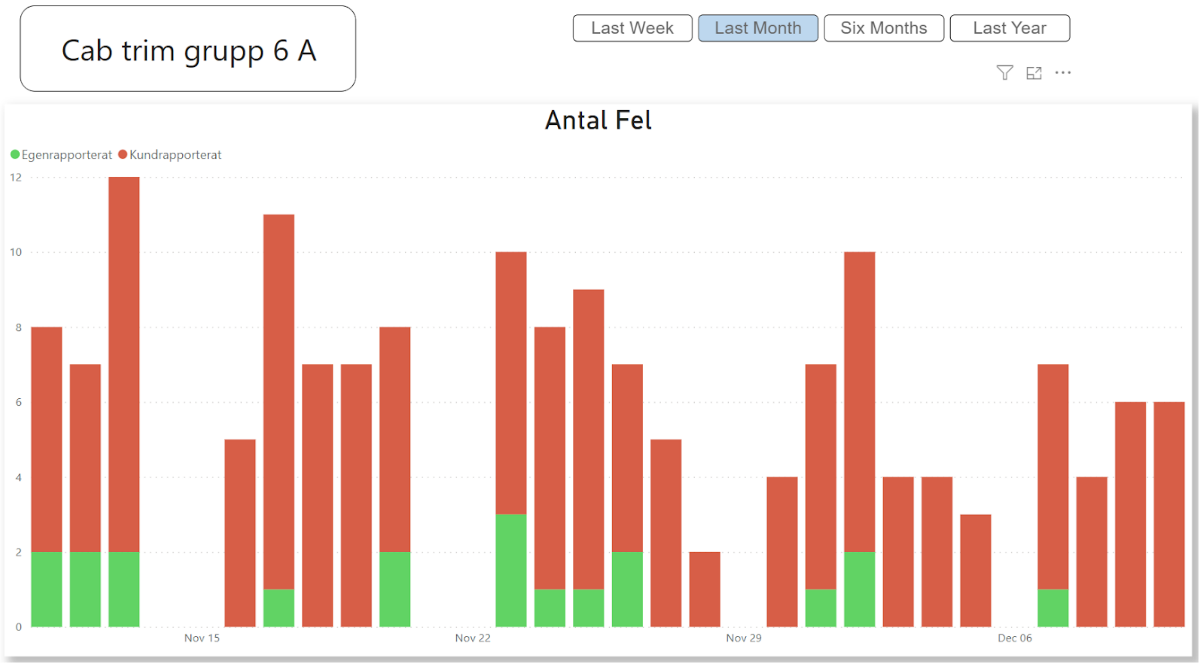

Figure 11- Visualization of the trend and distribution of problems reported by your own team compared to problems reported by others

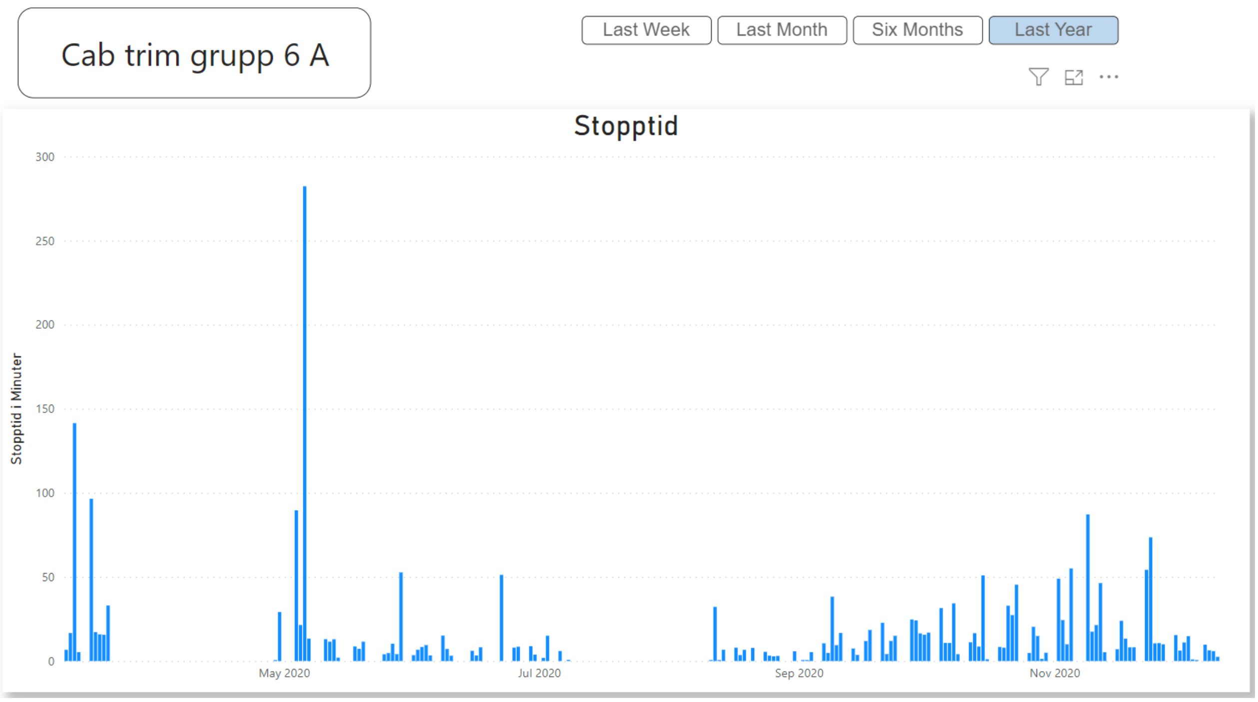

Figure 12 - Visualization of stop time trend

The same design principles used to develop the day-to-day dashboards were used for the trends as well, were strong focus has been put on Knaflic's (2015) emphasis on choosing appropriate visuals, eliminating clutter, and focusing attention. For example, although the heatmap in Figure 8 may seem somewhat cluttered, it provides a more intuitive visualization of the most common placements of quality deviations than, for example, a table would give. Overall, the dashboards have the possibility to increase the awareness of how the quality and detail of deviation loggings impact the analysis and selection process. This awareness might create an incentive to improve this process, since it would make the selection process even easier.

All in all, to answer RQ3, there are possibilities for Plant Y to ease decision-making through visualization. By focusing on the deliverance of information, the developed visuals can create faster absorption of information and decision-making. Furthermore, the visualization of trends concretizes and humanizes the data, presenting it in a more intuitive way, allowing for potentially faster and better decision-making. The streamlining of the daily preparation, namely, what the day-to-day dashboards seeks to accomplish, may also lead to improved decision-making since it frees up time by increasing efficiency. All these benefits may be accomplished given that the visualization is structured in an appropriate manner and include relevant information for its recipients. To increase the possibilities for success, the visualization of operational deviations should depart from the framework provided by Knaflic (2015), to make sure that the visuals are designed in the right way. Furthermore, Bilalis et al. (2002) stress the importance of clarity, visibility, and simplicity of information, and thus, the visualization should seek to transfer information in the same manner.

5.4 Implementation

For the implementation of the developed dashboards, it is suitable to depart from the change management literature provided in the theoretical framework. The implementation of the dashboards involves a change showing similar characteristics as *"Fine Tuning"* coined by Dunphy and Stace (1993) or *"Tuning"* by Nadler and Tushman (1989). There is no major disruption of today's procedures and practices, but rather an incremental improvement of internal processes. Luckily, the organizational culture at Plant Y strongly encourages improvements, and continuous improvement is one of the pillars that the production system rests upon. Furthermore, the implementation of above suggested frameworks and models does not involve significant changes to any artifacts, values, or assumptions. However, it is still worth acknowledging that resistance might occur. As argued by Aigner (2013), the lack of trust towards the visuals may create a reluctancy to incorporate the new practices. To counteract this, it is recommended to follow Hayes (2018) proposals to map out the different stakeholders and their attitude towards the change. This would create the possibility to direct attention and efforts to where it is needed. In addition, it can prove beneficial to acknowledge the informal networks among the recipients of the changes, namely, the team leaders. To gain credibility and acceptance, Battilana and Casciaro (2013) express the importance of gaining it from people with large informal networks, since they have a strong influence over others' perception.

To ease the implementation process, it is thus recommended to identify key stakeholders and employees with large informal networks for pushing the change forward. For this thesis, eight team leaders were selected to pilot the visualizations on, based on their initial enthusiasm. These team leaders will then act as somewhat of a key user by spreading the word and creating a need among other team leaders. Doing it this way, it may be possible to create a bottom-up need for the visualizations, which in turn, could ease the implementation process.

5.5 Recommendations and Future Research

The recommendations for Plant Y's following journey are divided into two areas, the data collection process and the visualization process. Activities related to each of those are further divided into short-term and long-term horizons, where short-term refers to within the current year and long-term covers a one to two-year horizon. In Table 2 below, the different suggested activities are presented.

Table 3 - Recommendations for Plant Y

Area	Short-term	Long-term
Data Collection	• Spread knowledge and way of working with today's methods and procedures • Continuously control and follow-up the way of working	• Digitize the reporting process • Ease the reporting process by making the input process Poka-Yoke
Visualization	• Continue and fulfill the ongoing initiatives • Put more efforts and resources into visualization initiatives • Scale the current dashboards vertically, to further streamline the reporting process	• Scale the solutions to different functions at Plant Y • Scale the solution to other plants within Company X

From an academical standpoint, further research is required within this area to quantitatively assess whether visualization of quality deviations has a significant impact on the quality for a manufacturing company. Furthermore, the models and framework developed in this thesis are developed for the specific context of Plant Y. It could therefore be of interest to investigate the impact of these in a different industry setting and how much adjustments that must be made, in order for them to function accordingly.

5.6 Discussion of Methodology

Due to time constraints and the COVID-19 situation, this thesis has only investigated the subject and its potential implications for one plant, within one company. It is thus possible to argue that the results may not be directly applicable for the entire truck manufacture industry. On the contrary, RQ1 has primarily been answered through the literature review, where the evidence is somewhat extensive. However, the conclusions in regard to RQ2 and RQ2 do face the risk of not being completely transferable due to the above-mentioned limitations. Furthermore, the obtained results have not been quantitatively assessed for significance, and it is thus possible to argue whether or not these are completely valid. It could therefore prove beneficial for further research to quantitatively assess the results, both at Plant Y, but also in general with other manufacturing plants or companies. Lastly, the use of convenience sampling may to some extent bias the results by only obtaining the early adopters' perception of the situation and their input. However, this was deemed as a negligible and acceptable risk due to the number of interviews conducted with various people within the organization. Although it is possible to obtain similar opinions from 18 different interviewees, this is not deemed as likely.

6. Conclusions

The overarching purpose of this thesis was to create both a framework for data collection and visualization of operational deviations, as well as to explore its potential impact on quality. To fulfill this purpose, theory that cover areas such as quality management, data quality, data-driven decision-making, and data visualization, have acted as a foundation. By applying this theory, to the results obtained by the thesis's data collection, the purpose has been fulfilled and resulted in the conclusions below.

First, through visualizing operational deviations, the possibilities to base decisions on facts increases. Additionally, visualizations will offer more opportunities of reducing waste and increasing transparency of information, hence possibly increasing the quality. Moreover, this transparency can not only act as a catalyst for creativity, but also support data quality improvements, where the people involved get more direct feedback of their input to the information systems. However, in order to reap these benefits and increase the chances of improving the quality for a manufacturing company, prerequisites such as ensuring data quality, valid visualizations, and digital maturity are essential.

Second, to facilitate the visualization process, the data collection methods and procedures in a manufacturing company should be structured and suitable for the visualizations in mind. Reporting of quality deviations should be done as soon as possible after occurrence, to avoid time- and knowledge gaps. In order to mitigate data quality issues, it may prove beneficial for the interface of the information systems to be Poka-Yoke, as well as including the right information fields that enable data analysis. Moreover, control- and continuous improvement efforts of the data collection's methods and procedures is of great importance for keeping the process up to date.

Third, visualization of quality deviations opens up for possibilities to ease decision-making and hence, becoming a more data-driven organization. Well-developed visuals can provide an easier and more accessible way of transferring and absorbing information. It can also create a greater holistic and objective understanding of how individual processes perform. Furthermore, automated visuals will free up time, which augments the decision-making process.

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Appendix A : Interview Template – Team Leaders

Below is a list of typical questions asked during the interviews with team leaders. These questions were continuously revised and adjusted to enable new knowledge to be gathered.

- *Project introduction* -

- What is your role and responsibilities?
    - How does a regular working day look for you?
- How does the error-logging take form today?
    - What do you feel works well and what doesn't with this process?
    - Do you believe that something is missing in QULIS?
    - Do you see any redundant steps in this process?
    - What areas of improvement do you see for this process?
- How long time does it take to prepare morning meetings?
- How do you work with resolving quality deviations today?
    - Are many remarks recurring?
- How do you use visualization today?
    - What is being visualized today?
        - How is this created?
        - By whom?
    - What are the procedures for making these visualizations?
    - What areas of improvement do you see?
- What would you like to have visualized in order to ease your decision-making process?
    - Why would you want this?
    - How can this help?
    - What is missing in today's visualization?
- What systems are you currently using on a daily basis?
    - Why do you do so, and to what purpose?
    - How do you believe these systems are functioning?

        - Do you see any areas of improvement?
- What is the most common problem?
    - How often do new problems occur?
    - In your experience, how often do problems get fixed without them being reported?
        - Why do you think this is happening?

Appendix B : Interview Template – Officials

Below is a list of typical questions asked during the interviews with officials. These questions were continuously revised and adjusted to enable new knowledge to be gathered.

- *Project introduction* -

- What is your role and responsibilities?
    - How does a regular working day look for you?
- When did you start at Volvo?
    - What previous positions have you had?
- Have similar projects been conducted in the past?
    - What were the takeaways?
- How does the data collection of quality deviations take form today?
    - Does it differ between different parts of the line?
    - How does QULIS work for the collection of data?
        - What is the structure and level of detail of the data?
        - Would it be possible, from the QULIS data, to automatically find the part/team/workstation responsible for the error?
    - Are any teams performing better than others when it comes to the collection and logging of error-data?
- What is your general perception of the data collection methods today?
    - What do you think can be improved?
- How is the collected data visualized in the different parts of the organization?
    - What is being visualized?
    - What do you think could be beneficial to visualize?
- How does the decision-making process make use of the collected and visualized data?
- What is your general perception of the decision-making and prioritization work today?
    - What improvements to this process do you see?
- How does quality improvement work today?
    - What are the most common problems detected?
    - How often do new problems occur?
    - Is there any follow-through on minor problems that gets “firefought”?
- What do you think are potential pitfalls and challenges for this type of project?

- Any additional thoughts that could be of importance for our project?

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