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A Holistic Quality Management Model for Optimization of Quality Assurance in Manufacturing

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Abstract

Quality Management (QM) is essential in manufacturing to ensure products are consistent and functional every time. Consumers expect high quality products that last, and industries unable to accomplish this are destined to fail. Therefore, product quality has always been at the forefront of manufacturer decision making, though it is normally viewed as a given more than as a goal. This means that businesses want quality because it is needed for their survival, but there has not been consideration for how to incorporate innovation into this essential field. Quality needs to be viewed holistically with regards to all manufacturing factors that affect it. A Holistic Quality Management (HQM) Model was designed through the identification of crucial pillars, themes, and metrics in literature. The relationships between these features and their effect on product quality were utilized and quantified to calculate a Quality Assurance (QA) score. This model represents a generic version that can be used out of the box for a variety of industries for immediate insight into their quality performance. It acts as a starting point for these facilities to cater to their specific needs. A user-friendly interface was developed to give both high-level scoring and allow for deeper dives to determine sources for quality shortcomings. The Future Factories (FF) lab in the McNair Aerospace Center at the University of South Carolina acted as a test bed for this project. To showcase the model's flexibility multiple versions were created for different industries where metrics would have different impact on product quality or where specific metrics may need to be added or subtracted. This holistic model acts as a guide on

what to focus on for QM and planning, improves QA through a straightforward score, and uncovers the metrics at the root of quality issues which leads to better Quality Control (QC). With the inclusion of live data, Closed-Loop Quality (CLQ) can be achieved where overall quality is improving for existing products. The facility can then shift left and improve the implementation of new products faster. This is all packaged into a simple interface that is accessible for the needs of users from the shop level to upper management.

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List of Abbreviations

AC .... Appraisal Cost

AFP .... Automated Fiber Placement

AHP .... Analytic Hierarchy Process

AI .... Artificial Intelligence

API .... Application Programming Interface

APQP .... Advanced Product Quality Planning

AQL .... Acceptable Quality Level

BD .... Big Data

BOM .... Bill of Material

BOP .... Bill of Process

CLQ .... Closed-Loop Quality

CM .... Corrective Maintenance

COGQ .... Cost of Good Quality

COPQ .... Cost of Poor Quality

COQ .... Cost of Quality

CPIP .... Control and Inspection Plan

CPPS .... Cyber-Physical Production Systems

DISW .... Digital Industries Software

EFC .... External Failure Cost

FAI .... First Article Inspection

FF ....Future Factories

FMEA .... Failure Mode and Effects Analysis

HOQ.. House of Quality

HQM .... Holistic Quality Management

IFC ....Internal Failure Cost

IH .... Insights Hub

IIoT .... Industrial Internet of Things

JIT .... Just-in-Time

L6σ .... Lean Six Sigma

MES .... Manufacturing Execution System

MHS ....Material Handling Station

Mx ....Mendix

Oc ....Opcenter

PC .... Prevention Cost

PLC .... Programmable Logic Controller

PLM .... Product Lifecycle Management

PM ....Preventive Maintenance

PMI ....Product Manufacturing Information

PPAP...Production Part Approval Process

PQM..Process Monitoring for Quality

QA .... Quality Assurance

QC ....Quality Control

QIP ....Quality Inspection Planning

QFD ....Quality Function Deployment

QM... Quality Management

RCA ....Root Cause Analysis

SCM ....Supply Chain Management

SMEs..Small and Medium Enterprises

SQC .... Statistical Quality Control

6σ...Six Sigma

Tc...Teamcenter

TcC ....TcConnector

TcQ .... Teamcenter Quality

TPM .... Total Productive Maintenance

TQM .... Total Quality Management

UI ....User Interface

VC ....Virtual Commissioning

VI ....Visual Inspection

WIP ....Work in Progress

Chapter 1 Introduction

1.1 Overview of Quality in Industry

Quality is the key to success for all manufacturing companies. Customers expect reliable and consistent products when they purchase crucial items, and industries unable to appease their customers are destined to fail. This has been true since the beginning of industry but there is an evident lack in research and innovation in this crucial field. To be truly competitive, companies must not only prioritize quality, but also continually push for improvement (Box & Woodall, 2012). It is critical that quality be at the forefront of all manufacturing breakthroughs because "high quality never happens by chance, it evolves over time due to experience" (Rostami et al., 2015). And it must be pushed from all levels not just quality specific teams. Successful implementation of new quality tools and techniques has been linked to the commitment of a company's employees to support it as a cultural shift within the entire organization (Maletič et al., 2014).

Quality as industry sees it today has been a priority for manufacturers since the 80s, when the start of many national level initiatives with a focus on total productivity emerged (Hon, 2005a). The four industrial revolutions are well known, but few know of the quality revolutions that emerged alongside them, though at slightly different paces as shown in Figure 1.1. The first three quality revolutions are defined by the emergence of a QM method as listed: Statistical Quality Control (SQC), Total Quality Management (TQM), and Six Sigma (6σ) (Escobar et al., 2021). The most recent revolution, Quality 4.0, is intended to work alongside Industry 4.0 to address the new challenges associated with topics such as Big Data (BD), Industrial Internet of Things (IIoT), and Artificial Intelligence (AI) (De Paula Ferreira et al., 2022)(Escobar et al., 2021).

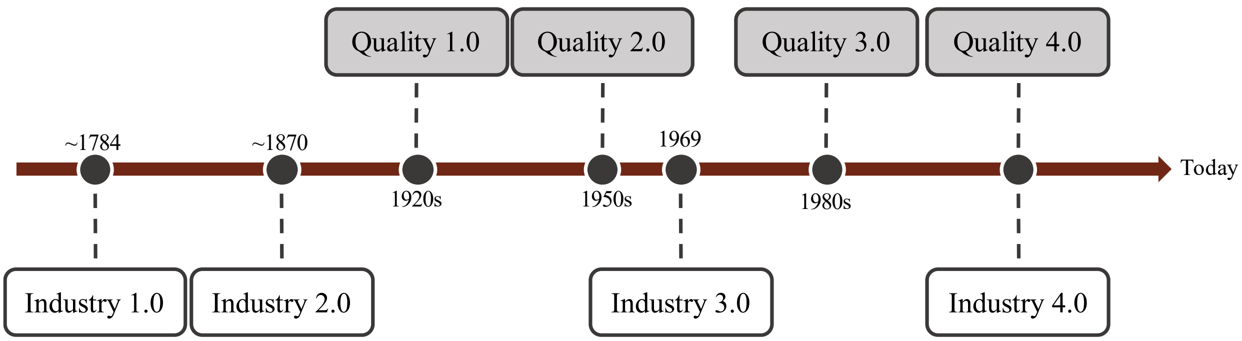

Figure 1.1: Progression Quality Revolutions compared to Industrial Revolutions

There are three aspects of quality at play in manufacturing: Quality Management, Quality Assurance, and Quality Control. Though these are separate topics they work together with much overlap. These topics have many different definitions due to their complex relationships, for this work they will be defined as follows: QM is the act of planning for quality and ensuring it is at the center of all manufacturing stages, QC is any actions taken to improve quality, and QA is checking final products to make sure that the plan was followed and that products are of acceptable quality. It is important to explore these topics as a starting point to creating a HQM method, to see the work that has been done and where is current research emphasis.

1.1.1 Quality Management

As mentioned previously the quality revolutions are associated with specific QM methods, though many others exist. Each method has different capabilities and improvements; therefore, companies should choose their methods depending on their specific quality issues, management techniques, and industrial standards. For example, it can be difficult to deploy quality management in Small and Medium Enterprises (SMEs) because they often lack resource availability. That is commonly not an issue for larger corporations. That said it is crucial that these SMEs adhere to strict quality regulations as they are often suppliers to large companies, which have high expectations when choosing where to purchase supplies (M. Kumar et al., 2014). This is one of many reasons for the emergence of so many different QM standards (Ebrahimi & Sadeghi, 2013). It is essential to learn the basics of popular QM techniques to discover existing gaps that the research discussed within this thesis will begin to improve. A brief introduction of the three main QM techniques will follow in timeline order.

1.1.1.1 Statistical Quality Control

SQC was one of the first QM tools and was introduced in the mid-1920s. The actual methods are not defined as this technique is based around monitoring quality through any available or relevant statistical methods. SQC is only effective in industries that conduct mass manufacturing where there is plenty of available historical data. In industries of today where the products have high-variety and low-volume, this method is not sufficient for QM. There have been some studies that combine traditional methods with tools that may remedy these issues, such as Bayesian process monitoring scheme (K. Wang & Tsung, 2022).

1.1.1.2 Total Quality Management

TQM was the next major QM method introduced in the 1950s. Its goal was to improve the overall company performance by improving product quality (Konecny & Thun, 2011). This method was the first to view quality in a holistic way by considering at all stages of the production process, from design to final product output (Kannan, 2005). There is also a heavy emphasis on the concept that quality relies on the entire organization opposed to an individual employee or department (Lau et al., 2009). Today, TQM is commonly implemented alongside other QM techniques and tools to improve its effectiveness and other factors such as cost reduction (S.-H. Chen, 2013). TQM is still being used in industry which speaks to its effectiveness. Though in companies that lack top management commitment TQM has often failed or struggled at being implemented, as this hinders its diffusion through the organization (Dubey et al., 2018).

1.1.1.3 Six Sigma

6σ or the beginning of Quality 3.0 started in the early 1980s. This method is one of the most prevalent in industry today and is noted as one of the most effective QM methods due to its ability to reduce manufacturing defects, improve product performance, achieve greater productivity, reduce costs, and increase customer satisfaction (Ben Romdhane et al., 2017). 6σ is unique in its requirement of Black Belt employees who act as experts to guide the company through implementation and to act as knowledge resources. Though it must be noted that this method has its largest success from deployment in large companies but has had difficulty reaching SMEs (M. Kumar et al., 2011). Some tactics to improve implementation in SMEs have been to avoid the use of Black Belts and simplify the structure and communication between employees and management (Ben Romdhane et al., 2017). Another factor that has assisted in 6σ's success was the introduction of Lean Six Sigma (L6σ) This combines the lean waste elimination strategies with the data-driven analyses of SS (Hilton & Sohal, 2012).

1.1.1.4 Quality 4.0

Throughout this section many of the primary QM methods have been discussed, but as Industry 4.0 has developed it has become obvious that none of the QM techniques fully account for all the new technologies: cue the development of Quality 4.0. This revolution is not associated with any specific QM strategy. That is because this field is still so incredibly new that many new techniques and new combinations or versions of existing methods have been created to keep up with all the new technology involved with BD, IIoT, and many more.

1.1.2 Quality Assurance

Product quality is important, but it is only useful when there is a system in place to monitor, identify, and assess quality problems. QA acts as the evaluation of how a company adhered to established goals from the QM phase. QA is an essential part of the research topic at hand since one of the primary goals is how to optimize QA. Therefore, it is important to briefly discuss current technologies and solutions in this field.

QA is defined primarily by the monitored metrics and inspection techniques. Previously the choice of technique has been left up to the opinion of the analyst depending on their strengths, specialty, and preference. With improvements in techniques, it is important to choose the tool which best fits the dataset not the employee (Rostami et al., 2015). First, determining the amount of quality metrics is essential. The Taguchi method is sufficient for monitoring single quality responses. More complex methods are necessary for multi quantitative responses (Hsieh & Tong, 2001). Most manufacturing facilities require capabilities far beyond single responses. Not only should the number of metrics be determined, but also which characteristics and how they should be monitored. There are many relevant quality characteristics needed to describe the state of a product, which also have complex interactions amongst themselves that need to be considered (G. Duan & Wang, 2015). When monitoring, it is essential to describe the products state through the entirety of manufacturing, including all relevant data for use (Wuest et al., 2014). Organizations that have low-volume production or high-levels of customization are at a particular disadvantage when it comes to inspecting products because many models are built from historic data which is not available in these industries (Ge et al., 2012). Automated on-line inspection improves detection time of irregularities without interrupting production and costs less than manual inspection though this adds complexity (Tušar et al., 2017). To improve QA techniques, it is essential to identify not only the root cause of defects but also factors critical to quality (Thomas et al., 2018). This field has also been influenced by BD style thinking and has prompted the development of Process Monitoring for Quality (PQM) (Abell et al., 2017). The larger amount of data needs to be contextualized through creation of ontologies through data mining (Z. Xu et al., 2018). PQM focuses on defect detection and blends process monitoring and QC founded on a BD model (Escobar et al., 2018).

1.1.3 Quality Control

Though QC is not a part of this research it is important to note its connection. QC utilizes QA as a guide, because QA identifies quality issues and important metrics, and QC uses those to choose control methods. QC is critical because it is important to ensure that the same issues do not continue to occur through the selection of the correct control plan and strategy. The complex interactions between these metrics as discussed in the previous section make QC tool selection more difficult.

1.2 Quality Pillars

After an extensive literature review of papers, which span from foundational to novel topics over the past 30 years, an attempt was made to fully view quality trends and find the most beneficial metrics and pillars. Papers were studied and categorized into five main categories or pillars, as shown in Figure 1.2 based off work already done in this field, this yielded the basis of the model that will be discussed. A sixth pillar is considered in cost as approximately 75% of papers read mentioned cost impacts. The pillars were defined within the realm of papers that consider each factor regarding their impact on end goal quality. These were then further split into subthemes and metrics, which will be explored in detail in Chapter 2. This method's basis was inspired by a similar paper which was creating a Sustainability Index (R. Harik et al., 2015).

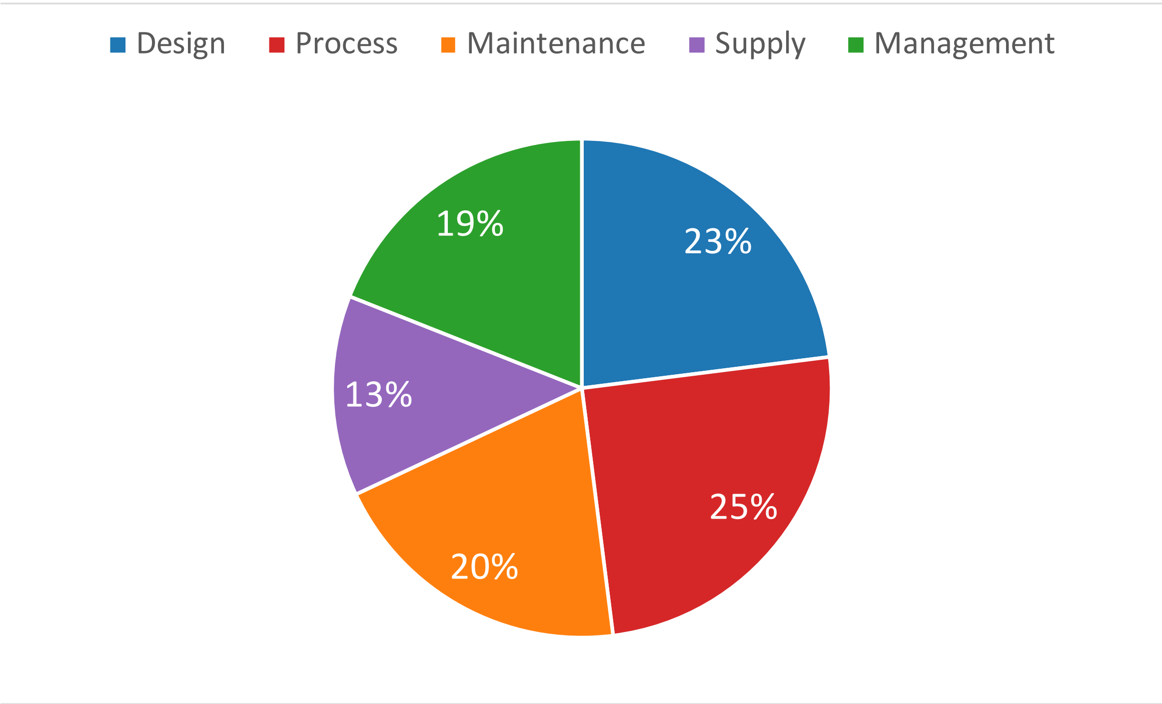

Figure 1.2: Classification of literature review papers to determine model pillars.

1.3 Quality Model

The model described in this paper is based off the literature and the pillars constrained in the previous section. These represent the top layer of relational value and will be explored in further detail in the remainder of this thesis. All these pillars are interconnected and affect each other and come with their own cost effects. For example, maintenance, specifically Preventive Maintenance (PM), increases cost with use of resources and decreases profit through production downtime. PM improves equipment age but can affect the production schedule and cause order delays. And when these delays occur operators may push equipment to max operating parameters to try and make up for lost time, which negatively affects the equipment. Then if the equipment fails from overuse even more time and money is lost. And this is only one scenario that needs to be considered to holistically assess quality.

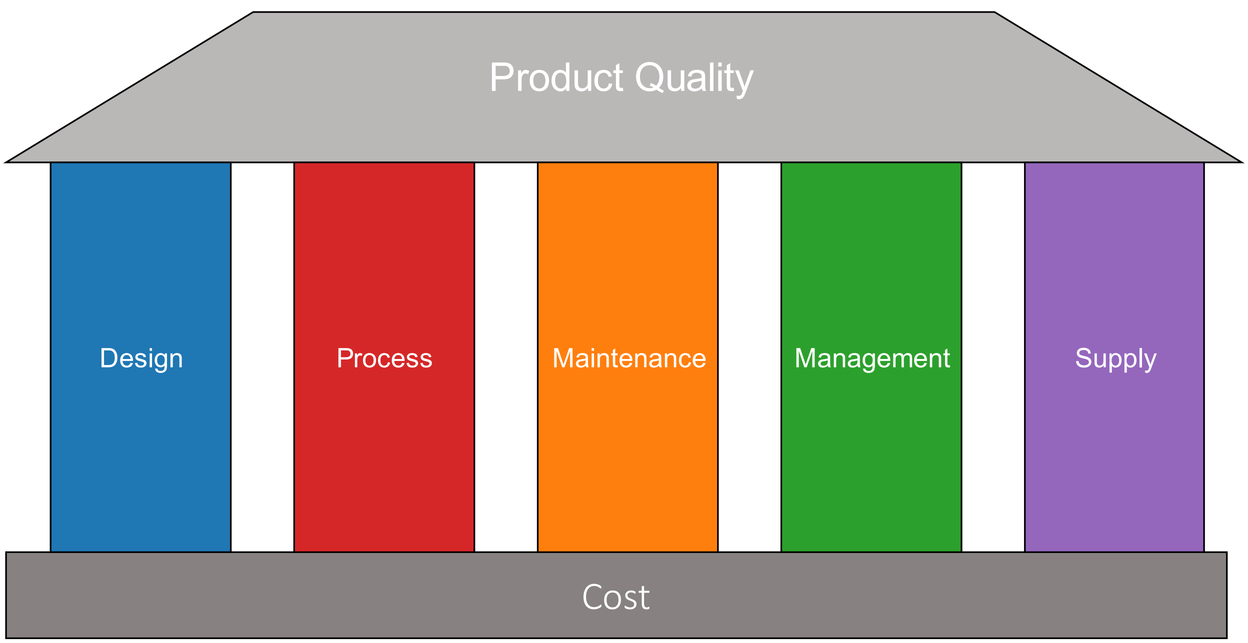

Figure 1.3: Visual representation of Holistic Quality Management model.

Since the possibilities of metrics and relationships are endless this model will be defined via the available literature read by the author, as was previously shown each pillar was associated with a percentage signifying its current representation in published papers. The model is visually represented in Figure 1.3. Product Quality acts as the roof for the model because it is the goal and the primary thread, and it is essential to consider the translation of product design and requirements in highest regard throughout the manufacturing process. Therefore, it is placed at the highest point on the model indicating its importance and signifying that if other pillars were to fall so will Product Quality. The five pillars are holding the roof representing that when a pillar falls the product quality will fail or succeed to a lesser level. Depending on which version of the model being analyzed the thickness of these pillars differs representing their weight of impact. Finally, Cost is placed as the foundation of the pillars and is also regarded differently. The Cost pillar will act as a check to ensure that the quality solution is feasible and within budget. Each of the pillars, other than Cost, is broken down into sub-categories and then into metrics which will be detailed in the following sections. Cost will be calculated via the Cost of Quality (COQ) equation fueled by costs incurred by implementing the other pillar's metrics.

The pillars will be represented by the colors contained within Figure 1.4 throughout the entirety of this thesis. This allow ease of understanding to the reader through consistent correlation.

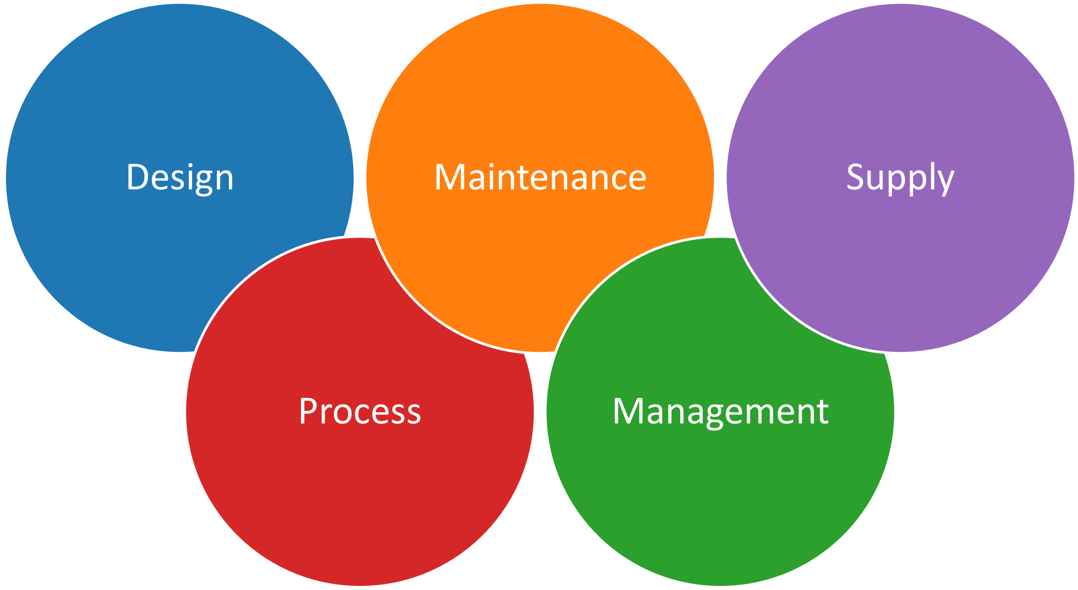

Figure 1.4: Pillars associated with their color theme.

1.4 Thesis Outline

This thesis utilizes and expands on the pillars discussed to include impacts of essential sub themes and metrics to create a HQM model. This model can quantify these complex relationships and interactions to output a QA score. This will aid a variety of manufacturing facilities to diagnose issues and improve overall product qualities. The remainder of this thesis is organized as follows. Chapter 2 contains an extensive literature review which shows the readers the discovery process of all sub-themes and metrics within each pillar. Chapter 3 details the creation of the complex relationships and formulas used to create the HQM model and the creation of the generic starting point model for out of the box use. It also shows how the base model can be specialized to specific industries. This thesis explores changing the weights within the model to fit both the pharmaceutical and composite industries, which represent mass manufacturing versus highly complex and specialized products respectfully. Chapter 4 introduces the implementation case of the model and shows how the standard model would perform in the Future Factories (FF) lab.

The base model is then tailored to create a FF specific instance and the results are compared. Chapter 5 shows how this model can be utilized as a guide for preexisting QM techniques or software through a collaboration with Siemens Digital Industries Software (DISW). Chapter 6 will conclude this work and expand on the pathway forward.

Chapter 2 Literature Review

This chapter will deep dive into each of the discussed pillars: Design, Process, Maintenance, Management, Supply, and Cost. To accurately assess each, a detailed background is included. After the background and concept is introduced, each pillar begins with a Sankey diagram to visualize the metrics that exist within the pillar and how they are sorted into sub-themes. This allows for not only placing weight on the importance of the high-level pillar and necessary metrics but also adds the complexity and detail of another level of impact. Then each sub-theme is further discussed by the addition of a table containing information specific for the metrics within that theme. The tables were filled based on available literature so that each metric is labelled as a positive or negative affect on product quality, whether it is qualitative or quantitative, and if there is a formula associated that will be used in this work. The chapter ends with a summary and discussion.

2.1 Design

The basis of any product begins at the design phase. The requirements and specifications set here must be upheld throughout the entire manufacturing process. This ensures the satisfaction and loyalty of customers, which is a key point for a successful business.

2.1.1 Background

The design has always been a crucial phase in the creation of a product to determine the necessary functions. To define this, there have previously been eight basic dimensions for evaluating quality of a product that are crucial to consider when in the design phase: performance, features, reliability, conformance, durability, serviceability, aesthetics, and perceived quality (Stylidis et al., 2015). On that note, there are also different types of quality to consider that a product must adhere to such as perceived quality (customer focused), actual quality (extent to which product delivers superior performance), product-based quality (nature and quantity of features), and manufacturing quality (conformance to specifications) (Stylidis et al., 2015). Some products also fall under imperfect quality versus defective quality, the difference between a product that may have an aesthetic mistake or error that does not affect the functionality of the product and a product that is unsellable. Oftentimes, customers may still be willing to purchase imperfect products instead of wasting time in remanufacturing, though the products normally need to be sold at a lower price (L. R. A. Cunha et al., 2018).

There are also different techniques for assessing product quality such as Kaizen, also referred to as “Global Customer Audit”, where the product is viewed from final customer point of view, it uses pareto charts, histograms, check sheets, and arranged defects according to intensity or magnitude of occurrence (R. Kumar, 2019). There have been numerous studies into statistical methods investigating quality factors, but these are often accompanied with issues in data integrity, lack of control, or technical constraints that restricts the feasibility of these solutions (Bang & Chang, 2013). For these to be successful for multi-response problems, there is a need for a solution that is easy-to-use, simple, flexible, and adaptable (Tansel İç & Yıldırım, 2013). Quality Function Deployment (QFD) planning processes is a commonly implemented method to prioritize design requirements. This process converts customer needs into technical requirements and utilizes House of Quality (HOQ) matrices to determine the relational intensity (L.-H. Chen & Chen, 2014). This tool improves the design process through earlier and fewer design changes, fewer startup problems, improved communication, improved product quality, reduced time, and cost (Franceschini et al., 2015).

2.1.2 Pillar Breakdown

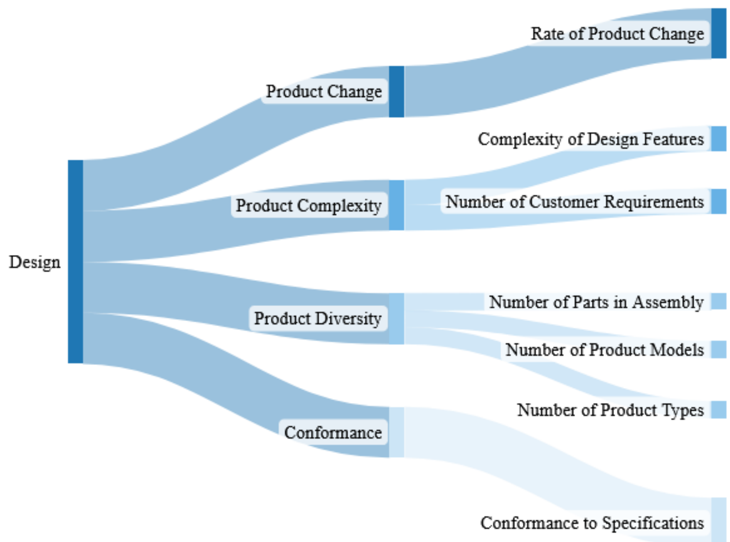

Figure 2.1: Pillar of Design split into themes and metrics.

2.1.2.1 Product Change

Table 2.1: Chart of product change metrics.

Title	Type	Impact	Description	Formula	Sources
Rate of Product Change	Quan.	Neg.	Rate of manufacturer product changes over time, either design or function	$= \frac{\sum Changes}{Time}$	(Benson et al., 1991)

All manufacturing companies create products that are either sold through a supply chain or directly to customers. To keep up with the changing market, products rarely stay the same forever and require innovations to stay competitive. While this trend is necessary, it can negatively affect quality depending on how quickly these changes occur and over what period. The higher this rate of change the more difficult it is to keep a high product quality level. High *rate of product change* will harm the effectiveness of QM as it causes disruptions in planning (Benson, Saraph, and Schroeder 1991).

2.1.2.2 Product Complexity

Table 2.2: Chart of product complexity metrics.

Title	Type	Impact	Description	Formula	Sources
Complexity of Design Features	Qual.	Neg.	Degree of complexity of manufacturing certain features such as curves or thin walls	n/a	(Benson et al., 1991; Kannan, 2005)
Number of Customer Requirements	Quan.	Pos.	Amount of customer requirements for a given product	$= \sum Requirements$	(Martí Bigorra & Isaksson, 2017)

Product complexity can be viewed regarding the *complexity of the design features* and the *number of customer requirements*. Companies' manufacturing processes greatly depend on the *complexity of product features*, meaning that certain types of features would require additional steps or higher technical skills to reach an acceptable level of quality. Features such as thin walls, hollows, or intricate structures are much more difficult to manufacture than simple structures (R. F. Harik et al., 2008). While higher complexity can negatively affect product quality, manufacturers who prioritize quality from the design phase and consider manufacturability and assembly can avoid some of these consequences (Kannan 2005).

Different industries have varying degrees of *complexity within their products*, this is greatly influenced by the *number of customer requirements* for these products. For example, an airplane would have far more requirements than a pen. The more requirements necessary, the more difficult it is to ensure quality across all requirements simultaneously. It is crucial for manufacturers to determine the difference between crucial requirements and the needs of the customer that fall into the delights category and to connect these needs back to customer satisfaction (Martí Bigorra and Isaksson 2017).

2.1.2.3 Product Diversity

Table 2.3: Chart of product diversity metrics.

Title	Type	Impact	Description	Formula	Sources
Number of Parts in Assembly	Quan.	Neg.	Number of individual parts within final product assembly	$= \sum Parts$	(Hon, 2005b)
Number of Product Models	Quan.	Neg.	Number of available models for a specific final product	$= \sum Models$	(Konecny & Thun, 2011)
Number of Product Types	Quan.	Neg.	Number of different final products available for sale from the manufacturer	$= \sum Products$	(Nourelfath et al., 2016)

Manufacturers with a higher variety in their products face more difficulties in enforcing product quality. This variety can be defined by the *number of parts within an assembly*, *number of product models,* and *number of types of products*. Assemblies that consist of many different parts are more complex than single part products. This is because each component in an assembly normally requires at least one additional step if not more to integrate it into the product during the manufacturing process. This can affect the number of necessary machines and the arrangement of the machines needed to manufacture. Another level of complexity is added because in today's manufacturing field it is rare for a company to manufacture all their necessary parts, causing them to rely on suppliers to produce components (Hon 2005b).

After considering the *number of parts in the assembly,* the next definition of product variety comes from how many different models are available for a given product. From the introduction of mass customization comes a concept of an individual product that can be configured with slightly different specifications that are unique to the individual user. A larger product mix will increase difficulty in achieving product quality because there are more potential combinations to consider (Konecny and Thun 2011).

The last definition is the *number of different types of products* produced from the same manufacturing facility. The more products being manufactured causes the addition of machinery and processes to successfully accomplish all manufacturing steps. An increase in any of these three definitions will increase setup costs for the manufacturer (Nourelfath, Nahas, and Ben-Daya 2016).

2.1.2.4 Conformance

Table 2.4: Chart of conformance metrics.

Title	Type	Impact	Description	Formula	Sources
Conformance to Specifications	Quan.	Pos.	Results of final product matching customer requirements	$= \frac{\sum SpecsMet}{\sum Specifications}$	(Konecny & Thun, 2011; Prajogo & Brown, 2006)

The last theme to consider when analyzing product quality is the ability of the manufacturer to conform to the necessary specifications. A product's quality performance is directly related to both the *conformance to specifications* and the product's capability to gain its customers' satisfaction (Konecny & Thun, 2011) Depending on what the specifications for a product are, this metric could be quantitative or qualitative; but regardless, the higher the conformance, the higher positive affect on product quality. This is a common theme in many QM ideologies such as TQM (Prajogo and Brown 2006).

2.2 Process

This pillar is crucial to ensure that the processes are meeting all the requirements set out in the Design pillar. Mistakes here can cause issues in product quality when a product is not manufactured correctly.

2.2.1 Background

The first of the internal pillars that will be discussed is how process affects product quality. Product quality was maintained solely by skilled operators based on experience and intuition (Kano & Nakagawa, 2008). One definition of process management describes it as efforts to reduce batch sizes to improve process performance (Wiengarten et al. 2013). Many QM philosophies aim to also consider external factors that affect quality. For example, TQM aims to integrate quality into all functions of bringing product to market (Inman et al., 2003). QM has been a system for continuous improvement, but has not been sufficiently coupled with the theory that it affects process innovation (Camisón and Puig-Denia 2016). Oftentimes output of process becomes input for later processes and compounds defects (Sik Kang et al., 1999). Insufficient knowledge of relationship between process parameters and corresponding responses due to continuous process with large amount of material can also affect quality (Chiang et al., 2002). It is a fine line between process optimization and rushing the process at the consequence of quality and the perceived quality of the customers (Calabrese and Spadoni 2013).

Historically human inspection was the only way to monitor and inform process control. One remaining philosophy from this trend is human jidoka, which is the practice of stopping the system when something suspicious occurs or is seen to prevent a series of defective parts, but oftentimes defects are independent of others and stopping production can negatively affect productivity without improving quality. In recent years there are new technologies to inform process control (Kim & Gershwin, 2005).

Oftentimes sensors measure variables, and the signals are correlated with tool state/process conditions then cognitive decision making makes final diagnosis to inform operator or controller (Teti et al., 2010). It is important to ensure quality of the assembly or manufacturing process because defects can be propagated and amplified to downstream process. These defects of assembly will affect quality and cost of product as it would require disassembly rework a solution for monitoring multi-stage assemblies with closed-loop intelligent control (X. Wang et al., 2015). The ability to extract features is essential to process monitoring. There are examples in the literature of deep autoencoder extracting features from complex data to improve reliability and safety (Lu & Yan, 2020). Data collection is also essential in identifying key performance indicators (KPI), which are important for efficient design and operation of complex manufacturing systems (C. Wang & Zhou, 2021). Virtual metrology utilizes process data collection to estimate a product's quality without inspecting the part directly (Dreyfus et al., 2022). Predicting quality defects in this method is difficult due to limitations in training samples, but it was proven that applying other methods can account for the lack of historic data (Li and Wang 2022). Previous methods are successful because the process variables are already identified or there is an explicit quality function. When these are not readily available, methods such as patient rule induction method can seek variables from historic data (Chong et al., 2007). Being able to predict based off process data through monitoring of abnormal operations could predict economic cost in advance (Zhao et al. 2021).

Process control is reliant on the ability to obtain necessary data from sensor technologies to be utilized in signal processing and decision-making (Teti et al., 2010). Statistical process control is a common method for industries with sequential processes because quality of product is affected by many factors with many relationships, inductive learning can extract rules from correlations (Sik Kang et al., 1999). It is possible to improve process capability through optimization of quality characteristics through neural networks and robust design methods (Chiang et al., 2002). An important aspect is to define root-cause machine set identification to identify which combinations of machines are producing defective products, this can be determined by association rule mining (W.-C. Chen et al., 2005). Data mining can be utilized to discover patterns in manufacturing processes which will improve ability to detect and prevent defects (Rokach & Maimon, 2006). It can be especially difficult for SMEs to implement process control, but the implementation of value stream design can be used to select and develop methods for coordination and control of processes and to improve information flow (Busert and Fay 2021).

Thus far the focus of research has just been in the intersection of quality and process control, but there are papers which propose a tool that returns optimal inspection points (Colledani & Tolio, 2011b). There has been the use of Quality Inspection Planning (QIP) based off an acceptable quality level (AQL) of the finished product to find the trade-off relationship between cost, lead time, and quality (Bettayeb et al., 2018). To optimize QIP the optimal time, place and extent of inspection activities must be determined while still maximizing system efficiency (Rezaei-Malek et al. 2019). Since the implementation of inspection points increases cost, there is an economic advantage to planning quality inspection as early in the manufacturing process as possible (Ben-Ammar, Bettayeb, and Dolgui 2020). Planning the number of inspection points is not the only crucial factor. It is also important to take into consideration the amount of time each inspection will consume (Hauck et al., 2021) This research has also been related to the factor that more defects are produced when the system is at an out-control versus an in-control state (Bettayeb et al., 2018) This is why research suggests coupling QIP with PM activities (Rezaei-Malek, Mohammadi, et al., 2019) The introduction of inspection plans are never perfect due to human error and technical issues means that there are normally defects that were not caught during a single round of inspection. Some studies have researched estimating the remaining number of defects left in a sample based off how many defects were discovered during each inspection round; one such study introduced a ‘beta-geometric’ inspection model where the inconsistencies of the detection probability were described by a beta distribution (Chun, 2016).

Cyber-physical production systems (CPPS) can be used to accomplish requirements through IIoT, AI, simulations, Manufacturing Execution Systems (MES), and advanced planning and scheduling systems (Lee et al., 2018). Digitalization is needed for continued improvements to avoid inconsistencies from paper-based quality practices (Dutta et al., 2021). CPPS assist in monitoring machines, parts, and products; allowing health monitoring, scrap avoidance, and process optimization (Saez et al., 2020). These manufacturing processes, where process performance is being monitored by sensor data, can be negatively affected by deficiencies in computing, manufacturing process accuracy, or sensor measurement (Nannapaneni et al., 2021). Gaps also form between theoretical models and real industrial practices due to assumptions in generations of these models (Hui et al., 2022) There are examples of cyber-physical implementation for automation in a variety of industries such as pharmaceutical labs (Coito et al., 2022). This facilitated the introduction of Digital Twin technology, where system is mapped via virtual space, and can assist in quality monitoring and control, online prediction, and quality oriented collaborative organization (Pei et al., 2021). To continue to improve and implement this technology, there is research into the use of machine learning in process control research to include customer, environmental, and human-in-the-loop aspects (Usuga Cadavid et al., 2020).

2.2.2 Pillar Breakdown

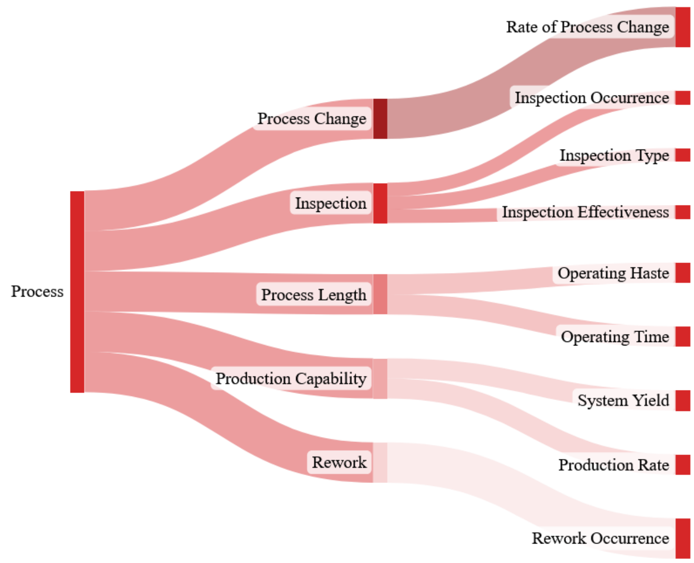

Figure 2.2: Pillar of Process split into themes and metrics

2.2.2.1 Process Change

Table 2.5: Chart of process change metrics.

Title	Type	Impact	Description	Formula	Sources
Rate of Process Change	Quan.	Neg.	Rate of manufacturer process changes, either design or function	$= \frac{\sum Changes}{Time}$	(Benson et al., 1991)

Similarly, the way that products change over time to meet market demands, the processes required to manufacture them change over time. As the process change rate increases, so does the potentially negative impact on quality. For a manufacturer to try and counteract this effect, it is essential for there to be clear process ownership and attempting to achieve 'fool-proof' process designs (Benson, Saraph, and Schroeder 1991).

2.2.2.2 Inspection

Table 2.6: Chart of inspection metrics.

Title	Type	Impact	Description	Formula	Sources
Inspection Occurrence	Quan.	Pos.	Amount of inspection stations or stages before a product reaches market	$= \sum Inspections$	(Ben-Daya, 2002; Ben-Daya & Makhdoum, 1998; Chun, 2016; Inman et al., 2003; Kano & Nakagawa, 2008)
Inspection Type	Qual.	Pos.	Number of inspection types within a facility, for example cameras or sensors	$= \sum Inspection\ Types$	(C. Da Cunha et al., 2006)
Inspection Effectiveness	Quan.	Pos.	Reliability that inspection identifies part defects	$= \frac{Correct}{Total\ Inspections}$	(Chun, 2016)

Inspections are essential to improve the overall quality, but implementing the wrong inspections can quickly cause more adverse effects than good. There are three critical variables to consider when adding inspections into a manufacturing cell, this includes *inspection occurrence*, *inspection type*, and *inspection effectiveness*. *Inspection occurrence* can be defined by both the frequency, or the number of inspection stations and the locations of stations. In general, the higher the *inspection occurrence* the higher the overall product quality. There are tradeoffs that need to be considered because inspections add time and cost, which can negatively affect a manufacturer. The optimal frequency needs to be determined depending on length of inspection and number of stations (Mohamed Ben-Daya 2002). The location of these inspections is also critical because the sooner errors are caught, the faster rework can be completed. This is opposed to traditional methods where inspections occur at the end of a manufacturing line (Inman et al. 2003). These inspection decisions become more efficient as more historic data is collected. This is especially effective for manufacturers with multiple locations where they can collect all data into a central integrated database (Kano and Nakagawa 2008). Not only should the products be inspected, but there should also be inspections focused on the equipment to give insights into the health and state of the process (M Ben-Daya and Makhdoum 1998).

There are many *inspection types* ranging from manual to sensors to visual systems. These different types of inspections can detect different types of defects. There are many tradeoffs to consider when choosing, because while one system can be most effective it could also be the most expensive, and depending on how many stations are necessary, this can greatly affect a manufacturers decision (C. Da Cunha, Agard, and Kusiak 2006). That is why the higher the number of *inspection types* at play in a manufacturing cell can positively or negatively affect quality; because the more types can increase effectiveness while also increasing complexity, which can introduce more errors.

After the *inspection occurrence* and types have been implemented, then the effectiveness can be calculated. This is determined via the number of correctly identified inspections versus the total number of inspections conducted. This is assuming that the effectiveness is a constant. There has been research into the heterogeneity in the detection probability (Chun 2016). The higher this effectiveness is, the more positive impact on product quality, because this means the process is running as it should.

2.2.2.3 Process Length

Table 2.7: Chart of process length metrics.

Title	Type	Impact	Description	Formula	Sources
Operating Time	Quan.	Neg.	Amount of time for a job to be completed	$= Time$	(Ben-Daya & Makhdoum, 1998; Hauck et al., 2021; Hon, 2005b; Konecny & Thun, 2011; Ruschel et al., 2017; L. Wang et al., 2019)
Operating Haste	Quan.	Neg.	Pressure for machines to run outside of recommended specifications for jobs to be completed faster	$= \frac{Speed\ of\ Jobs}{Recommended\ Speed}$	(Inman et al., 2003)

Another crucial aspect is process length, which consists of the amount of time required to complete a series of tasks. Depending on the industry, this may only include the tasks necessary to manufacture a product or it could include other tasks, such as set-up or inspection (M Ben-Daya and Makhdoum 1998). Some process lengths even include the delivery or maintenance time (Konecny and Thun 2011; L. Wang, Lu, and Han 2019).

Normally, an increase in process time can positively affect product quality because it could mean more time is being spent on each task and that inspections are occurring; however this can also represent inefficiencies and it is important to not extend time so far that the company is not meeting production goals. For example, in high volume production industries it is important to achieve the minimum cycle time where products are still of acceptable quality (Hon 2005b). There are also tradeoffs regarding manufacturing length and maintenance occurrence, the faster things are run the higher the failure risk factor and the decrease in component reliability (Ruschel, Santos, and Loures 2017). The *operating time* is also important when wanting to calculate the average cycle cost (Hauck, Rabta, and Reiner 2021).

Not only is the elapsed time important, but it is also necessary to analyze the haste in which manufacturing is occurring. There are many times where a manufacturer may be behind schedule, whether because of unexpected maintenance or a sudden increase in demand, and this can cause the system to be run faster than is ideal. While this may solve the initial problem, it can also cause longer-lasting issues such as machine failures or an increase in product defects. That is why the increase in operation haste negatively affects product quality. This is especially prevalent in manual manufacturing processes but has also been found in robotic manufacturing, and that is why it is essential to balance throughput with acceptable quality (Inman et al. 2003).

2.2.2.4 Production Capability

Production capability is a crucial aspect in analyzing process quality and it is necessary to consider both *system yield* and *production rate* for accurate representation. The *system yield* is the number of acceptable products produced versus the total throughput of the system; this represents the ability of the system to consistently produce high quality products (M. Colledani and Tolio 2006, 2011a). The *system yield* can be represented in a more complex function consisting of inspections, individual operation yields, buffer sizes, and operations policies (Kim and Gershwin 2005).

Table 2.8: Chart of production capability metrics.

Title	Type	Impact	Description	Formula	Sources
System Yield	Quan.	Pos.	Number of products produced that are of acceptable quality versus total throughput	$= \frac{Acceptable\ Products}{Total\ Throughput}$	(Colledani & Tolio, 2006, 2011a; Kim & Gershwin, 2005)
Production Rate	Quan.	Neg.	Number of products produced over time	$= \frac{Acceptable\ Products}{Time}$	(Y.-C. Chen, 2013; Fakher et al., 2018; Farid & Neumann, 2020; Khatab et al., 2019; Sarkar & Chung, 2020)

Production capability is a crucial aspect in analyzing process quality and it is necessary to consider both *system yield* and *production rate* for accurate representation. The *system yield* is the number of acceptable products produced versus the total throughput of the system; this represents the ability of the system to consistently produce high quality products (M. Colledani and Tolio 2006, 2011a). The *system yield* can be represented in a more complex function consisting of inspections, individual operation yields, buffer sizes, and operations policies (Kim and Gershwin 2005).

While the *system yield* is comparing the conforming products to the total number of manufactured products, the *production rate* compares this value to the amount of time elapsed to produce that many products (Fakher, Nourelfath, and Gendreau 2018). This rate increases when the system can produce more acceptable products over the same period. There is a tradeoff between *production rate* and customer demand because a manufacturer does not want to produce more products than it can sell (Khatab et al. 2019). Many papers consider flexible *production rate*s where the ideal rate changes based off the current customer demand (Sarkar and Chung 2020). It is crucial to determine the optimal *production rate* especially in manual operations, to ensure customer demand is met while avoiding risk of injury for operators (Farid and Neumann 2020). This is considering that the rate is constant throughout an entire shift, whereas some research has been dedicated to variable *production rates* (S.-H. Chen 2013).

2.2.2.5 Rework

Table 2.9: Chart of rework metrics.

Title	Type	Impact	Description	Formula	Sources
Rework Occurrence	Quan.	Neg.	Amount of products that have to be reworked out of total throughput	$= \frac{Reworked\ Products}{Total\ Throughput}$	(Inman et al., 2003)

Many product defects can be reworked, opposed to scrapped, especially if they are caught early in the manufacturing process. This is positive because it saves cost in wasted materials from scrap products, but still affects product quality negatively as the ideal scenario is that products are produced correctly the first time. The *rework occurrence* is analyzed by viewing the number of reworked products versus the total throughput of the system. To improve the chances of catching defects early, it is crucial to reduce batch sizes (Inman et al. 2003).

2.3 Maintenance

The process is crucial for design requirements being met, but if the equipment is in disrepair, then it can be impossible for products to be manufactured correctly. As well as poor maintenance practices can cause unplanned downtime and missed deadlines.

2.3.1 Background

Effective maintenance extends equipment life and improves equipment availability, but poorly maintained equipment leads to frequent equipment failures, poor utilization, delayed production scheduling, increased scrap, questionable quality, and frequent equipment replacement (Swanson, 2001). Two commonly investigated types of failure are when the system shifts to out-of-control or when system fails and must be repaired (Fakher et al., 2018). In recent years there has been a transition from reactive maintenance to predictive and PM (Swanson, 2001). Currently, maintenance occurs when a certain amount of deterioration occurs opposed to specified period or usage, and completion of PM activities can reduce the age proportionally (Iung et al., 2005)(Ben-Daya, 2002). An important aspect of maintenance is to identify influential equipment, actions, and environmental factors, to assist in predicting failures (Navinchandran et al., 2022). It is also important to monitor not only the health of equipment, but also of tooling because deteriorated tools can lead to poor quality and tool failure, and excessive replacements increase production losses and costs (W. Xu and Cao 2015). One downside of improving maintenance tactics is that testing can be time consuming when production must be stopped, especially when factors have effect on multiple processes and are tested multiple times (Khan et al., 2022).

There are examples in literature of authors attempting to connect product quality with pillars of the model described in this paper, but none holistically views all aspects. There are examples of the connection between process, maintenance, and product quality in literature. It is essential to consider these factors simultaneously and define as a set of values to align customer orientation, quality responsibility, and process orientation (Maletič, Maletič, and Gomišček 2014). Creation of Weibull model to connect maintenance policies to economic production quantity (EPQ) to determine optimal design of control chart and optimal PM, the issue is this study assumed that the process never fails and always produces parts of acceptable quality (Ben-Daya & Makhdoum, 1998). To update their previous work the Weibull model was considered in a degrading system (Ben-Daya, 1999). There is also a management style that connects these three aspects called Total Productive Maintenance (TPM) which is related to low cost, high quality, and on-time deliveries and how these relationships can relate to manufacturing performance through structural equation modelling (McKone et al., 2001). The general concept of TPM is to maximize overall equipment effectiveness so productivity is increased (Konecny & Thun, 2011). There are connections between concepts of TQM and TPM and how they improve production, both these techniques focus on human resources strive for continuous improvement, organization involvement, and reduction of waste (Konecny & Thun, 2011). Therefore, they are often implemented simultaneously. These factors are also connected back to cost since changes in inspection, maintenance, and production will affect overall cost (Khatab et al. 2019).

Many tools have been created to improve product quality through maintenance actions. There is a relationship between the amount of machine deterioration and the rate of defective items, and studies have attempted to analyze these relationships and include them in PM strategy planning (Hajej, Rezg, and Gharbi 2018). When deterioration increases the amount of defect also increases and to solve this maintenance actions must be completed, but to accomplish these tasks the system's availability decreases (L. Wang, Lu, and Han 2019). There has also been research into introducing a maintenance decision-making tool to allow the system to select the best maintenance action, through a four-step process of monitoring, diagnosis, prognosis, and then decision-making (Iung et al., 2005). Another option is an integrated maintenance decision making model concept to improve operational efficiency through minimizing risk through the implementation of a digital twin; this would simulate the physical counterpart characteristics, behavior, life, and performance (Szpytko & Salgado Duarte, 2021). Yet another example is a profit maximization model that integrates PM, quality, and production through multi-period multi-product capacitated lot sizing which improves classic lot sizing and ignores the possibility of deterioration and existence of non-conforming items (Fakher et al., 2018). Many of these research cases fail to account for unexpected situations, which was then considered in a condition-based maintenance solution (Sakib & Wuest, 2018). Another condition-based method focused on product quality and machine reliability to reduce maintenance cost

(Nguyen et al., 2019; Shivajee et al., 2019). A more recent model of a Variable-Parameter Shewhart control scheme that is utilized to monitor processes, was implemented so that when an alarm is issued PM action is initiated but Corrective Maintenance (CM) action would still be required after failure (Tasias & Nenes, 2018). Anomaly detection is crucial for monitoring and identifying changes that indicate fault and when to perform maintenance (Quatrini et al., 2020). Many industries perform selective maintenance meaning that designated time slots are created to perform maintenance based off priority of actions and amount of time. Models have been created to assist in optimizing the maintenance performed based off limited maintenance resources (C. Duan et al. 2018). To successfully implement any of these tools it is essential to ensure that there are effective tools at work to mine the necessary operational quality data containing machine health information (Z. Chen et al. 2019). Some industries struggle to obtain sufficient data due to few failures or lack of historic data; some proposed solutions include a Bayesian method using reparameterization of the Weibull distribution (Zhang, Pan, and Goh 2021).

2.3.2 Pillar Breakdown

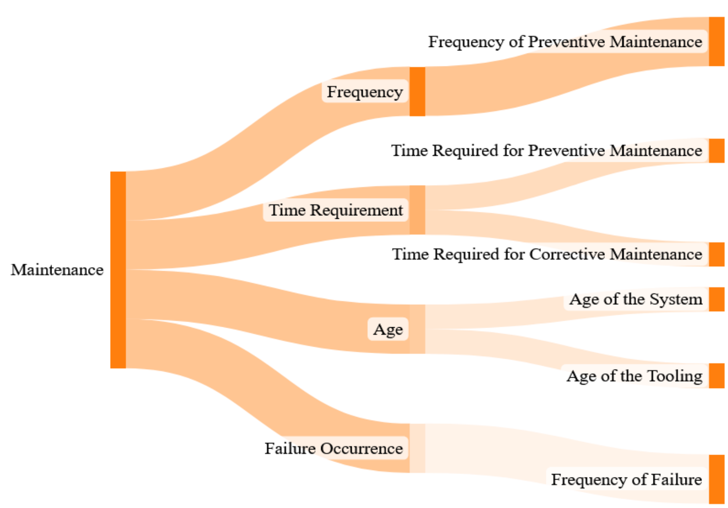

Figure 2.3: Pillar of Maintenance split into themes and metrics.

2.3.2.1 Frequency

Table 2.10: Chart of frequency metrics.

Title	Type	Impact	Description	Formula	Sources
Frequency of Preventive Maintenance	Quan.	Pos.	Occurrence of preventive maintenance activities to avoid failure	$= \frac{\sum Maintenance\ Activi}{Time}$	(Ben-Daya & Makhdoum, 1998; Pandey et al., 2011; Ruschel et al., 2017)

It is essential to perform PM activities to keep equipment at peak operating condition. PM helps to avoid equipment failure and unplanned downtime. This is only true on the assumption that technicians performing this maintenance and that no faulty procedures were followed (Ben-Daya & Makhdoum, 1998). These activities occur over a designated period, and it is assumed that the time between activities is always the same. The lengths of these periods can be determined from factors such as the age of the machine prior to PM, the processing time for batches, the time to complete PM, and the time to repair the system when a failure occurs (Pandey, Kulkarni, and Vrat 2011). The more often that these PM activities occur, the better the system performs which positively affects product quality, but it is important to pick the optimal frequency because sometimes the cost of these activities can outweigh the cost being saved from machine failures (Ruschel et al., 2017) PM activities are also often coupled with QC inspections, so that after a designated number of inspections occur a PM activity occurs (M Ben-Daya and Makhdoum 1998).

2.3.2.2 Time Requirement

Table 2.11: Chart of time requirement metrics.

Title	Type	Impact	Description	Formula	Sources
Time Required for Preventive Maintenance	Quan.	Pos.	Amount of time utilized to perform preventive maintenance activities over the specified time	$= \sum TimeUtilized$	(Ben-Daya & Makhdoum, 1998; Hadian et al., 2021; Pandey et al., 2011; Radhoui et al., 2009)
Time Required for Corrective Maintenance	Quan.	Neg.	Amount of time utilized to perform corrective maintenance activities over the specified time	$= \sum TimeUtilized$	(Mehdi et al., 2010)

Maintenance is essential to ensure the health of the system so that products are meeting quality requirements, but these activities cause downtime which can negatively affect the process and the throughput of the system. This downtime can either be planned for PM or unplanned when CM is needed for machine failure. The *time required for preventive maintenance* has a positive effect on product quality, so long as the downtime is successfully balanced to not negatively affect the ability of the system to satisfy customer demand. This can be remedied through buffer stocks between machines to ensure a continuous supply during these planned downtimes (Radhoui, Rezg, and Chelbi 2009). This way if the time elapsed is accurate to what was planned there is never a shortage; if there were mistakes in calculations then there will be shortages (Hadian, Farughi, and Rasay 2021). It is also important to note that the level of the PM activity will determine the length of the necessary downtime, which is essential for successful planning (M Ben-Daya and Makhdoum 1998).

Regarding corrective maintenance, this is unplanned maintenance which means that any elapsed time will negatively affect the system's throughput. Though buffer stocks also help to prepare for these failures, there is still a negative impact (Mehdi, Nidhal, and Anis 2010). Therefore, it is important to avoid any downtime for corrective maintenance.

2.3.2.3 Age

Table 2.12: Chart of age metrics.

Title	Type	Impact	Description	Formula	Sources
Age of the System	Quan.	Neg.	Overall age of machinery	$= Time$	(Ben-Daya, 2002; C. Duan et al., 2018)
Age of the Tooling	Quan.	Neg.	Overall age of tooling	$= Time$	(Hon, 2005b)

The *age of the system* or tooling is an important factor because the older equipment is, then the higher the risk factor for failure. The *age of the system* includes any equipment or resources needed to manufacture products. Since the risk of failure increases as age increases, this means that age also can negatively affect the quality of the process. The occurrence of PM activities can reduce the *age of the system* proportionally to the level of the PM activity (Mohamed Ben-Daya 2002). Many studies consider this relationship in a more complex manner because most PM activities are imperfect, meaning this relationship is not proportional (C. Duan et al. 2018). This change in age affects the number of nonconforming items, restoration costs, and the length of production (Mohamed Ben-Daya 2002).

The concepts discussed are similar for the tooling as it is for the system, but the tooling is what the machines use to manufacture products. Tooling is often replaced more often than repaired, meaning that PM is not normally performed, but like the system an increase in age negatively affects output product quality. The tool life has a direct impact on cost, time, and quality (Hon 2005b).

2.3.2.4 Failure Occurrence

Table 2.13: Chart of failure occurrence metrics.

Title	Type	Impact	Description	Formula	Sources
Frequency of Failure	Quan.	Neg.	Occurrence of machine failure causing shutdown of line or full system	$= \frac{\sum Failures}{Time}$	(Agard & Bassetto, 2013; Ben-Daya & Makhdoum, 1998; Radhoui et al., 2009; Ruschel et al., 2017; Tasias, 2022; Tasias & Nenes, 2018; L. Wang et al., 2019)

Frequency of failures is a direct indicator of the quality of a manufacturer's maintenance, because the more often a system fails the worse the health of the system. This causes a negative impact on product quality due to the disrepair of the system. This increases the rate of non-conforming items (Radhoui, Rezg, and Chelbi 2009). Therefore, this concept is represented quantitatively by the sum of the failures over a period. PM would decrease the *frequency of failures* and return the system to a state that is between “as good as new and as bad as old” (M Ben-Daya and Makhdoum 1998). Successfully decreasing this frequency is difficult without sufficient historical data to accurately plan a schedule, but some studies have attempted to address this issue (Ruschel, Santos, and Loures 2017). Failure frequency also negatively affects process quality, because the higher the frequency the longer the downtime and lower expected availability of the equipment (Tasias and Nenes 2018). Changes in operation conditions will have direct impact on the *frequency of failures* (L. Wang, Lu, and Han 2019).

2.4 Management

The Management pillar is essential as this is where all decisions for the facility are decided, meaning that shortcomings here will have lasting affects throughout the facility.

2.4.1 Background

The next internal pillar is Management, which can relate to anything from employee training to quality regulations. Previously organization theory was the primary trend, but there should be a switch to focus on mix of external and internal critical factors such as: product/service design, training, employee relations, top management leadership, corporate support for quality, past quality performance, managerial knowledge, extent of external quality demands (Benson et al., 1991). Role of QM has previously had six practices: small group problem solving, top management leadership for quality, information and feedback, process management, customer focus, and supplier involvement (Murat Kristal et al., 2010).

Some studies have attempted to shift the idea that quality should be both customer and stakeholder focused, not only should the products meet customer needs, but all stakeholders should be involved in prioritizing quality (Mellat-Parast 2013). To achieve a work environment that is conducive to quality improvement it is crucial to have visionary leadership where the top management is committed to employee involvement and planning, learning where all employees are trained and have open access to management, continuous improvement when employees work in teams strive for this goal together, and employee fulfillment so that all employees have high morale and low pressure and stress (Wiengarten et al. 2013). The necessary training and culture shifts will induce higher costs. Some industries have resorted to temporary workers that reduce these costs especially during economic downturns, but studies have shown that there is an association between this trend and deteriorating quality highlighting the importance of employee quality training (Wiengarten et al. 2022). The survival of organizations depends on ability to gain, bind, and enthuse customers; this is highly dependent on quality of management (Weckenmann et al., 2015). Oftentimes managers do not have quality training, meaning adoption of QM could fail or lead to increased expenditure (Sahoo & Yadav, 2018).

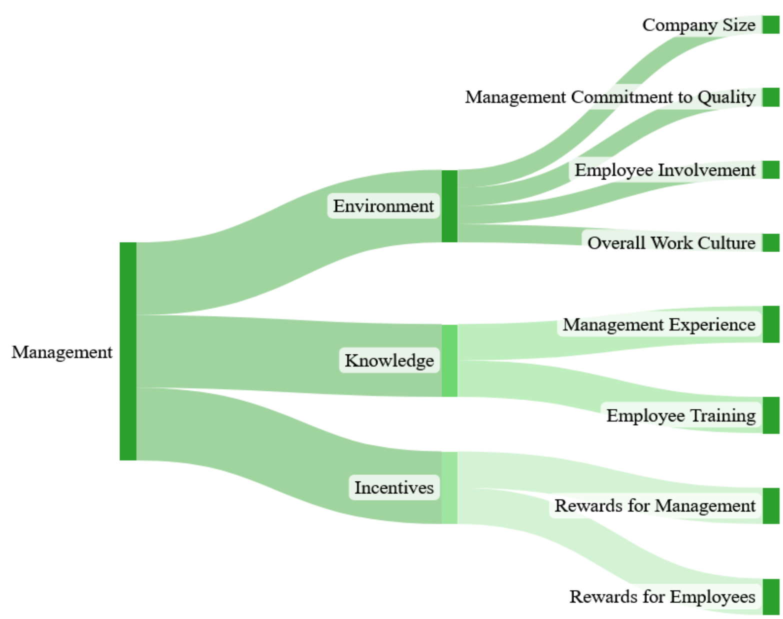

Figure 2.4: Pillar of Management split into themes and metrics

2.4.2 Pillar Breakdown

2.4.2.1 Environment

Table 2.14: Chart of environment metrics.

Title	Type	Impact	Description	Formula	Sources
Company Size	Quan.	Pos.	Number of employees within company	$= Number\ of\ Employees$	(Benson et al., 1991; Calvo-Mora et al., 2015; Prajogo & Brown, 2006; Psomas & Antony, 2015)
Management Commitment to Quality	Qual.	Pos.	Upper management commitment and involvement in improving quality practices	n/a	(Dubey et al., 2018; Ebrahimi & Sadeghi, 2013; Kannan, 2005; M. Kumar et al., 2011, 2014; Mellat-Parast, 2013)
Employee Involvement	Qual.	Pos.	Involvement of employees in quality planning and activities	n/a	(Ebrahimi & Sadeghi, 2013; Inman et al., 2003; M. Kumar et al., 2014; McKone et al., 2001; Mellat-Parast, 2013)
Overall Work Culture	Qual.	Pos.	Other variables impacting an employee’s work environment such as job satisfaction or injury frequency	n/a	(Farid & Neumann, 2020; Hon, 2005b)

The environment of the workplace can have a huge effect on quality, because if the *work culture* is bad, then none of the employees will have the motivation to champion or prioritize quality (Psomas and Antony 2015). This can be analyzed through the *company size*, *management commitment to quality*, *employee involvement*, and the *overall work* *culture*. The *company size* is based on how many employees are currently employed by a manufacturer. Larger companies normally have the resources to support the culture change that comes with the implementation of a QM program, meaning larger companies normally can reach a higher level of product quality (Benson, Saraph, and Schroeder 1991), though many standards such as ISO 9000 and TQM have attempted to create a template that can be implemented regardless of *company size* (Prajogo and Brown 2006). To have a more accurate picture of this concept more research needs to be conducted into how size affects the ability to implement QM (Calvo-Mora et al. 2015).

The only way to ensure a successful implementation of QM is to have top management committed to these programs' success. Since managers are responsible for the facilitation of ideas and concepts to the employees, that means that higher levels of commitment cause a positive impact on product quality (Dubey et al. 2018; Kannan 2005; Mellat-Parast 2013). Managers can help employees to understand the reasoning behind the implementation instead of just expecting them to accept it, this is especially prevalent in companies that follow Six Sigma (M. Kumar, Antony, and Tiwari 2011). Strong management also becomes more crucial in SMEs (M. Kumar, Khurshid, and Waddell 2014). This means that it is essential to enforce management participation in training (Ebrahimi and Sadeghi 2013).

Once the information and concepts have diffused from upper management, the implementation of QM practices relies on *employee involvement*. QM requires a culture shift within an organization and that is not possible if employees are not involved in this process, meaning all employees from management to shop-floor workers (McKone, Schroeder, and Cua 2001). Therefore, the higher the involvement then the higher the chance of a successful implementation (Mellat-Parast 2013). Much of the literature also recommends teamwork to better integrate all employees (Inman et al. 2003). Not only should they be involved in the implementation, but all employees are also encouraged to assist in the decision-making process which encourages creative thinking (Ebrahimi and Sadeghi 2013; M. Kumar, Khurshid, and Waddell 2014).

Having a positive *work culture* is also crucial for successful implementation of QM. This can include recruitment, training, morale, and job satisfaction (Hon 2005b). This is since employees will not give their all to implementation if they are not at a job that supports them. There has also been a focus into how injury risk negatively affects job satisfaction, which in turn would negatively affect QM (Farid and Neumann 2020).

2.4.2.2 Knowledge

Table 2.15: Chart of knowledge metrics.

Title	Type	Impact	Description	Formula	Sources
Management Experience	Quan.	Pos.	Average amount of time that management has spent working in quality	$= Years\ of\ Experience$	(Benson et al., 1991)
Employee Training	Quan.	Pos.	Average amount of training employees receives on quality topics	$= Hours\ of\ Training$	(Hon, 2005b; M. Kumar et al., 2011, 2014; McKone et al., 2001; Mittal et al., 2012; Psomas & Antony, 2015; Sahoo & Yadav, 2018)

To implement QM in a way that is beneficial, requires experience and training of both the management and employees. Manufacturers with management that have pre-existing experience in QM are more likely to succeed because they already have a lot of the knowledge necessary to diffuse through the company (Benson, Saraph, and Schroeder 1991).

Employee training is also crucial in implementation of QM, since many employees are not hired with experience it is important to supply training opportunities. Even employees who do not work directly on implementation teams or in quality engineering need some knowledge of the importance of QM, this ensures quality prioritization and the ability for team members to be cross-trained (McKone, Schroeder, and Cua 2001). This training starts at the top where managers receive training first and then systematically spreads throughout the organization, this helps to avoid lack of awareness which is normally a direct result of lack of training (Hon 2005b; M. Kumar, Antony, and Tiwari 2011; Sahoo and Yadav 2018). SMEs can spread through the hierarchy more quickly, but normally do not have the resources for mass training like larger enterprises (M. Kumar, Khurshid, and Waddell 2014; Mittal, Kaushik, and Khanduja 2012). Training should also be implemented long-term to refresh knowledge and keep up with changing standards (M. Kumar, Antony, and Tiwari 2011).

2.4.2.3 Incentives

Table 2.16: Chart of incentives metrics.

Title	Type	Impact	Description	Formula	Sources
Rewards for Management	Qual.	Pos.	Incentives for management to improve and uphold high quality	n/a	(Benson et al., 1991; M. Kumar et al., 2011)
Rewards for Employees	Qual.	Pos.	Incentives for management to improve and uphold high quality	n/a	(Calabrese & Spadoni, 2013)

Another way to encourage involvement in QM implementation is by rewarding both management and employees for participation. The amount or quality of the awards will positively affect QM. Specifically for management, the *rewards* should be self-motivated rather than external *rewards* (M. Kumar, Antony, and Tiwari 2011). Literature has shown that for employees an incentive system has proven successful for QM and created a consistent level of quality (Calabrese and Spadoni 2013).

2.5 Supply

The supply encompasses the themes surround the inventory and supply chain for a specific manufacturing. The only way to achieve high quality is if the material utilized in the products are also of high quality.

2.5.1 Background

The next pillar is inventory because the quality of the material and its availability affects product quality. It is essential that companies choose suppliers based on quality and reliability. It is important to include suppliers in QM plans because their participation in design of products would improve supplier awareness (Radej et al., 2017). The combination of quality and inventory control decisions began in the mid-1980s to meet objectives, preventing excess scrap, and enhance productivity (Bettayeb et al., 2018) There is a connection between TQM and two of the inventory management philosophies: Just-in-Time (JIT) delivery, Supply Chain Management (SCM), and inventory reduction (Kannan, 2005).

JIT eliminates waste by simplifying production processes, reducing setup times, controling material flows, emphasizing PM, reducing excess resources (Kannan, 2005). Waste has previously been defined in seven categories: overproduction, inventory, transport, waiting times, movements, overprocessing, and defects (Realyvásquez-Vargas et al., 2018). This method requires cooperation with suppliers to ensure material is consistently delivered on time (Wiengarten et al. 2013).

While SCM integrates buyers and suppliers into decision-making processes, with the goal of improving material flow through supply chain, reducing lead times and material costs, and improving product quality and responsiveness (Kannan, 2005). It is also imperative to outsource from reliable suppliers when necessary to ensure high quality material and on-time deliveries (Farahani & Tohidi, 2021). Suppliers should be selected based on quality, cost, delivery, flexibility, or other necessary criteria (Pearn et al. 2019). There have been methods proposed to filter out unsuitable suppliers, for example a two-phase selection framework to evaluate performance of suppliers (Yang and Chen 2019). Also, to be effective there needs to be punishments when supply chain members supply inferior products to buyers (Wen, Li, and Xiao 2019). Many industries are gaining competitive advantage by increasing collaboration among their supply chain frameworks, and integrating production, inventory, and quality through a mathematical model and optimal solution procedures to minimize total costs (Alfares and Attia 2017).

Another method that is mentioned in literature is lean manufacturing which, reduces inventory on the floor by reducing Work in Progress (WIP) (Kim & Gershwin, 2005). Reductions in inventory improve product quality because quality defects can be detected more quickly and will not be compounded through the manufacturing process (Rezaei-Malek, Siadat, et al., 2019) It is essential for companies to recognize capabilities of suppliers and understand supply chain dynamic because this will have a significant impact on performance and manufacturers that participate in frequent outsourcing are commonly under pressure to leverage supplier and customer relations (Kannan, 2005).

2.5.2 Pillar Breakdown

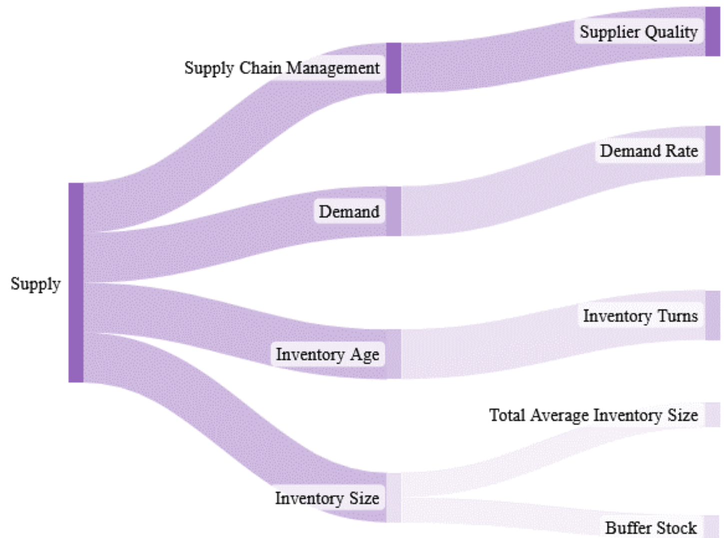

Figure 2.5: Pillar of Supply split into themes and metrics.

2.5.2.1 Supply Chain Management

Table 2.17: Chart of supply chain management metrics.

Title	Type	Impact	Description	Formula	Sources
Supplier Quality	Qual.	Pos.	Quality of incoming products and materials from suppliers	n/a	(Agard & Bassetto, 2013; Calvo-Mora et al., 2015; Hon, 2005b)

Supply chain management is important to quality to ensure that the suppliers in a manufacturing chain are producing quality items because if they are not, then from the start of the manufacturing process the products are destined to be poor quality. The higher the incoming quality level the better the quality of the finished product. Industries must be able to trust their suppliers to identify unreliable components prior to shipping and for their receiving departments to be able to identify defects that the supplier missed (Agard and Bassetto 2013; Calvo-Mora et al. 2015). Many companies have implemented that their suppliers are adhering to certain quality standards such as ISO 9000 for them to purchase (Hon 2005b). Not only should suppliers produce quality parts, but they also need to be consistently delivered on time (Hon 2005b).

2.5.2.2 Demand

Table 2.18: Chart of demand metrics.

Title	Type	Impact	Description	Formula	Sources
Demand Rate	Quan.	Neg.	Demand for inventory at various manufacturing inputs throughout facility	$= \frac{Demand}{Time}$	(Ben-Daya, 2002; Ben-Daya & Makhdoum, 1998; Y.-C. Chen, 2013; L. R. A. Cunha et al., 2018; Hauck et al., 2021)

Material not only has to be delivered to a manufacturer, but it also must travel throughout the facility and arrive where and when it is needed for all manufacturing processes. That is why it is important to consider the *demand rate* within these facilities because the higher the demand the more complex a problem arises to ensure that material is moving correctly. These demands are constant and must be met for everything to run smoothly (M Ben-Daya and Makhdoum 1998). The *demand rate* can be represented through a ratio of demand per unit time (Mohamed Ben-Daya 2002). It is a balancing problem to ensure that these demands are met without oversupplying and backlogging the manufacturing lines (S.-H. Chen 2013; L. R. A. Cunha et al. 2018). Oftentimes, to solve this problem literature suggests that the inventory level is just enough to cover demand and that it begins to be restocked based off how quickly it is consumed and how long it takes for more material to arrive at the needed location (Hauck, Rabta, and Reiner 2021). To fully assess this complex problem, many features must be considered such as backlogging, reworks, demand, random defective items, false positives, and false negatives (Hauck, Rabta, and Reiner 2021). Many of these concepts apply to deliveries within a facility and to the supply chain.

2.5.2.3 Inventory Age

Table 2.19: Chart of inventory age metrics.

Title	Type	Impact	Description	Formula	Sources
Inventory Turns	Quan.	Pos.	Amount of full inventory refresh over a specified period	$= \frac{Net\ Sales}{InventoryPrice}$	(S.-H. Chen, 2013; Hon, 2005b; McKone et al., 2001)

Manufacturers require an inventory to fuel their processes and create their products, but inventories can have a negative impact because if the inventory is not being utilized efficiently and is not being sold then it can be a cost drain. That is why *inventory turns* are crucial to ensure and calculate how often the inventory is being completely replaced and the higher the value the better impact on product quality (McKone, Schroeder, and Cua 2001). *Inventory turns* can be modeled by the net sales divided by the average inventory selling price or the total monetary value of the current inventory (S.-H. Chen 2013). This can also improve product quality because many materials and parts can expire from sitting in an inventory for an extended period (Hon 2005b).

2.5.2.4 Inventory Size

Table 2.20: Chart of inventory size metrics.

Title	Type	Impact	Description	Formula	Sources
Total Average Inventory Size	Quan.	Neg.	Average size of a manufacturers inventory	$= Units\ in\ Inventory$	(Colledani & Tolio, 2012)
Buffer Stock	Quan.	Pos.	Amount of material set aside in case of shortage	$= Units\ in\ Buffer$	(Colledani & Tolio, 2006, 2011b, 2011a; Hajej et al., 2018; Inman et al., 2003; Kim & Gershwin, 2005; Mehdi et al., 2010; Radhoui et al., 2009; Ruschel et al., 2017)

Inventory size is an essential value to keep track of to know how much inventory is in stock to either calculate *inventory turns* or be able to accurately plan for the movement of material through a factory. Depending on the utilization of the inventory the effect of it on product quality can be positive or negative. It is also important to note that keeping a minimum *inventory size* is helpful in identifying quality problems earlier per the philosophies of lean manufacturing (Marcello Colledani and Tolio 2012).

The other aspect of inventory size is *buffer stocks*. These consist of the amount of inventory on the manufacturing floor to avoid shortages when unexpected downtime occurs (Hajej, Rezg, and Gharbi 2018; Radhoui, Rezg, and Chelbi 2009). Larger *buffer stocks* can positively affect the product quality by ensuring that delays in production do not occur, but can also negatively affect it because it makes it more difficult to locate defects with more inventory on the floor (Inman et al. 2003). Large buffer sizes can increase *production rates* because material accumulates between operations, but it can decrease the *system yield* (Kim and Gershwin 2005).

2.6 Cost

After exploring the five pillars of this model and the metrics accompanied with them, it is crucial to consider cost. Cost runs manufacturing. Any piece of equipment, process change, or innovations must be related back to cost because any solution that ruins a company financial can never be implemented in the real world. To give this model validity there will be a cost check associated with all quality scores to ensure that the solutions in place are cost effective for the company. This cost check will occur through a COQ calculation, which for this work will utilize Equation 1. This formula considers both the Cost of Good Quality (COGQ) and the Cost of Poor Quality (COPQ). COGQ is broken down into Prevention Cost (PC) and Appraisal Cost (AC), which are costs incurred through activities prior to manufacturing to prevent quality issues and costs to detect defects respectfully. COPQ is broken down into defects that are detected before or after sale, which is known as Internal versus External Failure Costs (IFC)(EFC). All the pillars have costs associated with these variables that will make up a COQ calculation for the model. This will then be compared to the company's budget to assess the performance.

$$COQ = COGQ + COPQ = (PC + AC) + (IFC + EFC) \qquad \text{Equation 1}$$

2.7 Summary

To truly achieve HQM all these pillars are crucial. Each one represents a different piece of the puzzle regarding what can affect the product of a manufacturer. The metrics included in this literature review are only a fraction of what is possible, but they give an initial attempt at collecting such a wide variety. There have been many papers that attempt to connect a portion of what is included here, but none that include all of what is mentioned. That is why this field requires continued effort to fully analyze all the factors that can affect quality. These factors must be related through the model at hand and need to map between individual metrics to give a true picture of the cause and effects at play. Other pillars that may be included in future works would be customer metrics such as customer satisfaction, product returns, complaints, and brand image (Wiengarten et al. 2013). Another would be considering sustainability as its own pillar for continuous improvement (Chaudhuri & Jayaram, 2019)

This literature review acts as the basis for the model developed in this thesis. Each pillar was split into sub-themes and metrics, which will be utilized to quantify a facility's QA. The model, relationships, and calculations to complete this task will be described in detail in Chapter 3.

Chapter 3 Holistic Quality Management Model Development

This HQM model is organized into pillars, sub-themes, and metrics, which were described previously in Chapter 2. Thomas Saaty's Analytic Hierarchy Process (AHP) was used to weigh the levels of this model, giving it three levels of complexity. Then the metrics are standardized on a scale of 0 to 1. The specific process is detailed throughout Chapter 3. At the end of the chapter the model weights will be configured to specific industries to highlight its flexibility.

3.1 Analytic Hierarchy Process

The goal of this model is to calculate a QA score through a holistic index, which is based around the AHP methodology. This score gives a composite view of the state of the manufacturing facility and can also be used to quickly compare multiple facilities. The power of the AHP method allows for the combining quantitative and qualitative factors within a complex question. It also defines it on a numbering scale and then by combining it with live data it becomes the perfect base for this model.

Each instance of each level of complexity (pillars, sub-themes, and metrics) are placed within a matrix. An example of one of these matrices is shown in Table 3.1. Across the matrix a paired comparison is utilized and placed, depending on the impact of the row and column's relationship and the impact on the QA within a generic manufacturing facility. For this specific matrix, the pillars were rated between 1-11 because of the number of items within the matrix, so that no number is repeated to fill the entire table. The inverse of each of these values is also included for that paired comparison. This process was repeated for the sub-themes within each pillar and the metrics within each sub-theme. Some sub-themes contain only a single metric, and in those cases the matrix is not required, as that metric makes up the entire weight of the sub-theme. The matrices are used to find the relative weights of each level of the HQM model to calculate an objective QA score.

To give this method validity, the out of the box generic solution was filled out via the opinions of industrial quality professionals who have worked across a variety of manufacturing fields. This is crucial as the placement and rank values are subjective and it is necessary for an accurate model to have input from area experts. Contrarily, this also adds to the model's flexibility because the generic version can be configured based off the opinions of employees in a specific factory or field.

Table 3.1: Matrix of quality pillars to implement the AHP method.

Index	Design	Process	Maintenance	Management	Supply
Design	1.0000	2.0000	5.0000	0.2500	6.0000
Process	0.5000	1.0000	7.0000	0.3333	9.0000
Maintenance	0.2000	0.1429	1.0000	0.1250	10.0000
Management	4.0000	3.0000	8.0000	1.0000	11.0000
Supply	0.1667	0.1111	0.1000	0.0909	1.0000

The AHP methodology was used as the backbone of the model detailed throughout this thesis. As previously mentioned, the top level of this model is separated into five pillars, these are split into multiple sub-themes. And each sub-theme consists of metrics that are crucial when considering the performance of quality within a manufacturing facility. This structure is what builds this HQM model, but multiple instances of this model containing these factors were created. The primary instance is referred to as generic because it is supposed to be an out of the box easy implementation into any factory or line. A survey was distributed to a panel of industrial quality professionals to gather opinions on the impact of the factors throughout this section on product quality. This survey consisted of ranking questions for individual factor impacts and relationship impacts at all three levels of complexity. Through this survey the matrices were populated and weights for all the levels of this model were calculated. The model weights for this instance will be presented and discussed in this section.

3.2.1 Pillars

Starting at the top or pillar level, the five pillars consist of Design, Process, Maintenance, Management, and Supply. The results are shown in Figure 3.1.

The Management pillar accounts for almost half of the impact due to the importance of having a strong QM technique. All but one member placed Management as the most influential pillar. Management is the basis for all the other pillars as well because it is the pillar that decides how everything in a facility is handled. If quality is not being accounted for from the get-go and in every stage and every department, then product quality will suffer. Both Design and Process make up approximately a fifth of the impact each. These pillars directly affect the product and make the difference in the product meeting requirements and satisfying the consumers. Design is slightly more impactful as this is the base for the product and should be the initiation of high-quality practices. Process is also essential as it is the pillar that ensures the design and plans were met, it also facilitates CLQ through the execution of manufacturing and ensuring all quality issues are caught and looped back into the system for quality improvement. Maintenance is an essential pillar as it ensures that the process and equipment are running correctly. Supply is crucial because if material enters the facility with issues, then the products will be bad quality immediately. Also, if suppliers are unreliable, it can cause issues within the facility. Supply was placed in fifth place due to many of these quality issues in this pillar are outside of the control of the facility and quite often failures are due to these external companies. With these results, Figure 3.2 shows how the original model image changes to account for these new weights.

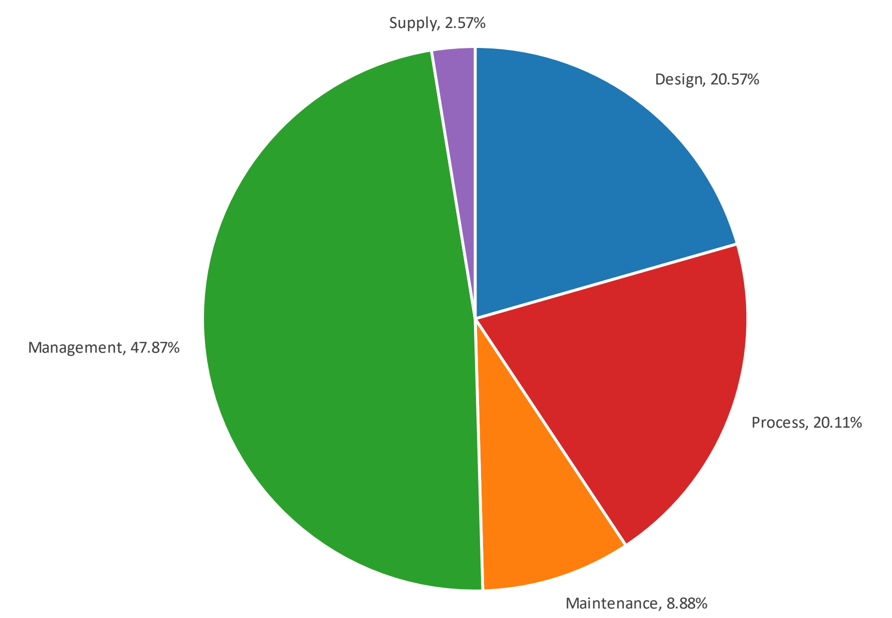

Figure 3.1: Pie chart of the weights of the pillars acquired from expert survey.

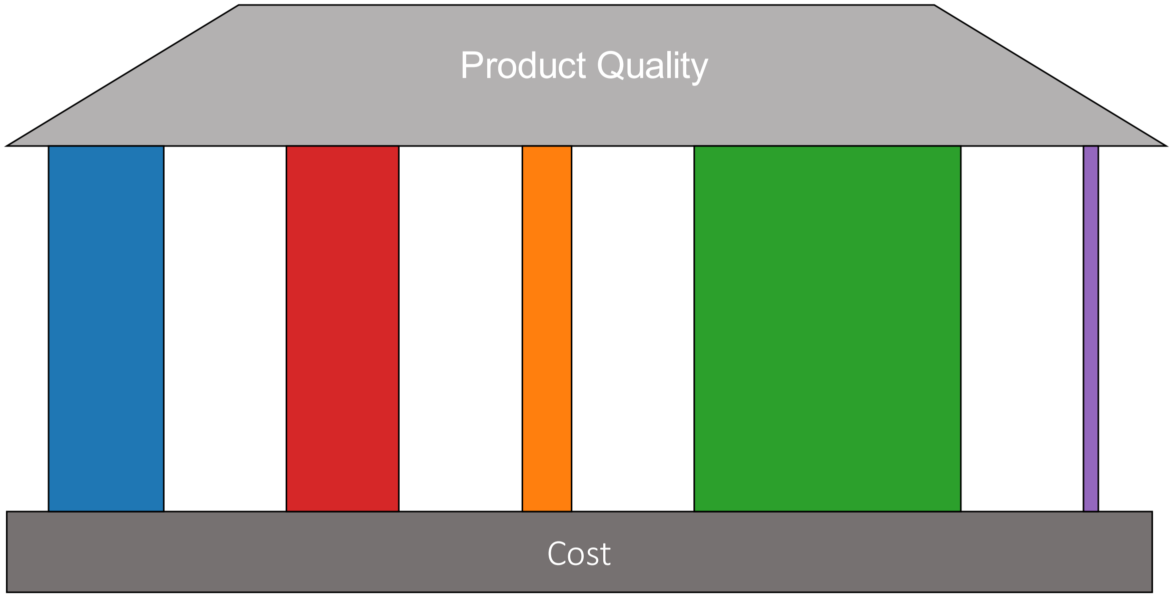

Figure 3.2: Model visual updated to match generic weights.

3.2.2 Design

Now to explore each pillar discussed in the previous section, the first being Design. The weights and sub-themes are shown in Figure 3.3. The most impactful sub-theme is product complexity because when metrics in this category increase so does the difficulty for manufacturing to meet necessary requirements. Next is conformance because this is a crucial theme to judge whether product quality was achieved or if it missed the mark. Meeting quality goals also becomes more difficult when products are constantly changing, especially when the parts are of high product complexity. The least impactful sub-theme is product diversity. A facility with many products can make product quality more difficult to achieve, but if the other sub-themes and pillars are successful then this sub-theme will not have a large impact.

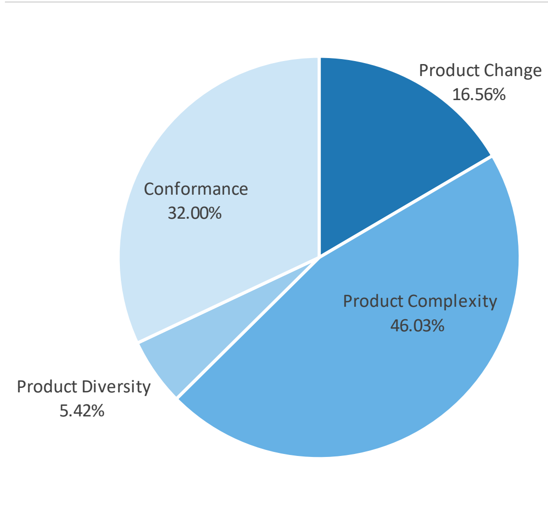

Figure 3.3: Design sub-theme weights results.

3.2.2.1 Metrics

Each of these sub-themes consist of crucial metrics that are weighted as well and are shown in Figure 3.4. The conformance and product change currently only contain one metric each, therefore these metrics make up the entire weight of these sub-themes.

Product complexity is primarily impacted by the *complexity of the design features*. The more complex the features are, the more difficult it will be to achieve high scores in the other Design sub-themes, but it will also greatly affect the Process pillar as more complex features entail more complex manufacturing processes.

Product diversity is split into three levels. First, and the top level, is how many *product types* are manufactured at this facility, an example of which is Samsung manufactures phones, home appliances, and TVs, which are *product types*. Next is *the number of product models* per product type, which is defined by the manufacturer but will be products of the same type that may be customizable for consumers. The last level is how many parts are in the assembly of a product. The number of models is the most influential, because mass customization has increased the difficulty to achieve consistent high quality. The *number of product types* is the second most influential, because if many *product types* are being manufactured it may require a facility to have a wider range of equipment that all needs to be maintained and operated efficiently. Lastly, is the *number of parts in an assembly*, because this may raise complexity; but, if it is a product with many parts that are simple to assemble it would not affect the end quality as heavily as the other metrics in this sub-theme.

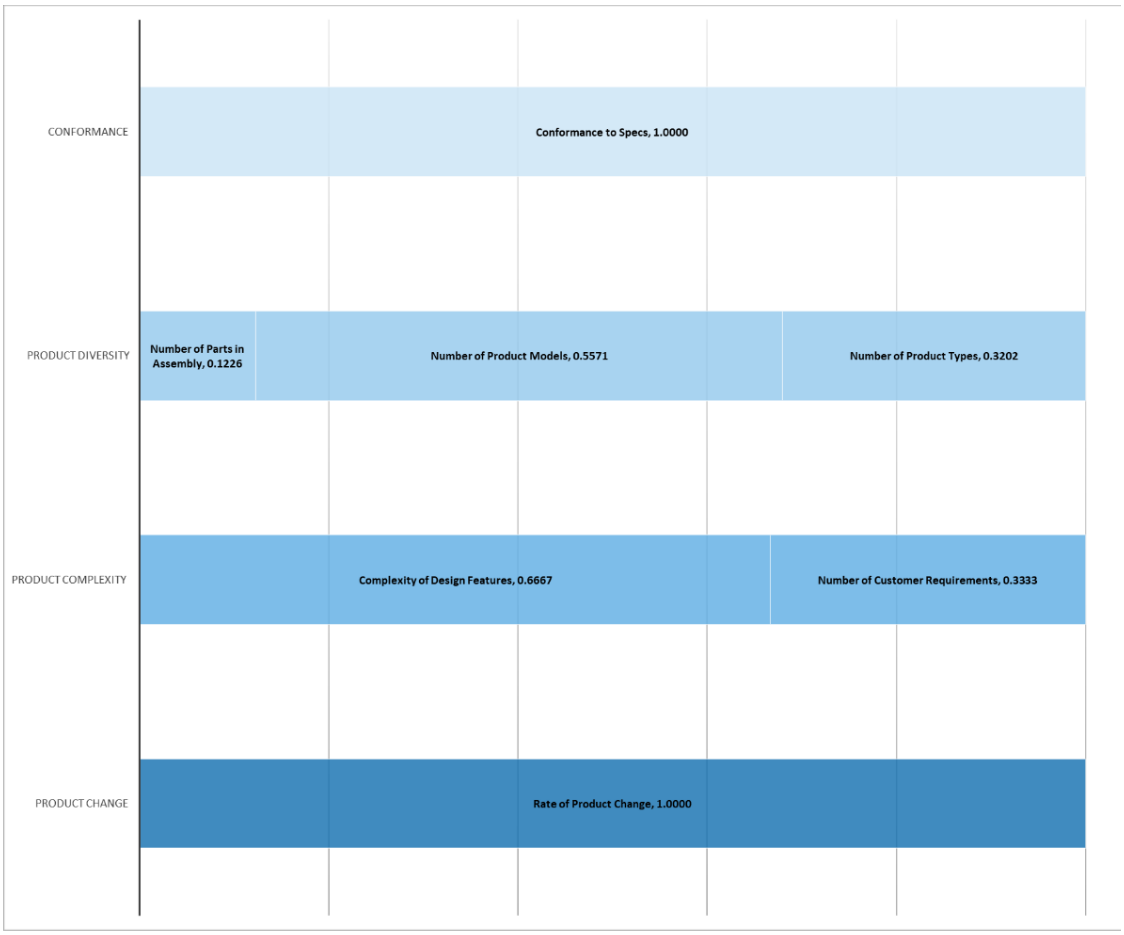

Figure 3.4: Breakdown of the metric weights within Design.

3.2.3 Process

The next pillar is Process and the distribution of weights amongst its sub-themes is shown in Figure 3.5. The inspection sub-theme is the most impactful for this pillar. The ability of a system to monitor and document anomalies is crucial for quality improvement. It is the key to achieve CLQ and learn from manufacturing batches to utilize for subsequent runs and future products. Process change and production capability make up similar weights on this pillar. Changing the process in a facility often causes issues, especially if it is accompanied with a rush from management to implement. The ability of a facility to manufacture products and meet quotas is also going to be important and this is encompassed in the production capability sub-theme. With the introduction of robotics and automation, the process length sub-theme has become less influential because the equipment can create products with higher consistency than people with less injuries and exhaustion. The least impactful sub-theme is rework because if the other sub-themes are successful there should be little to no rework necessary.

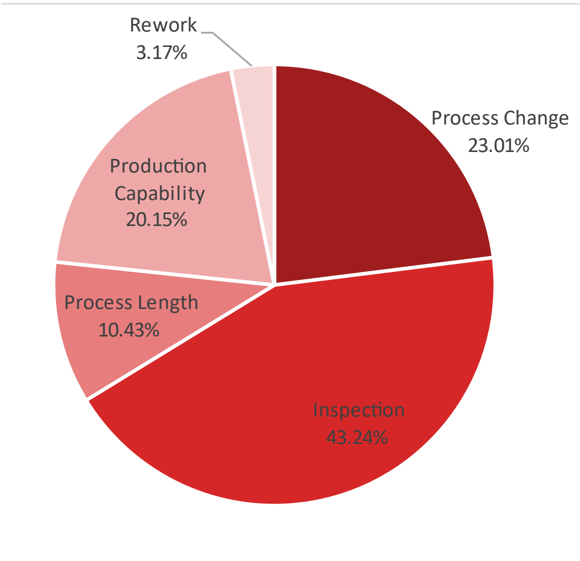

Figure 3.5: Process sub-theme weights results.

3.2.3.1 Metrics

The five sub-themes within Process also have weighted metrics as shown in Figure 3.6. The process change and rework sub-themes have one metric which makes up the entirety of that sub-theme.

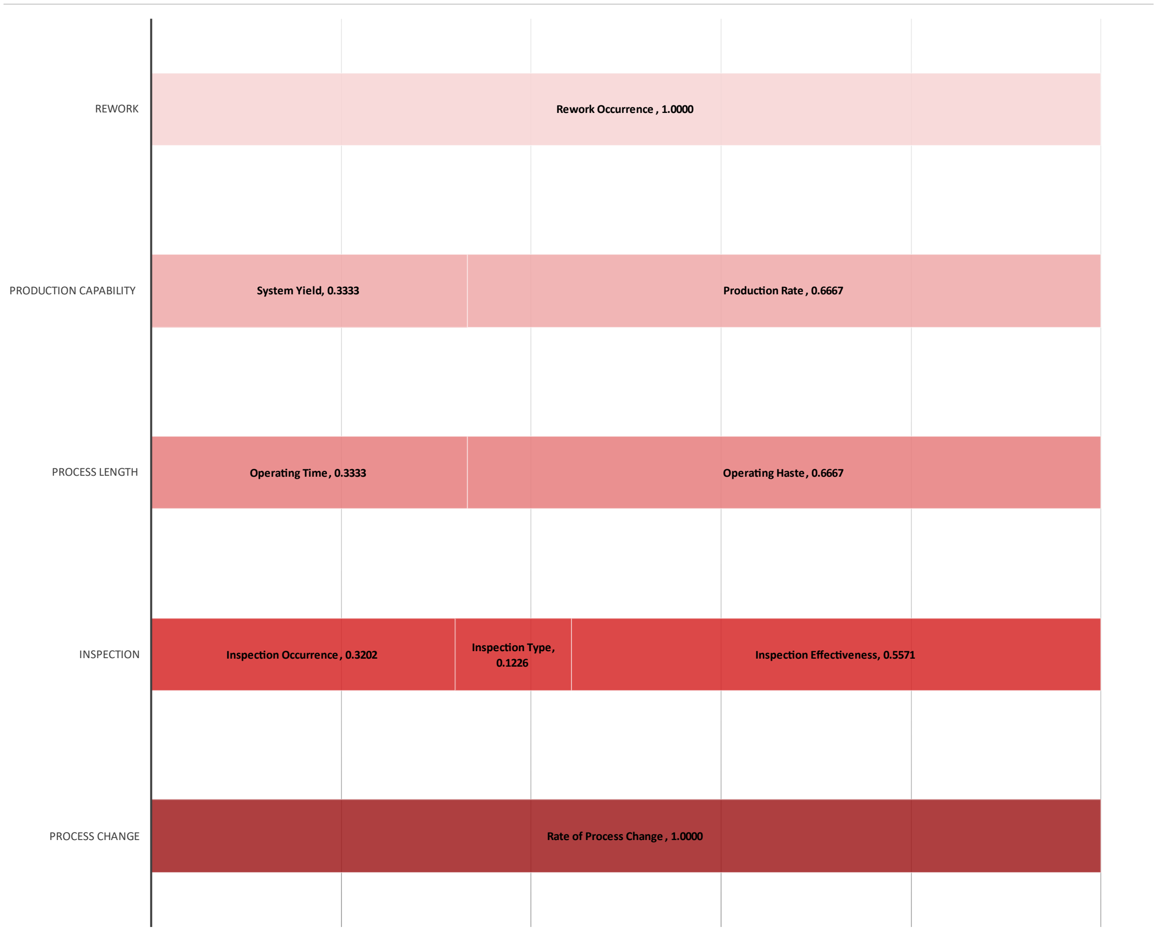

Figure 3.6: Breakdown of the metric weights within Process.

Inspection is split into three metrics, the most impactful being *inspection effectiveness*. As previously stated, inspection is crucial, so its ability to effectively detect defects will be important. Next is *inspection occurrence*. Increased occurrence will improve the odds of finding all defects, but it is a tradeoff because the more inspection stations, the higher the PC of the facility. The last metric is *inspection type*. The more types of inspection in a factory can improve the inspection, but if the number is smaller and the types are extremely effective then it will not negatively affect manufacturing.

Within process length the metric of operation haste is more influential than *operating time*. Haste encompasses the speed at which the equipment or employees are working at compared to the recommended speed. That is why haste greatly affects quality, because this will increase defects as corners are cut to meet deadlines.

The last sub-theme in Process is production capability and it is broken down into *production rate* and *system yield*, which is comparing the system's useable throughput against total throughput or time respectfully. According to the results of the survey, *production rate* is more influential on product quality.

3.2.4 Maintenance

The third pillar is Maintenance, split into four sub-themes shown in Figure 3.7. The primary sub-theme is failure occurrence as this is an immediate indication of the state of maintenance in a factory. A higher number of failures normally correlates to inadequate maintenance practices. The frequency of maintenance activities is also crucial. Frequent maintenance leads to healthier equipment and higher product quality, though it is important to balance this with other factors, the frequency should not compromise deadlines or draw out downtime. Time requirement for maintenance activities is important but less influential than the previously mentioned metrics. It is more important to plan efficient maintenance than increase the time required. Age is a crucial sub-theme though it is less impactful especially when maintenance is successful at caring for and decreasing the overall age of equipment.

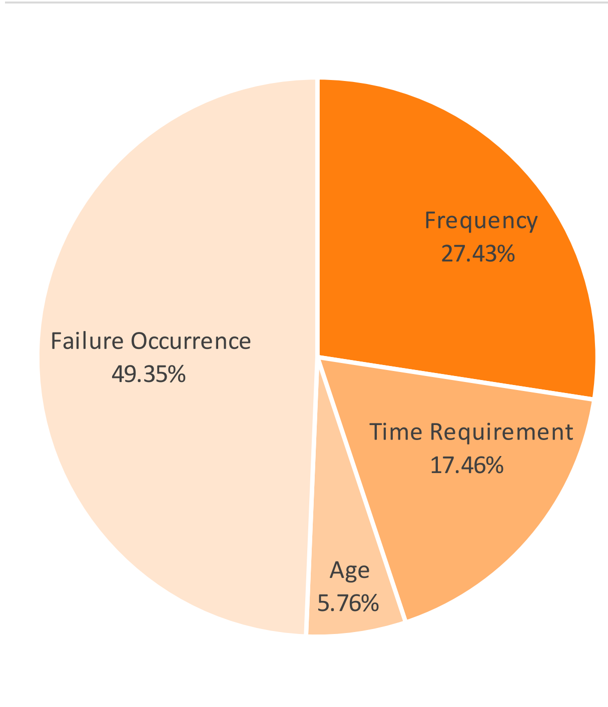

Figure 3.7: Maintenance sub-theme weights results.

3.2.4.1 Metrics

The sub-themes within Maintenance are split into the metrics shown in Figure 3.8. Two of these sub-themes, frequency and failure occurrence, are made up of a single metric. Therefore, no analysis to obtain metric weights was necessary.

Time requirement is split into two categories, *time required for preventive and corrective maintenance*. PM is higher weighted as it can greatly improve the product quality in a facility through the care of its equipment. Whereas the goal should be to designate little to no time to corrective maintenance as it is normally triggered by failures.

The final sub-theme, age, is also split into two metrics. According to the survey the *age of the tooling* is more impactful than the *age of the system*. The tooling normally has a shorter lifecycle than the equipment and it is less likely that maintenance activities could improve its age contrary to the equipment. Therefore, this metric would have the higher impact.

Figure 3.8: Breakdown of the metric weights within Maintenance.

3.2.5 Management

As shown in Figure 3.9, the Management pillar is split into three sub-themes. Knowledge is the most influential within this pillar. The basis of all management in a facility is the ability of the employees to make decisions that will benefit product quality. This sub-theme makes up over half of the weight of this pillar. Then environment plays a huge role to ensure that quality is a priority throughout the entire company. Last is the incentives, because this can improve quality because it motivates employees to implement, but it is seen more as a bonus.

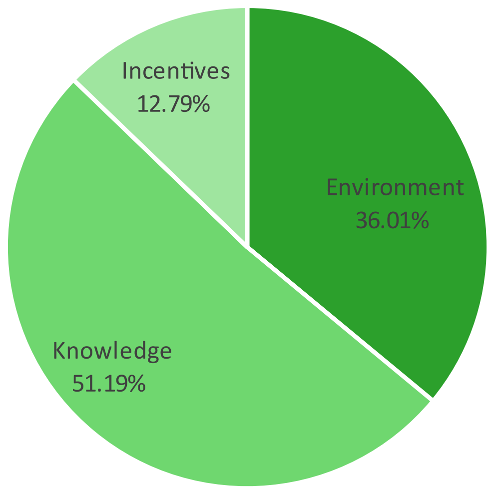

Figure 3.9: Management sub-theme weights results.

3.2.5.1 Metrics

The Management pillar is split into three sub-themes and shown in Figure 3.10. Environment is split into four metrics, and they all make up a portion of the weight in this sub-theme. Many of these metrics are qualitative meaning that in many methods they would be difficult to include, but with AHP it is successful. First, and the most influential, is *upper management's commitment to quality*, this is crucial because quality should be spread through all phases and departments, and this starts with the management. Next, comes the *overall work culture*, which encompasses anything regarding the employee's satisfaction with their job. Employees satisfied with their work environment have the peace of mind to focus and prioritize on the bigger picture, whereas when they dislike their job, they would lack this motivation. Approximately a third of this sub-theme comes from *employee involvement* in quality decision making because it encourages employees to be invested in quality success. Finally comes the *company size*, which is the only quantitative metric in this sub-theme. Larger companies tend to have simpler access to the necessary resources to facilitate full factory quality.

Figure 3.10: Breakdown of the metric weights within Management.

Knowledge is divided between the years of experience the managers have in quality and the number of hours that employees receive on average of quality training. The management's knowledge is more influential than the employees, because the quality best practices begin at the upper management level and filter down from there.

Finally, the incentives' sub-theme is also split between *rewards for management* and employees. The *employee rewards* have a higher impact because they them to follow best practices. And, since they commonly do not see the big picture and bonus of consistent high quality, these *rewards* can boost motivation.

3.2.6 Supply

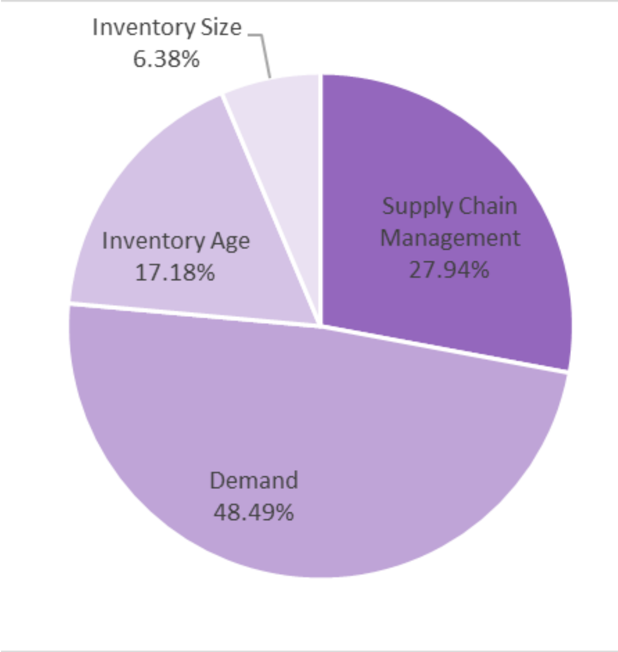

Figure 3.11: Supply sub-theme weights results.

The final pillar is split into the sub-themes shown in Figure 3.11. Almost half of this pillar relies on the demand of the supply and how quickly material is utilized throughout the facility. Slightly less than a third of this pillar is built upon supply chain management and how reliable the suppliers are when being judged on quality, delivery, or any other crucial factors. Inventory age is also essential, as many types of material lose quality and performance the longer they sit in storage. The least influential sub-theme is the inventory size, because large inventories can cause a decrease in quality or add difficulty in detecting defects, but if the facility is designed to handle the inventory size, the impact shrinks.

3.2.6.1 Metrics

This pillar is split into the sub-themes as shown in Figure 3.12. The Supply pillar is one of the least represented in current literature, therefore three of the four sub-themes only contain one metric. Which similarly to the previous sections, means that individual metric weights are not necessary.

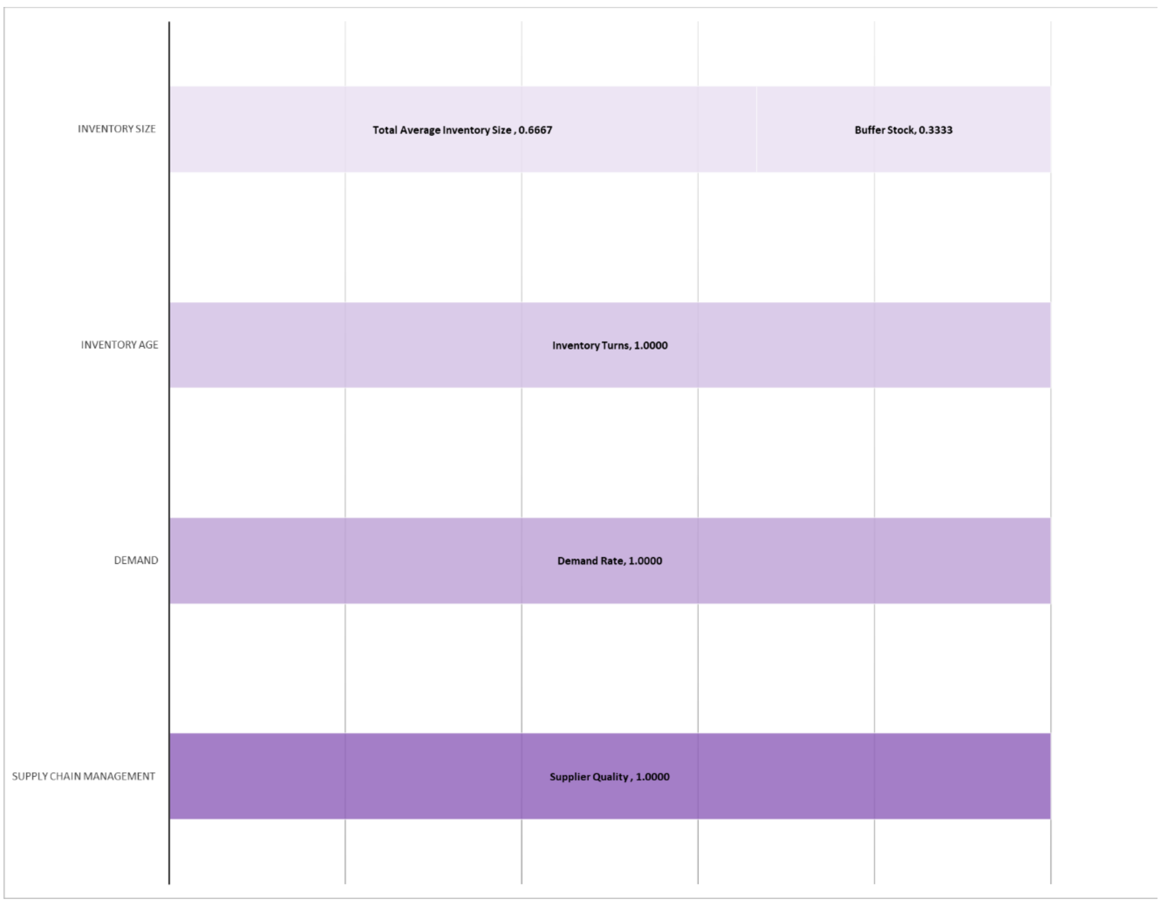

Figure 3.12: Breakdown of the metric weights within Supply.

The inventory size sub-theme is split into the *total average inventory size* and the *buffer stock*. From the insights of industrial professionals, the *inventory size* is more influential. This is commonly where material can sit for longer than recommended, and negatively affect the product quality. While *buffer stocks* are traditionally used up then replaced and can assist in lean manufacturing, but they are not commonly responsible for negative quality impacts.

3.3 Normalized Metrics

The metrics contained within this model cover a wide range of data and to implement them within the same model, there needs to be normalization. Since the metrics are so varied, multiple techniques of normalization were used. The four types were normalized over time, normalized over products, averages, and qualitative entries. The metrics are sorted into their method as shown in Figure 3.13. All indicators range between 0 and 1 and can affect the overall score either positively or negatively. The methods will be discussed in greater detail throughout this section.

3.3.1 Over Time

Most of the metrics are normalized over time utilizing either Equation 2 or 3 depending on whether the metric has a positive or negative effect on quality respectfully.

$$I_{N,ijt}^{+} = \frac{I_{ijt}^{+} - I_{min,jt}^{+}}{I_{max,jt}^{+} - I_{min,jt}^{+}} \qquad \textit{Equation } 2$$

$$I_{N,ijt}^{-} = 1 - \frac{I_{ijt}^{-} - I_{min,jt}^{-}}{I_{max,jt}^{-} - I_{min,jt}^{-}} \qquad \textit{Equation } 3$$

Where I within the formula represents the value of the metric being collected from the facility, this is also referred to as an indicator. The max and min values are the highest and lowest value over the designated span of time. These metrics are grouped here as their impact often relies on the trend of the available data; for example, consider the metric *inspection occurrence* where it represents the number of inspection stations. This metric increasing over time could indicate that the factory is improving its defect detection, which is a positive impact on quality. Whereas if the *time required for corrective maintenance* is increasing, it indicates the facility is struggling to maintain its equipment, resulting in poor quality and increased defects. The time span under consideration or the individual units of each metric can be catered depending on how things are defined for a particular manufacturer.

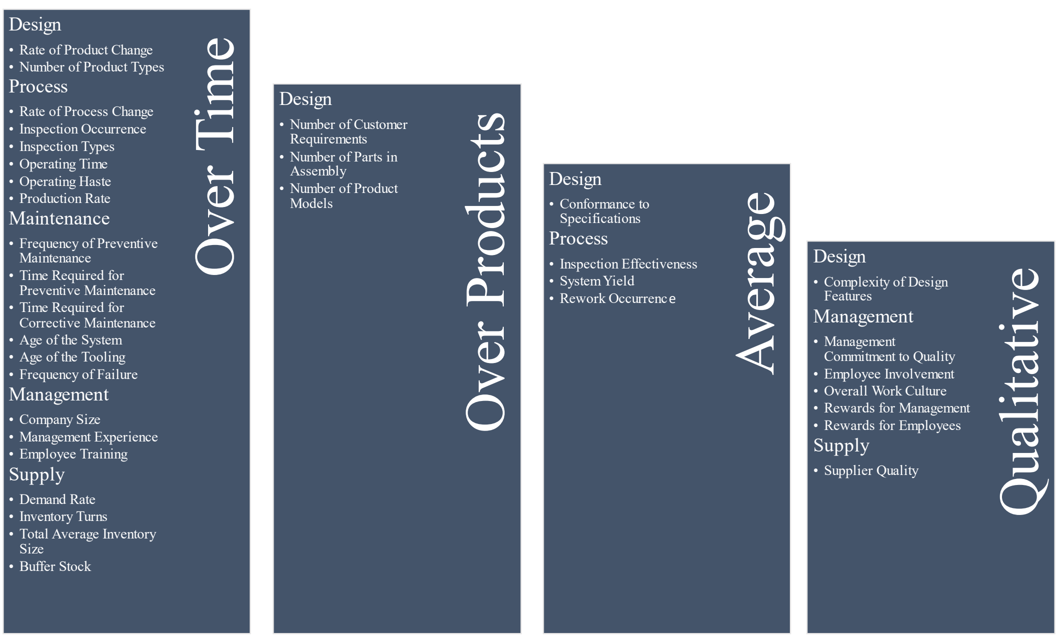

Figure 3.13: Metrics grouped into the type of normalization used.

3.3.2 Over Products

Three of the metrics within the Design pillar are normalized over products instead of over time. For this methodology Equations 2 and 3 are still in use, but instead of considering the minimum and maximum value over the period it is looking at the current minimum and maximum of all the products in production. The normalization formula is then repeated for all the products to see what the value is on average for the entire facility. The value for all the products could simply be averaged together or the final value could be a weighted average, depending on the percentage of sales made up by each product, if there is data available. That way the value for the product most influential on sales will also have the most influence on the final normalized value. An example is the *number of parts in the assembly*, if all the products for sale consist of many parts this would increase the complexity of the manufacturing process, which in turn would increase the difficulty of achieving high quality across the board.

3.3.3 Average

The third methodology is simply considering the average ratio or percentage that the facility is achieving. This section would contain metrics such as *operating haste* or *conformance to specifications*. *Operating haste* is the speed at which the equipment or employee is completing tasks compared to the recommended speed. The higher the haste the more likely for defects to be introduced. It can also increase maintenance issues or injuries. *Conformance to specifications* is defined by the *number of customer requirements* being met compared to the total number of requirements. Both metrics are examples of metrics that can be defined most accurately by a percentage to determine its quality impact. These percents or ratios are then averaged over the time span.

3.3.4 Qualitative

The final category contains the metrics which are best defined qualitatively. These metrics are assigned a value from 0 (low) to 5 (high) these values are associated with a value on the 0 to 1 normalized scale used for all other metrics. Examples of these metrics would be *overall work culture*, *complexity of design features*, or *supplier quality*, to name a few. These metrics are not traditionally defined by quantitative values or live data and therefore need to be integrated differently.

3.4 Final Calculation

So far in this chapter the model weights (W) and normalized indicators (I) were explained. These sections are then combined to compute the final QA score, I_{Qt}, through Equation 4.

$$I_{Qt} = \sum_{pt}^{n} W_{pt} \times \sum_{jt}^{n} W_{jt} \times I_{jt} \qquad \textit{Equation } 4$$

The weights for the pillar level and sub-theme level are represented by W_{pt} and W_{jt} respectfully. The indicator for each sub-theme level, I_{jt}, is calculated through Equation 5.

$$I_{jt} = \sum_{jit}^{n} W_{ji} I_{N,ijt}^{+} + \sum_{jit}^{n} W_{ji} I_{N,ijt}^{-} \qquad \sum_{ji}^{n} W_{ji} = 1, W_{ji} \geq 0 \qquad \textit{Equation } 5$$

The weights input into these formulas were detailed throughout this chapter for the generic calculation. The next section will explain how these weights were catered to the pharmaceutical and composite industries to display the model's flexibility. The indicator normalization was also explained in this chapter and the results of integrating live data will be explained in Chapter 4.

3.5 Industry Specific Instances

This model offers an out of the box implementation for a holistic QA score, but it is extremely flexible allowing for the creation of industry specific instances. To prove this capability, two industries were selected, pharmaceuticals and composites. These fields represent opposite ends of the manufacturing sector proving that this model can be tweaked to fit any facility. Pharmaceuticals represent high volume and low complexity industry as drugs and medical equipment are commonly mass manufactured and due to FDA restraints product change is slow. In comparison, composites are low volume and high complexity. For the sake of this thesis, the focus will be composites in the aerospace industry, as it is common in this field for every plane that is manufactured to be different in some aspect from the last. With the input from an industry professional in each field, an instance of the HQM model was created and will be explained in the following sections.

3.5.1 Comparing Composite and Pharmaceutics

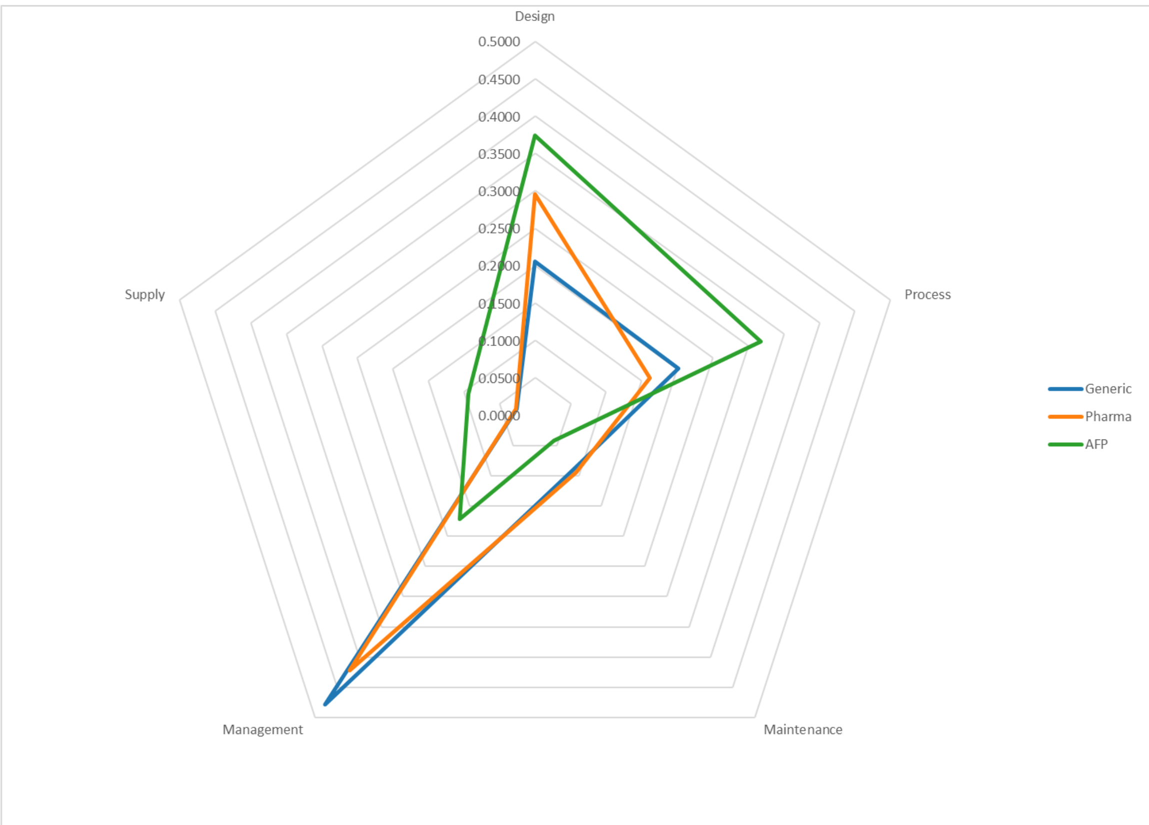

Figure 3.14: Radar chart of each instance in comparison to the pillar weights.

As shown in Figure 3.14 it is already clear the differences between these industry specific instances and the generic original instance. Pharma follows closely to the original, whereas the composite instance is visually a much different shape. It shows that this field relies more on the Design and Process pillars when the pharma instance is most heavily affected by the Management pillar. Not only does the overall distribution of the pillar weights change, but so do the individual sub-theme and metric weights inside each pillar. Each pillar has a section to investigate the differences and are accompanied by a Table that gives a high-level view of the sub-theme fluctuations.

3.4.1.1 Design

The Design pillar is the most impactful of the five for the composites instance as the design of the parts is critical for the quality because slight changes can cause huge defects that compromise the function, as carbon fiber is very particular regarding orientation and how the plies are stacked. As well curved parts need to be carefully designed to avoid the defects that result when rectangular tows are forced into curved shapes, this is especially prevalent in Automated Fiber Placement (AFP) composites manufacturing.

Product complexity is the most influential sub-theme in Design for the new instances and the original. Though composites have it weighted the highest of the three, because as previously mentioned composite parts are extremely complex. Not only do the normal complex features such as thin walls and curved surfaces exist, but it is also crucial to consider how the complex inner design of the fiber and resin can affect the total product complexity.

Conformance and product change consist of one metric each therefore the internal makeup does not change depending on the instance, unless a metric is removed or added. Both industry instances weight conformance lower than the generic model, but each instance handles product change differently. Pharmaceuticals weigh it heavier than the generic, while composites weigh it less. This could be since composites change products constantly it is not as influential on the quality as it is a common occurrence, whereas products do not change as often in pharma, meaning that new changes can result in more defects as the facility settles into a new rhythm.

The product diversity sub-theme influences the new instances more than the generic instance, but within the individual metrics is where the real differences are shown. The pharmaceutical instance is most concerned with the *number of parts in the assembly*, or in this case, it could be the different ingredients or chemicals within the medication, which is extremely impactful on the effectiveness of the drugs for end users. Composites is most focused on the *number of product types* as these differences often require entirely different mandrels or molds per product.

Table 3.2: Deviations of the Design sub-theme weights for industry specific instances.

	Pharmaceutical	Generic	Composites
Product Change	↑0.1410	0.1656	0.0082↓
Product Complexity	↓0.0006	0.4603	0.0408↑
Product Diversity	↑0.1245	0.0542	0.0072↑
Conformance	↓0.2649	0.3200	0.0399↓

3.4.1.2 Process

Similarly, to design composites relies heavily on the Process pillar to ensure high quality products. Depending on the manufacturing method, whether it is hand layup, vacuum resin infusion, or AFP, these greatly change what designs are possible and the product's properties. Small mistakes in the process can have catastrophic effects on the quality of the products as once the curing process is complete rework becomes nearly impossible if classic thermoset material is being used.

Two of the sub-themes in this pillar consist of a single metric, process change and rework. Both instances weigh process change at a lower value than the generic model. Rework is less influential to the pharmaceutical instance, but is much more influential for composites. Since manufacturing with carbon-fiber is extremely expensive in regards to both the material itself and the manufacturing and curing processes. That is why it is very important to do any possible rework strategies before curing occurs or to work with thermoplastics as this material can be remolded after curing.

Inspection is the most influential sub-theme across all instances as this catches any defects that may occur in manufacturing. Pharmaceutical focuses on *inspection effectiveness*, because inspection of drugs can be extremely difficult when searching for issues such as microscopic particles. Composites is concerned with that metric, as well as *inspection occurrence*, because it is essential to ensure defects are caught before curing if possible.

Since pharmaceuticals are commonly mass-producing products, the production capability sub-theme is more influential in this instance than in the original, but composites manufacture at a slower rate, meaning that this sub-theme is less influential. Both instances are more focused on the *system yield* metric over the *production rate*.

Table 3.3: Deviations of the Process sub-theme weights for industry specific instances.

	Pharmaceutical	Generic	Composites
Process Change	↓0.0515	0.2301	0.1337↓
Inspection	↓0.1177	0.4324	0.0493↑
Process Length	↓0.0065	0.1043	0.0793↓
Production Capability	↑0.1821	0.2015	0.0500↓
Rework	↓0.0065	0.0317	0.2138↑

3.4.1.3 Maintenance

The Maintenance pillar is defined by the failure occurrence sub-theme as it is the most heavily weighted for all existing instances. Determining how often equipment fails is essential to avoid line shutdowns or increased defects from malfunctions. This sub-theme as well as *frequency of preventive maintenance* activities are made of single metrics. Across both industry specific instances, both these sub-themes are weighed less than the generic instance.

Time requirement for either corrective or preventive maintenance activities is more influential to the pharmaceutical instance than the composite. This could be since the equipment for drug manufacturing is run at higher speed and produces more products meaning that the downtime is more detrimental to this industry. Pharmaceutical is also more interested in PM to avoid unplanned maintenance for corrective, but composites is more concerned with corrective maintenance.

The age sub-theme is more influential on both industry instances than the original according to the industry professionals' opinions. Both fields focus more on the *age of the system* than the *age of the specific tooling*.

Table 3.4: Deviations of the Maintenance sub-theme weights for industry specific instances.

	Pharmaceutical	Generic	Composites
Frequency	↓0.1985	0.2743	0.1045↓
Time Requirement	↑0.1143	0.1746	0.1238↓
Age	↑0.1155	0.0576	0.2664↑
Failure Occurrence	↓0.0314	0.4935	0.0381↓

3.4.1.4 Management

The Management pillar is the most influential of the five pillars for the pharmaceutical instance like the original model weights. This section is an example of how when the model is being specified to a certain industry or manufacturer, some pieces of the model can be copied to the new instance for a seamless transition even when other weights are being changed. Therefore, the weights for the sub-themes of the pharmaceutical version are the same as the original model. Where the composite instance is much less concerned with this pillar.

Even though the sub-theme weights are the same as the original, the underlying metric weights can still be altered. The knowledge sub-theme according to the weights is the most important across all instances. The original model weighs the manager experience as the most crucial metric but both instances weigh *employee training* higher. This is due to both industries relying heavily on the operators for product quality. It has been stated that small process mistakes in composites can have disastrous effects and these commonly occur due to lack of employee training. And as for pharmaceuticals employee training, especially regarding clean room operations, can be the difference maker in whole batches being recalled. Mistakes in this field can also cause deaths in end users if the mistakes are not caught in time. This is true in any industry, but it is much more common in this field.

Next most influential sub-theme for all instances is the environment. This sub-theme consists of four metrics: *company size*, *management commitment to quality*, *employee involvement*, and *overall work culture*. The focus of these being the ability of the *upper management to commit to quality* as a trend across the entire facility and the *work culture* meaning that the employees overall are satisfied with their jobs. The least influential sub-theme being the incentives for management and employees, but the *rewards for the employees* are more important to encourage the adherence to quality principles.

Table 3.5: Deviations of the Management sub-theme weights for industry specific instances.

	Pharmaceutical	Generic	Composites
Environment	←	0.3601	0.0399↓
Knowledge	←	0.5119	0.0452↑
Incentives	←	0.1279	0.0053↓

3.4.1.5 Supply

Out of the original model and the industry specific instances, the Supply pillar has the biggest effects on the composites. The supply chain management sub-theme is crucial for both industries, but for pharmaceuticals the importance of this category was brought to the forefront during the COVID-19 pandemic. Having reliable suppliers for high quality material and on time deliveries is essential due to the high demand and the dire circumstances when patients lack required medication.

Demand for material within a facility is crucial in the original model, but industry specific instances subtract weight from this sub-theme. Particularly composites reduce it by over half of its original weight due to the low *demand rate* required in this industry.

Composites drastically raises the weight of the inventory age sub-theme. This change is to account for carbon fiber's strict guidelines for storage. Due to this, it is far too easy for material to go bad without warning due to small shifts in environment variables. That is why this sub-theme is essential for this industry.

As for inventory size both instances rank the *buffer stock* metric as the greater influence on product quality. And though the results are similar, the reasoning is much different. As mentioned, carbon fiber can go bad when outside of storage, meaning *buffer stock* at the workstation is vulnerable. Pharmaceuticals on the other hand commonly adhere to the ideology of lean manufacturing, meaning a reduction in *buffer stock* to allow for better detection of defects.

Table 3.6: Deviations of the Supply sub-theme weights for industry specific instances.

	Pharmaceutical	Generic	Composites
Supply Chain Management	↑0.1318	0.2794	0.0446↑
Demand	↓0.1392	0.4849	0.3151↓
Inventory Age	↓0.1012	0.1718	0.2836↑
Inventory Size	↑0.1086	0.0638	0.0130↓

3.6 Conclusion

The HQM model developed in this chapter creates an out of the box solution for any manufacturer to implement within their facility to calculate a QA score. This is the basis of the implementation explored in the next chapter. The weights and metric normalization for the generic solution were then catered to suit the needs of specific industries to prove out the flexibility of the model.

Chapter 4 will introduce the FF cell that will act as the environment for the implemented use case. It will also walk the reader through the steps to implement this model from the beginning. It will start by identifying where metrics will be coming from and whether it will be live data or manual entry. And metrics that are not present in this cell will be removed to prove out another flexibility aspect. Once everything is identified a user-friendly interface application was developed to allow everyday users can visual the results and can deep dive to uncover the short-comings within a facility. The model will then be specified again to create an instance specific to the FF lab and the results will be compared.

Chapter 4 Implementation of Holistic Quality Management Model

4.1 Introduction to Use Case

The model discussed in the previous chapter will be implemented into the FF lab, which will act as the testbed to prove out its capabilities. This lab is in the McNair Aerospace Center at the University of South Carolina and acts as a test environment for a variety of manufacturing research topics. These topics consist of robotics, flexible manufacturing, Virtual Commissioning (VC), Visual Inspection (VI), AI, augmented/virtual reality, quality, IIoT, and many more. The lab consists of true industrial grade equipment such as five robotic arms, four conveyors, a Programmable Logic Controller (PLC), an edge device, and a wide variety of sensors pulling live data from the cell. Figure 4.1 shows an image of the physical cell and its digital model created in Siemens Process Simulate. This space is best referred to as a fishbowl environment for students and industrial professionals alike to display and implement proof of concept projects and technologies with standard equipment without interrupting the resources in a full factory.

The cell is currently configured to complete a simple assembly process of 3D printed model rockets. The rockets sit in the Material Handling Station (MHS) until they are introduced onto the first conveyor via robotic arm. The rocket is assembled by the two interior arms, which is done collaboratively as the tray passes between two conveyor stops. Once the rocket is assembled, the rocket is returned to the tray. Then the tray travels around the conveyors to the final robotic arm to be disassembled and returned to the MHS. This process can be repeated continuously for data collection via a variety of sensors and cameras. This is the real factory use case that the HQM model will be implemented in.

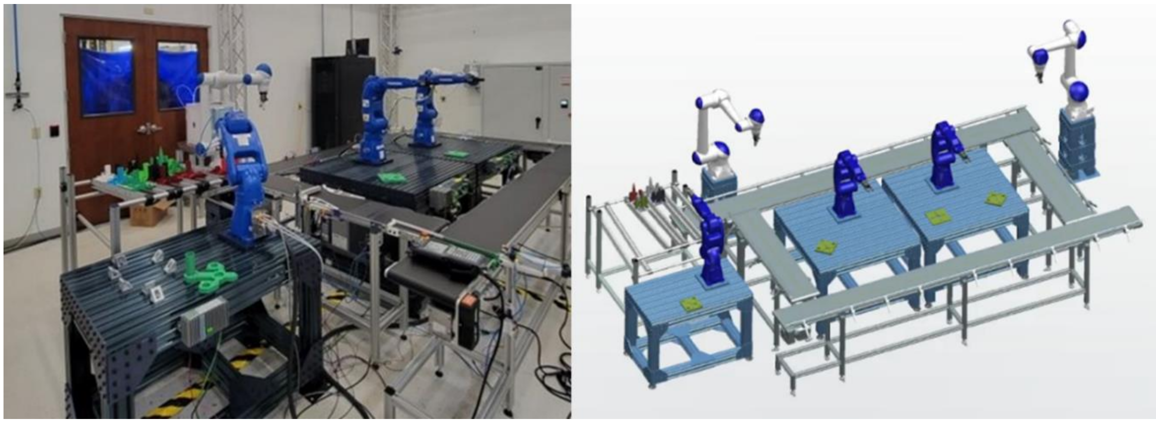

Figure 4.1: Image of physical and virtual Future Factories lab at the University of South Carolina McNair Center.

4.2 Metric Sources

With the wide variety of metric types contained within this model, along comes a variety of multimodal data that can give this model full CLQ capabilities; though there is the option to input all data manually if live data connection is not available for a particular manufacturer. The metric sources for this implementation will be explained in detail throughout this chapter, but sources can be configured to different sensors or software depending on what is available in a facility.

Within the FF lab there are some metrics that will be manually entered, whether it is due to them being qualitative or not accessible via available solutions. All live metrics are coming from one of three sources available in the cell, all of which are Siemens solutions, but can be replaced through similar tactics that may be open source or from a different company. The first will be live data collection from sensors within the cell. This data is being collected by the PLC and transferred to the edge device, an IPC227E, through a wired S7 connection. This data is then mapped to the cloud on Insights Hub (IH) and REST Application Programming Interfaces (APIs) are utilized to pull the data into the application, which was designed on Mendix (Mx). This can be replaced by a different edge device or cloud gateway to make the data accessible to either the original Mx application created within this thesis, or an app created on a different platform or for a different manufacturer. The second data source is the MES, which for the FF is Opcenter Core (Oc). The final source is the Product Lifecycle Management (PLM) solution or Teamcenter (Tc). The specifics for each metric will be explained for each pillar.

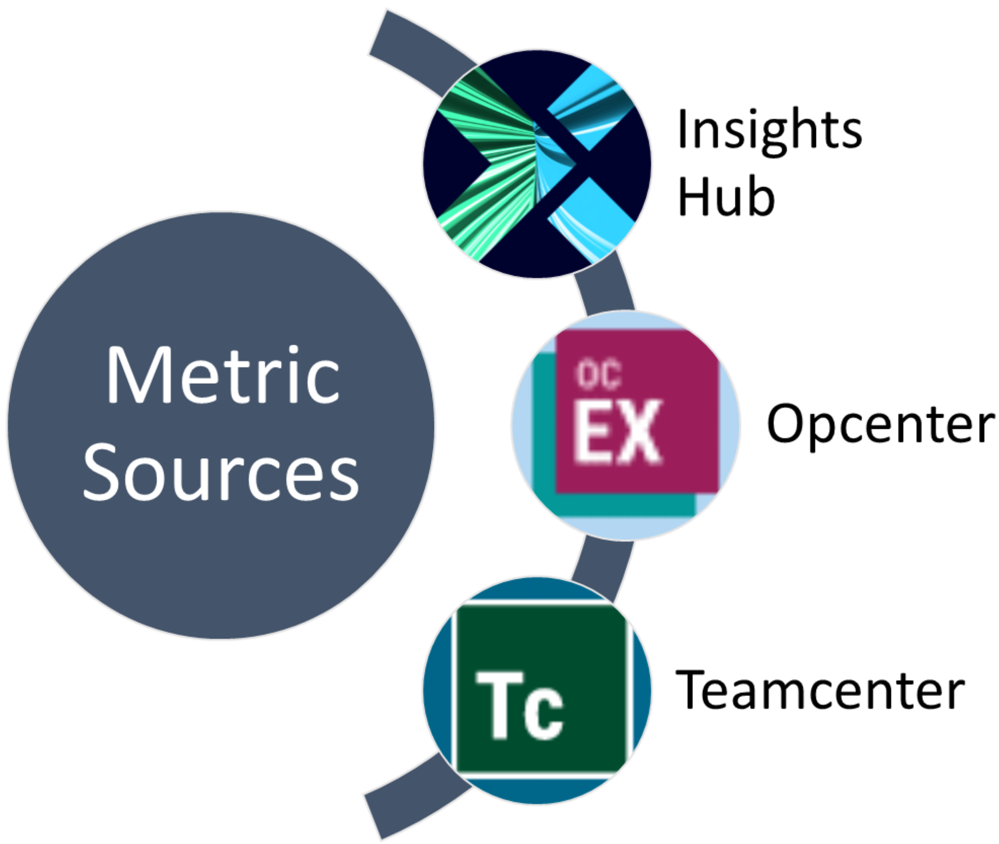

Figure 4.2: Live data metric sources for the FF lab.

4.2.1 Design

The Design pillar is split into four sub-themes similarly to how it has been discussed throughout this thesis. There is one metric within product change, and it can be gathered from Tc via a Mx module, TcConnector (TcC). Tc keeps track of an item revision attribute for every product in a facility, and through this module a query for each product number can be completed. The item revision can be compared over the designated time to calculate the average rate.

The *complexity of the design features* is a manually entered qualitative score and is not being pulled live. The *number of customer requirements* can be pulled via TcC. There are requirement items within Tc that are associated with products, and these can be queried for all products being manufactured, but as the cell has no customers this metric is removed from this instance of the model.

Product diversity contains three metrics. For this implementation, the *number of product models* and *number of product types* will be manually entered but items in Tc can be utilized to pull this information live. The *number of parts in the assemblies* can be pulled from Tc via a REST API referred to as getOccurrences which pulls the children within each assembly. These can be summed to gather the total.

Within Teamcenter Quality (TcQ) there is an Advanced Product Quality Planning (APQP) module which tracks all deliverables, checklists, due dates, and events needed to complete a project or program. The specifications needed for a product can be correlated to a checklist where each question represents a specific requirement. Then the questions and answers can be pulled to sum the number of yes responses to total number of questions, which would represent the *conformance to specifications*.

4.2.2 Process

The *rate of process change* can be collected similarly to the *rate of product change*. This is because Tc also keeps track of item revision attributes for operations, similarly to how it keeps track of product revisions.

The inspection metrics can be pulled from Oc. For *inspection occurrence* and type, it is crucial to create specific resources within the Oc Modeling. These resources are going to contain "Inspection" in their names, and these will be added to a resource group specific to FF. This resource group can be pulled via REST API and filtered to only the resources within the group, to then sum the remaining entries for the occurrence metric. The *inspection type* metric can pull the resources and sum the resource types that contain "Inspection". For *inspection effectiveness*, two types of failure modes were created in the failure modes can then be associated to events and when one of these modes is met, a new event is generated. These events can be pulled by failure mode and the sum of the defects caught mid production will represent successful inspections and this will be compared against the sum of both event types.

For process length, both metrics can be calculated from data collected within the cell. For *operating time*, there is a PLC tag, **Q_Cell_CycleCount**, that counts every time a new cycle is started, and the time elapsed between each start or count can be utilized for this metric. If the facility wants to focus on individual equipment *operating time*, then the FF lab has Boolean PLC tags which represent whether the robots are in their home position or not, which is an indicator for when they are moving and operating. One such tag is labelled **I_R01_WorkHomePos**. *Operating haste* is currently a manual entry metric, but eventually the data could be live and pulled from Process Simulate, which is a robotic path planning software. The speed of each robot is assigned within this software and can be compared to the recommended running speed within the robotics manual.

The *system yield* of the factory is represented by the acceptable products versus total throughput. The throughput can be gathered by summing all cycle counts, via the same PLC tag, over the specified period. The acceptable products can be calculated by subtracting the found defects from the total throughput and then dividing the two values. This is a similar process for *production rate*, but it is the acceptable products over time.

The rework sub-theme is not included in this implementation as no rework is performed on the 3D printed rockets.

4.2.3 Maintenance

The *frequency of preventive maintenance* metric is included in this instance of the model as it is crucial for equipment care. That being stated, PM activities are not completed within the FF lab; therefore, it will act as a deduction in the final score. This also means that there is no live data source for this metric.

The *time requirement for preventive maintenance* will also be an empty metric or deduction on the QA score. The *time for corrective maintenance* can be collected via the amount of time the cell spends in ESTOP during production runs, as that is the state when failures are being repaired. There are PLC tags for all the ESTOPs within the cell, for example **I_R01_ESTOP**. When one ESTOP is triggered, the system state shifts for all tags.

The age sub-theme for this implementation is a manual entry for the *age of the system* and tooling metrics. The *age of the system* could be gathered from live data as the robot pendants have the hours of operation saved, but it currently is not being fed to the PLC for data collection.

The *frequency of failure* can be pulled from Oc. Production events can be created every time failures occur within the cell. This list can then be accessed via REST APIs and then summed for the designated period. Another option is since the ESTOP triggers are already being collected from IH, events can be created within this cloud every time the cell shifts into this mode and then these events could be summed for this metric.

4.2.4 Management

Many of the metrics within this sub-theme are qualitative entries, meaning an operator must manually fill in these values for the implementation of this model. Both incentives metrics and three out of the four environment metrics fall into this category. The final metric for environment is the *company size* or the number of employees. While this is not qualitative, it is still a manual entry for the FF lab. This could be live data by grabbing all the Tc users for this factory, but currently not all employees have an account.

The third sub-theme in this pillar is knowledge or the amount of *management experience* or *employee training* hours for quality. These two metrics are currently manual fill ins as well, but TcQ has a training and qualification module that will be available in the near future and this could be a way to integrate live data for these metrics.

4.2.5 Supply

Supplier quality is a qualitative entry, meaning that it must be manually filled in by an operator. That is the only metric within the supply chain management sub-theme, meaning that there is no live data for this category.

The *demand rate* for the material in the cell can be collected via sensor data from the MHS, which triggers a Boolean PLC tag for each rocket color, for example **I_MHS_GreenRocketTray**. The sum of these occurrences can be utilized for the *demand rate*.

The *inventory turns* for this implementation are a metric that is being manually entered. The *total average inventory size* is also being manually entered, but with the integration of more sensors on the MHS, these could be used to gather how much material is located at this station. The cell does not utilize *buffer stock* and is removed for this instance.

4.3 Costs

The COQ formula is explained in Chapter 2 and is utilized for the calculation within the application for this model. The first part of the formula consists of COGQ, or the AC and PC for the facility. For many of the production runs, since this is a research facility, defects are intentionally introduced for data collection; therefore, there is no PC, because defects are not actively being prevented. The lab has spent approximately $1,000 on various sensors, cameras, and inspection devices over the designated period. The COPQ is defined by IFC and EFC. There is IFC because of the spent electricity costs to run the cell, but no cost was added for the product itself because the rockets can be disassembled continuously. For this use case, the IFC will be set to $500 for the period. There is no EFC because no products are leaving the facility. To reiterate, the cell is a research facility, meaning no products are being sold, so the lab is not collecting profit. This means that the COQ for FF is negative.

4.4 Application Development

An application was created on Mx for a user-friendly and easy to understand User Interface (UI) to host this HQM model. The home screen has the QA score with a corresponding color, depending on the performance of the facility. The COQ is also shown similarly and is green or red, depending on if the facility is within budget or making a profit. Also shown on the home screen is a bar graph for the individual pillar scores to give the user an idea of where the quality shortcomings are originating, so that the user can deep dive into the sub-themes and metrics to solve the issue. This allows the capability of CLQ because these metric issues can be utilized to complete Root Cause Analysis (RCA) and improve the QA score for the next manufacturing batch or future product lines. The metrics and shortcomings can also be used to improve the robustness of the Failure Modes and Effects Analyses (FMEAs). There is also a pie chart showing the pillar weights for each to show how impactful the score from the bar graph is on the QA score. The app has a setup page to input weights for specific instances of the model and to input new factories. The live data can be integrated when the new factories are being input to the app. Then the main screen allows the user to swap between factories and model instances so that the home page updates live. Finally, there is a Tc configuration and login screen to allow for data collection from Tc.

4.5 Future Factories Specific Instance

The generic model, that was implemented for the FF lab in the previous sections is the starting point when configuring the HQM model to a facility. There are many features of the model that need to be configured for the model to give better insights into the cell's QA performance based off differing priorities or inapplicable metrics. The remainder of this chapter will show how the model can be tailored to the FF lab, similarly to the industry specific instances, and the differences between this specific instance and the general.

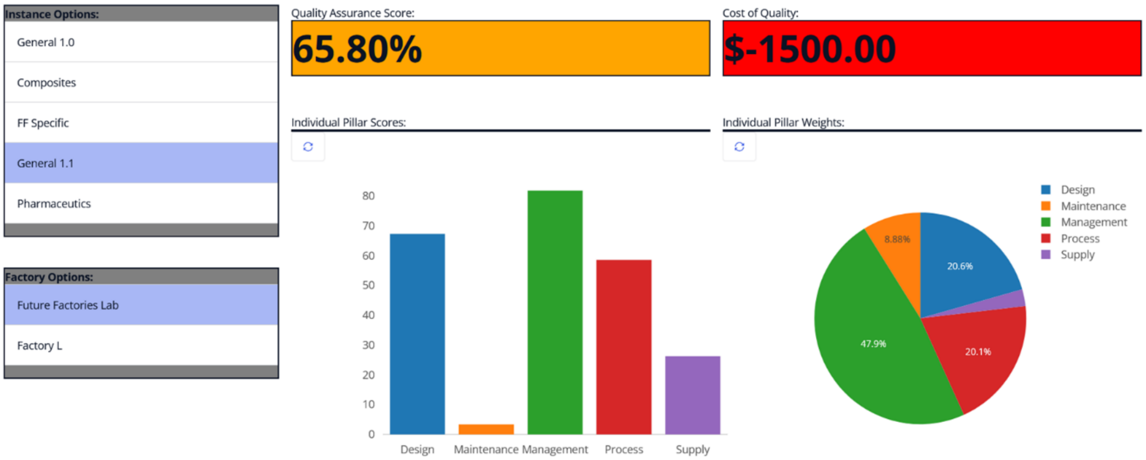

Figure 4.3: Image of the User Interface for the HQM model application.

The biggest difference between this instance and the original is the Management pillar. In the generic model, this is the most influential pillar, but, in the FF specific instance, it is the least influential, as this is a research lab, and the management of the cell is handled extremely differently than a true manufacturing facility. The Design and Maintenance pillars are like the generic. The Process pillar is the most influential here as the main goal of this cell is to act as a testbed for manufacturing techniques and research that can be used to improve the overall process and launch manufacturing into the next industrial revolution. The Supply pillar has also become more influential as the supplier of the PLA material for the model rockets can be unreliable and it makes a huge impact on not only the products, but many fixtures and tooling are made from the same material, causing effects throughout the manufacturing process.

Figure 4.4: HQM model visual updated for the FF specific instance.

4.5.1 Design

The product change sub-theme is less influential, as there is little to no change in the products being produced within the cell, and there are no plans to change the rocket design, as the product is less important than improving the process that creates it. Product diversity, on the other hand, is more influential as there are plans to implement new products, instead of changing older designs, to work towards truly flexible manufacturing. Conformance and product complexity are similarly influential, as ensuring the products are being manufactured successfully and increasing complexity will make the process more complex as well.

The metrics within conformance and product change did not change for this instance. Product complexity is now only comprised of the *complexity of design feature* metric, because the *customer requirements* are not influential. This is because the FF lab is a research facility and there are no customers for the products produced. There are slight differences in the specific weights of the metrics within product diversity, but the distribution is similar.

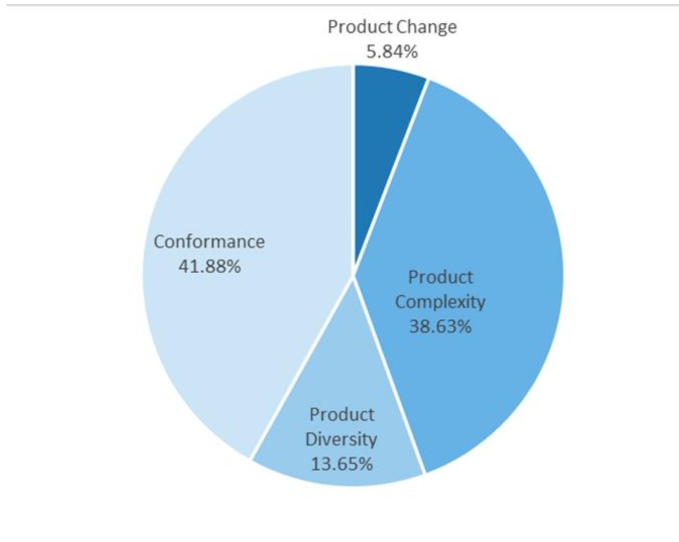

Figure 4.5: Design pillar split into new sub-theme weights for FF lab.

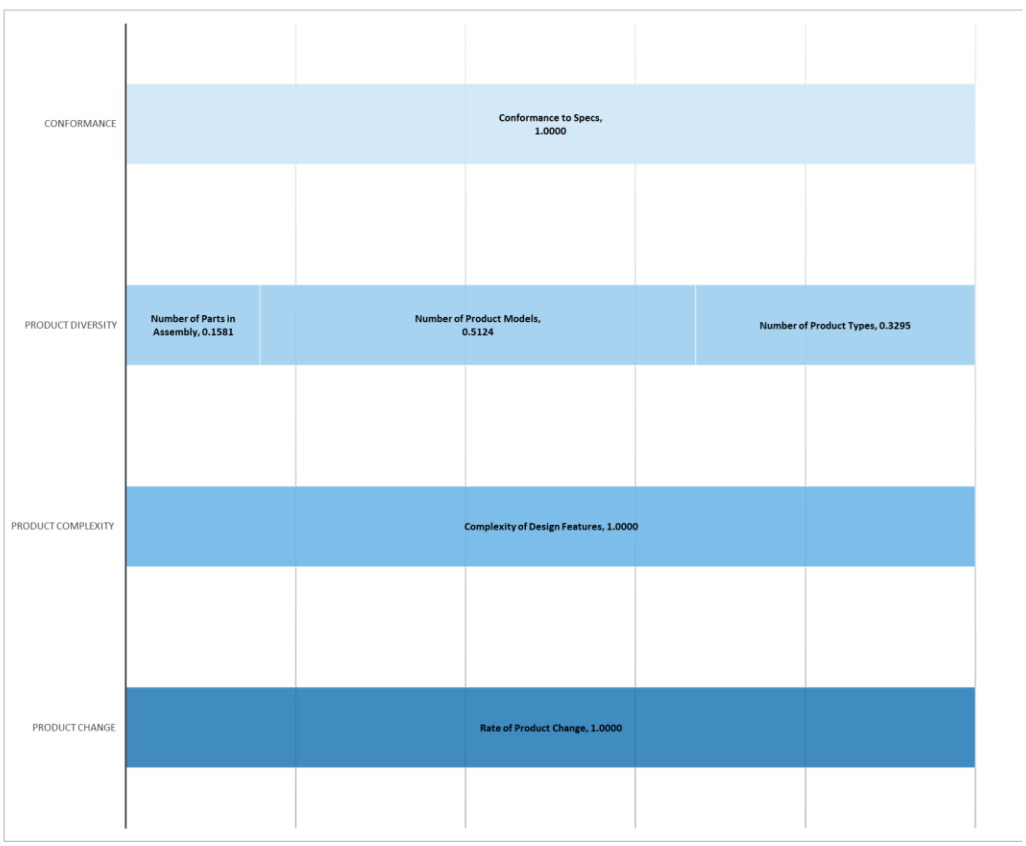

Figure 4.6: Design pillar split into new metric weights for FF lab.

4.5.2 Process

The rework sub-theme has been completely removed from this instance, as there are no rework activities being completed in the cell. The process changes and process length weights stayed close to the generic version, as these are still important sub-themes as the process is updated more often than the product and the length of the process can be an indication for whether the process is being optimized. The process length paired with production capability can also represent if the process is improved without compromising the throughput. The production capability is less influential in this instance, because throughput is not a priority of a research lab and many defects are purposefully introduced, which negatively affects the *system yield*, but this is intentional so it should not result in heavy point reductions for the QA score. The inspection sub-theme is more influential, as so much of the research for this lab is focused on improving this activity.

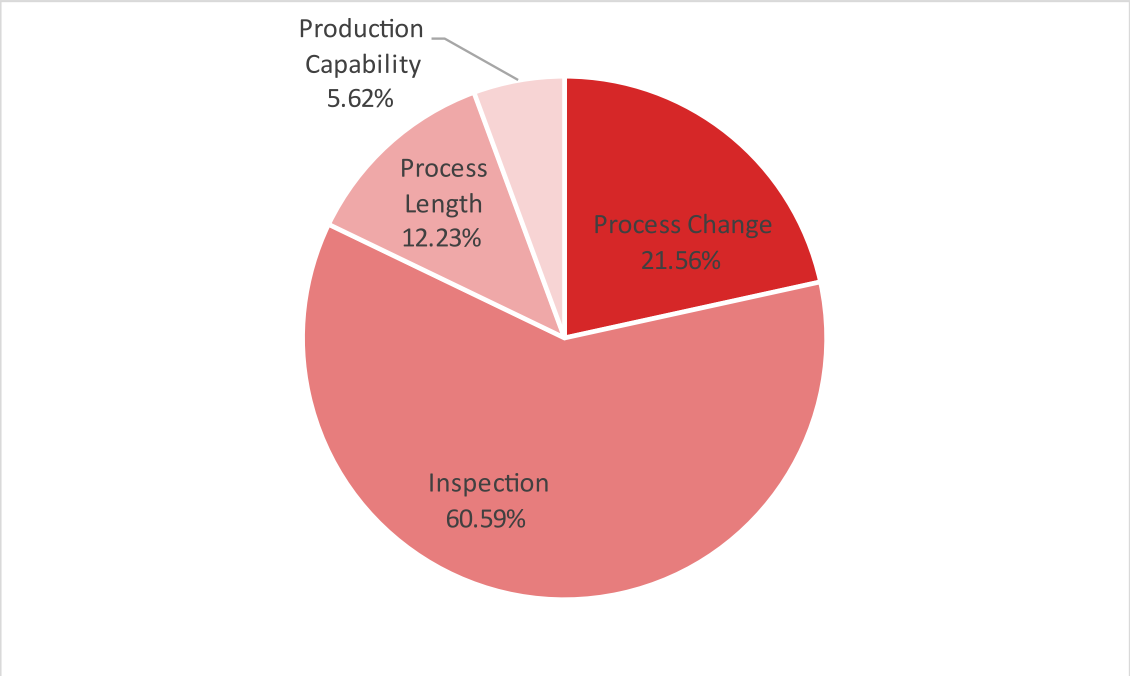

Figure 4.7: Process pillar split into new sub-theme weights for FF lab.

The metric makeup of all the sub-themes is weighted similarly to the generic model, as many of the ideologies hold true for the FF lab. The main difference, again, is that the entire rework sub-theme has been removed, which was already mentioned.

Figure 4.8: Process pillar split into new metric weights for FF lab.

4.5.3 Maintenance

In this instance the frequency sub-theme has been drastically reduced as PM activities are not performed in this facility. The time requirement sub-theme has been slightly increased, because CM is performed commonly due to the lack of PM. This sentiment also caused a large increase in the influence of the age sub-theme. The tooling age is particularly important for this increase, because the grippers, fixtures, and mounts are created with PLA which can age and become brittle quickly and cause failures. Failure occurrence is crucial in the generic model and this specific instance has weighed it similarly.

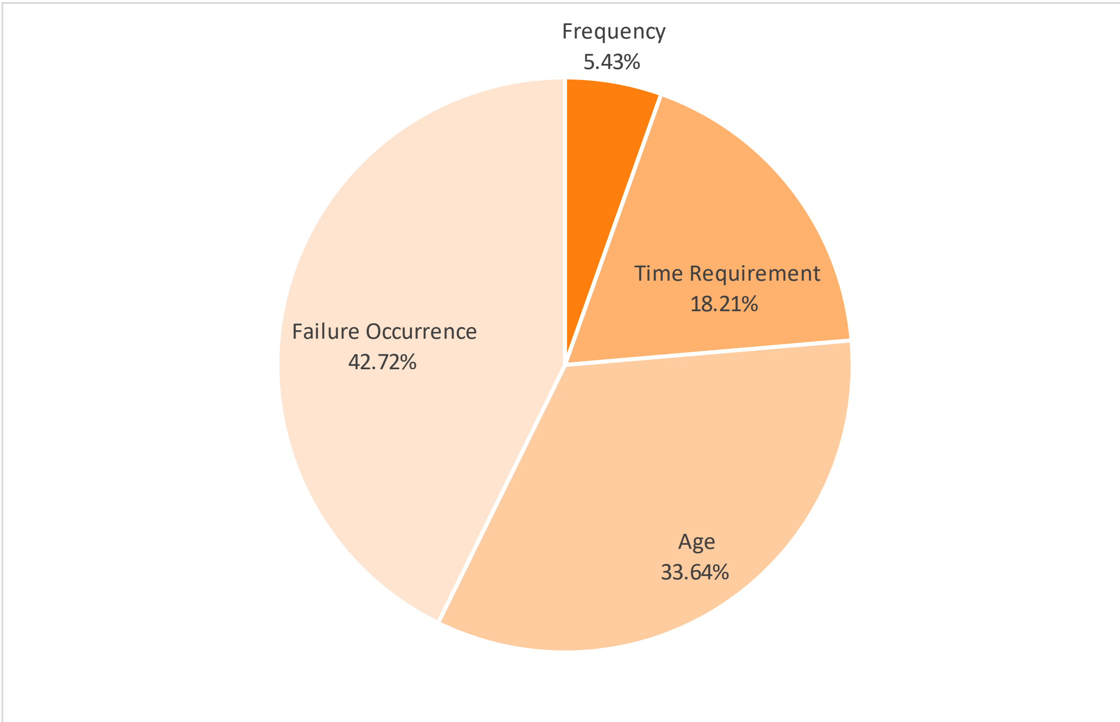

Figure 4.9: Maintenance pillar split into new sub-theme weights for FF lab.

The frequency and failure occurrence metric weights have not changed as they each have a single metric. As previously mentioned, PM is not performed in the cell and is therefore weighed less in this instance, causing the time for CM to be increased. The age sub-theme also stayed the same as the *age of the tooling* is more impactful, especially considering the material used is meant primarily for prototyping and can age quickly.

Figure 4.10: Maintenance pillar split into new metric weights for FF lab.

4.5.4 Management

The weights of the sub-themes within the Management pillar are like the generic model, as the knowledge of the management and employees (students) for the FF lab are the biggest influence on the quality for the products being produced. The environment is also a big influence, with the incentives being the least influential sub-theme.

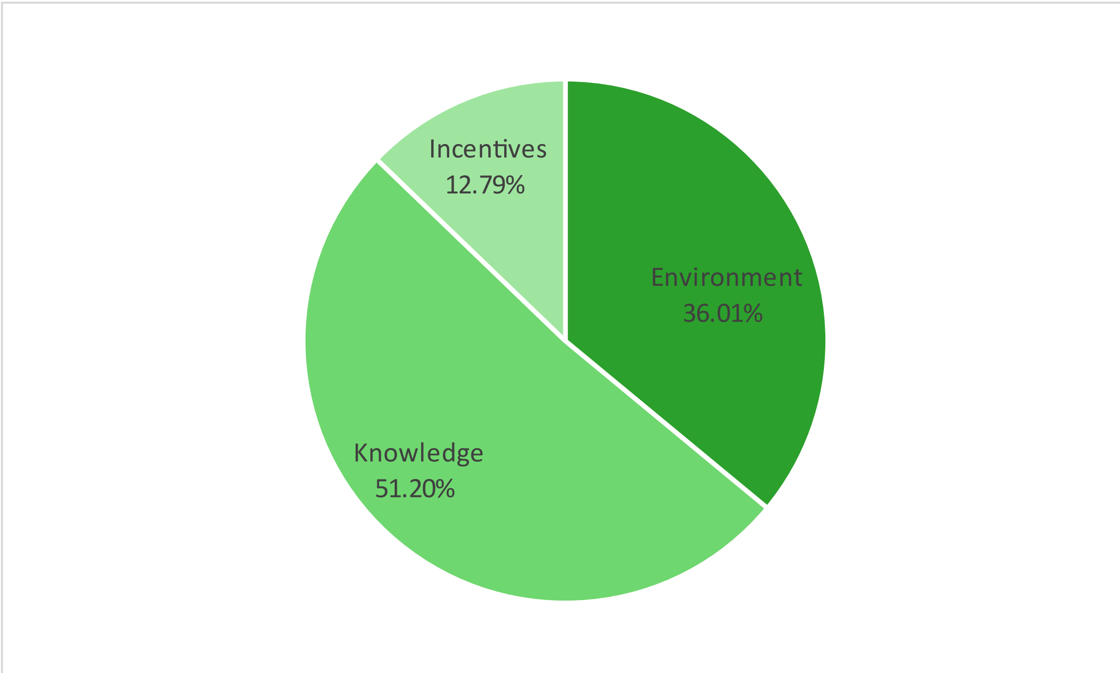

Figure 4.11: Management pillar split into new sub-theme weights for FF lab.

The weight split amongst the environment sub-theme is slightly different from the original model. The *company size* is more influential, because the size of the "company" or the team of students working the lab has grown drastically in the last year, increasing the influence. The *management commitment to quality* has lessened slightly, because as previously mentioned the management for the testbed factory is organized differently than a real factory. The *employee involvement* has lessened, as everyone works on individual research topics, meaning that there is less of an impact on the factory, if not everyone is prioritizing the quality. Finally, for the environment sub-theme, the *overall work culture* metric has grown in influence from the generic model. The knowledge and incentives breakdown are the same as the original. The *management experience* is more impactful than employee training, because, again, the employees are all working on individual projects. The incentives for the employees are more important than for the management, as the team needs to be self-motivated to complete projects.

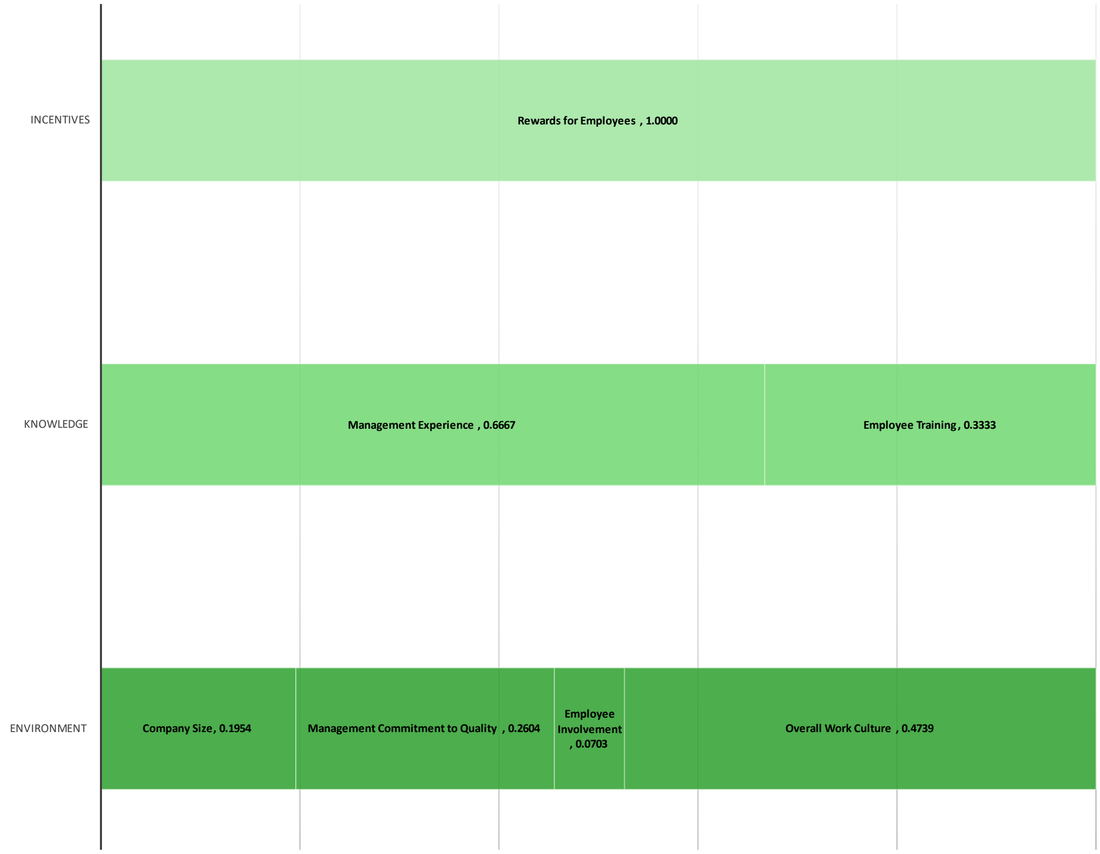

Figure 4.12: Management pillar split into new metric weights for FF lab.

4.5.5 Supply

Supply chain management is more influential, as there are known problems with the supplier for the 3D printing material. The demand sub-theme has been hugely reduced in weight. This is because a research facility does not have any quotas or deadlines to meet where a specific number of products must be manufactured per day. This means that the *demand rate* on the inventory is far less important to the QA score. On the other hand, the inventory age weight has been increased, because the material being utilized for printing can become brittle when it is allowed to sit for long periods of time before being used. The inventory size has also been increased from the original model.

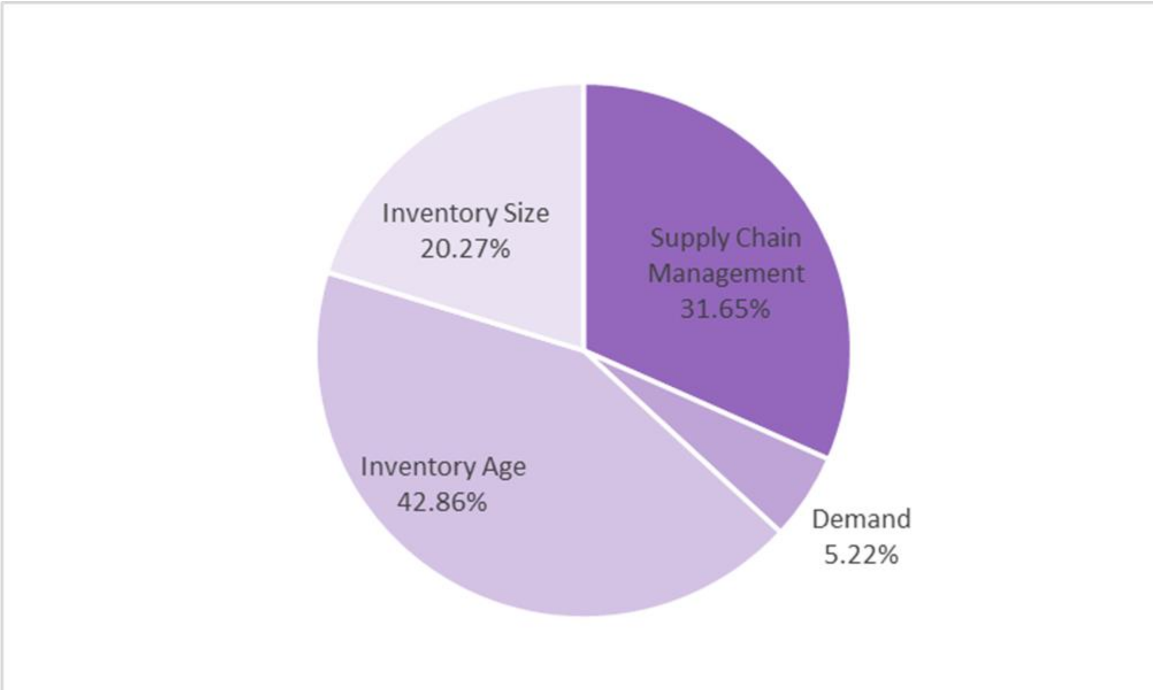

Figure 4.13: Supply pillar split into new sub-theme weights for FF lab.

The supply chain management, demand, and inventory age sub-themes all contain a single metric meaning that the weights are no different from the generic model. For inventory size, there is no *buffer stock* in the lab, meaning that the *total average inventory size* makes up the entire weight of this sub-theme for this instance.

4.6 Scoring Results

Now that the generic model and FF specific instance of the HQM model have been implemented in the FF lab, it is important to compare the results. The generic model is sufficient, but that the specific allows for deeper insights and a more accurate result.

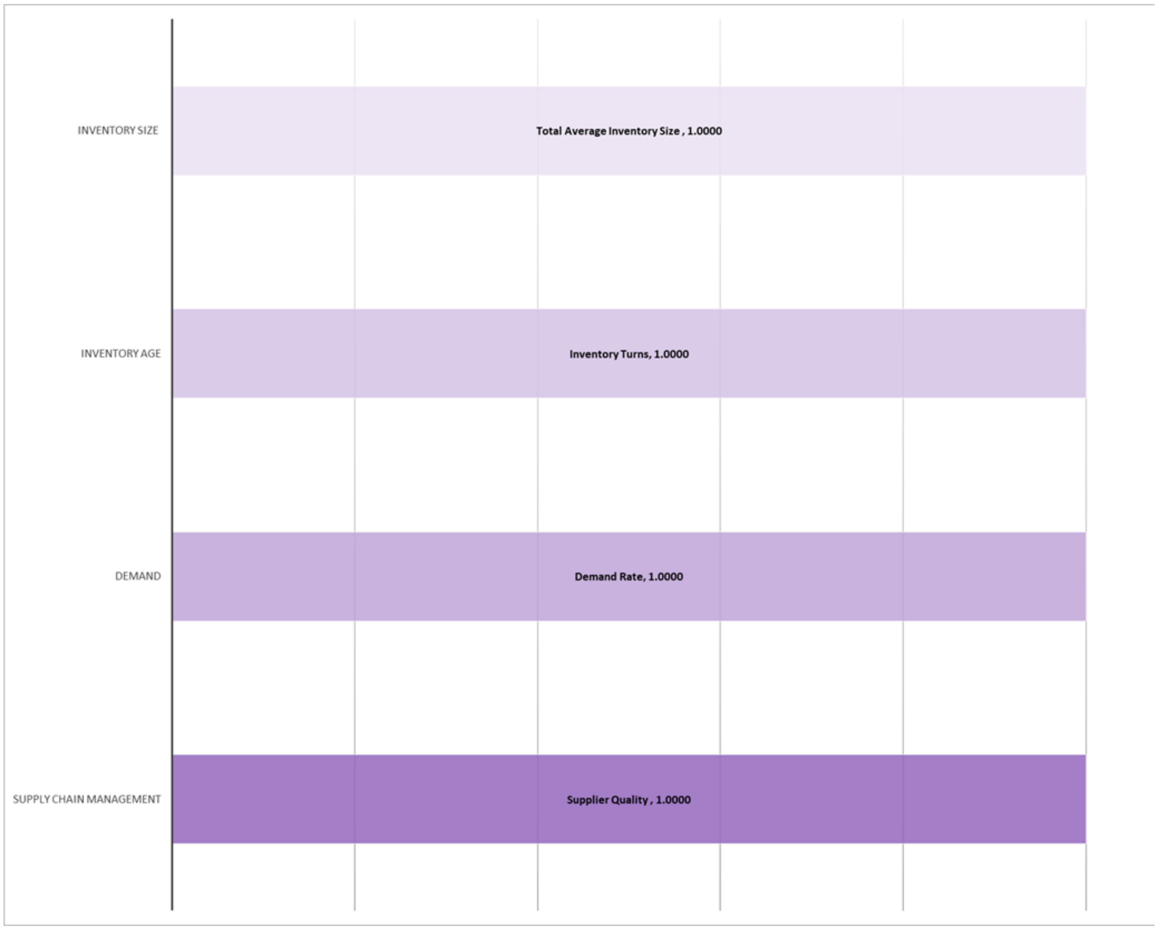

Figure 4.14: Supply pillar split into new metric weights for FF lab.

4.6.1 Comparing Model Instances

Figure 4.15 visually shows the results from both instances in the FF lab for each pillar. The overall QA score for the generic model is 68.77% and the score for the FF specific is 61.83%. While the lab performs better in the original model and the score is higher, the new score is more beneficial for improving quality within the facility. It means the lab is suffering in the categories that are more influential on quality performance, which helps with insights to assist with RCAs and achieving CLQ. This occurs because the lessons learned in the scoring can be fed back into each new manufacturing batch.

Design is not only more important in the new instance, but it is also shown that the lab performs worse in this pillar, based off the new instance causing a reduction in the overall score. The lab performs better in the Process pillar of the new instance and it is worth considerably more, but even with this improvement the results still show worse QA achievement based off the overall scores. The Maintenance weight on the scores barely changed, but with the consideration of the lack of PM activities it allows for the cell to perform better. The Management score for the pillar is virtually the same, but it is worth only a fraction of the score in the specific instance versus the generic. Finally, the Supply pillar score is better for the specific instance, and it is weighted more. Based off these results, the Maintenance pillar needs to be investigated for overall score improvement.

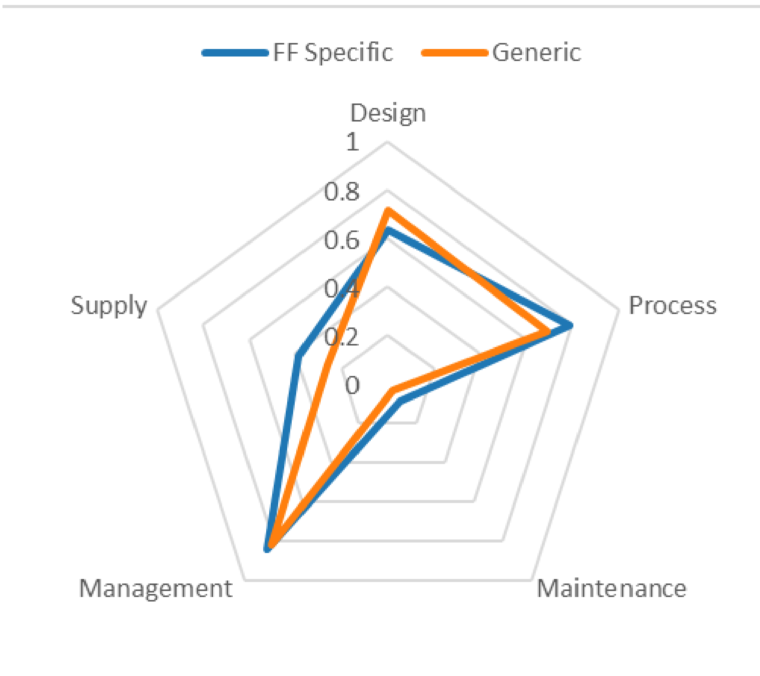

Figure 4.15: Individual pillar results for the FF lab in the specific versus the generic model instances.

Now that the model has been utilized to start from scratch in a facility with no QM method, or in one that is starting an entirely new method, Chapter 5 will explore how an existing QM tool in industry, TcQ, can be adapted to adhere to the principles contained in this new model.

Chapter 5 Industrial Alignment of Holistic Quality Management Model

5.1 Motivation

Throughout this thesis, a model has been designed to encompass a holistic view of factors that affect quality throughout a manufacturing facility. This model offers an out of the box solution for a company to calculate the QA score utilizing the standard model based off weights that came from an AHP methodology fueled by industrial quality expert input. This model not only accomplishes this calculation, but also acts as a guide for QM to ensure focus on critical metrics. Most of this research has been focused on this model functioning as the sole QM tool, but many companies already have a solution in place and there exist many companies selling their own quality solutions. It is not feasible to assume that all other tools will be abandoned and replaced with this model, therefore it is crucial to consider how to better align existing solutions to work alongside this model.

This chapter will investigate how to take one of these existing tools, TcQ, and configure it to match this ideal model. The crucial goals that need to be met to prove this alignment are summarized in Figure 5.1. These are the same goals that were set for the HQM model. The QA score calculation is a way for the model to optimize this assurance process and move towards CLQ. Therefore, the QA process for TcQ must be identified and improved for this tool. The five pillars of this model contain sub-themes and metrics powered by live data.

Siemens DISW has a wide range of software that are optimizing and improving every stage of manufacturing, one of which is TcQ. These solutions can be mapped over the pillars in the HQM model, and utilizing the data from them to reach CLQ would satisfy the second goal. Finally, it is important to present this solution in a user-friendly package as all employees and departments are needed for high quality. Not every employee needs the in-depth detailed knowledge of a quality expert, but they need some degree of accessibility to their tasks that affect end quality. The rest of Chapter 5 will introduce TcQ and explain how the author aligned this solution to the HQM model.

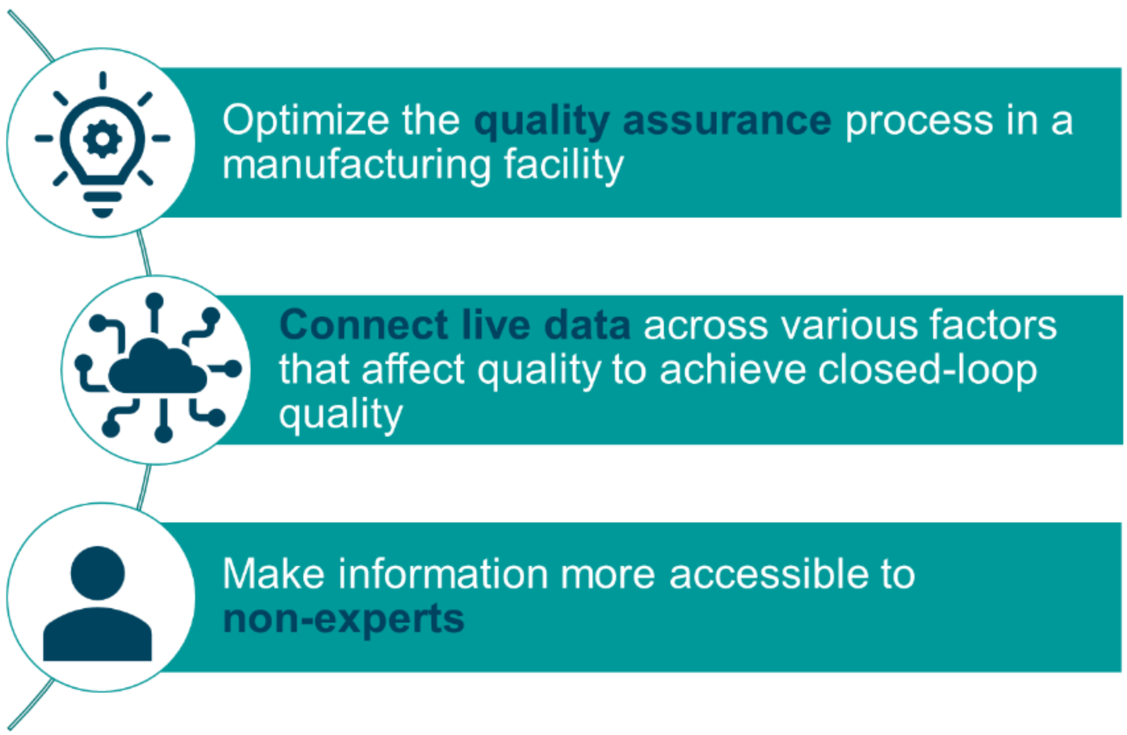

Figure 5.1: Summary of the HQM model goals

5.1.1 Platform Introduction

TcQ is a quality solution integrated with Siemens PLM solution, Tc. The goals of this software begin with breaking silos between departments in manufacturing that have historically operated separately, such as engineering, manufacturing, and QM. Tc and TcQ act as a repository for all the data used across different departments and act as the single source of truth, allowing for traceability throughout the entire facility and controls change management of existing data. Now all employees are positive that the data being used is the most up to date and accurate.

TcQ aims to give a holistic view of the process to introduce a new product through the structure in Figure 5.2. This structure shows the loop of implementing a new product and how CLQ is utilized to loop back through the four wheels (Design for Quality, Quality Planning, Quality Execution, and Quality Improvement). It begins with requirements, as this is the basis for how the product must be designed and manufactured. Without this, there is no way to ensure that quality goals were met. These lead into the creation of the necessary Bills of Material and Process (BOMs and BOPs). These support Design for Quality. Moving into Quality Planning management creates necessary APQPs, which contain crucial documents such as First Article Inspections (FAIs) and Production Part Approval Processes (PPAPs). The requirements are fed directly into the FMEA module, then into the Control and Inspection Plan (CPIP) module of TcQ, along with the identified failure modes. Once these are completed the product would move into production and Quality Execution. The issues and nonconformances are then identified and documented and saved as items in TcQ. These are then used for problem solving, which, in this case, the module uses the 8D (disciplines) methodology. Through this, RCAs will be completed, TcQ has Ishikawa and 5Why built into the solution. This result will then be used for change management. To begin looping back and achieving CLQ, this solution has audit and training/qualification modules, if investigation or retraining is necessary depending on the changes implemented. Everything learned is then included to improve the drawings and Product Manufacturing Information (PMI) for the next batch or product. Now, this powerful and functional solution will be improved further through alignment of the HQM model.

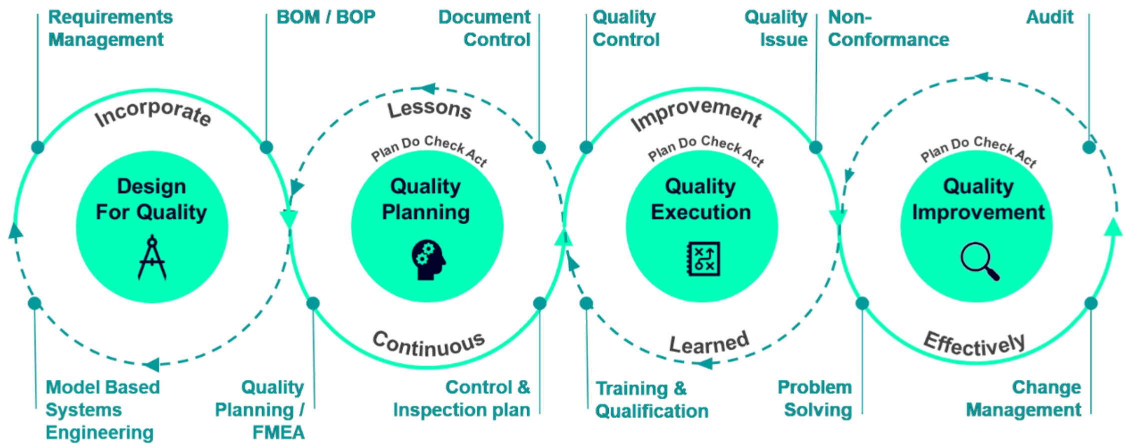

Figure 5.2: New product introduction structure used in TcQ for a holistic view.

5.2 Gap Identification

After using this software, gaps were identified that when eliminated, can achieve the goals described at the beginning of the chapter.

5.2.1 Quality Assurance Optimization

TcQ incorporates QA into its APQP module. This module manages all the deliverables, checklists, events, and deadlines needed to complete a project or manufacturing batch. This tool is powerful, as it allows management to see a high-level view of how everything is progressing and if there are issues or late tasks it is quick to dive in to see responsible parties. The QA is attached to the checklists in this module. Checklists are created in response to whatever the deliverables are within an event or program, and are answered manually yes or no, depending on if things were completed correctly. Then depending on these responses, a quality rating is marked as red or green, again depending on if things were completed correctly. The TcQ interface is shown in Figure 5.3.

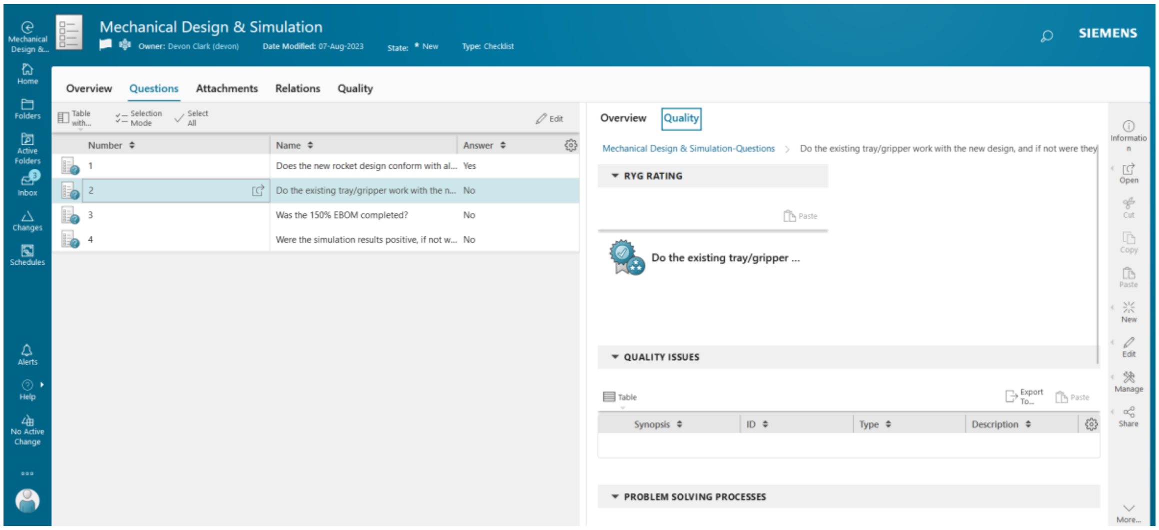

Figure 5.3: TcQ APQP module interface.

This system allows room for user error as things are manually entered. Users could answer incorrectly accidentally or to try and cut corners to stay on track. Then a manager looking at this higher level would only see that final quality rating as correct and may not catch these errors that lie within checklists within events. Mistakes can also occur to an added difficultly for employees responsible for answers. Oftentimes, answering these questions requires attachment of files for proof or operators must exit TcQ and go into other solutions to check before responding. Meaning they must work their way back to where their specific question was located, which is not efficient. On top of these issues, if workflows are not enabled or correct, it can be easy for employees to miss them when they are responsible for questions.

The solution to optimize this process and achieve the goals is to create a Mx face for this TcQ module. This app will improve the usability for employees, when completing their tasks. The app will also connect in other solutions to auto-fill checklists or access needed data through the UI. This will eliminate user error when responding to checklists. This will be elaborated on in the following sections.

5.2.2 Inclusion of Live Data

To achieve the second goal, it is important to identify which Siemens solutions may act as sources for each of the pillars within the HQM model. The full list of possible solutions is shown in Figure 5.4. The software is split into which pillar it could support depending on what a facility is using and from where their metrics originate. Many of the ones included were fully explained in Chapter 4, when the metric sources for the FF specific use case were introduced. There are solutions that are not currently in that use case that will fall into Chapter 6 for future work to improve what was done in this thesis. Also, there are existing TcQ modules that could be better connected to match the pillars.

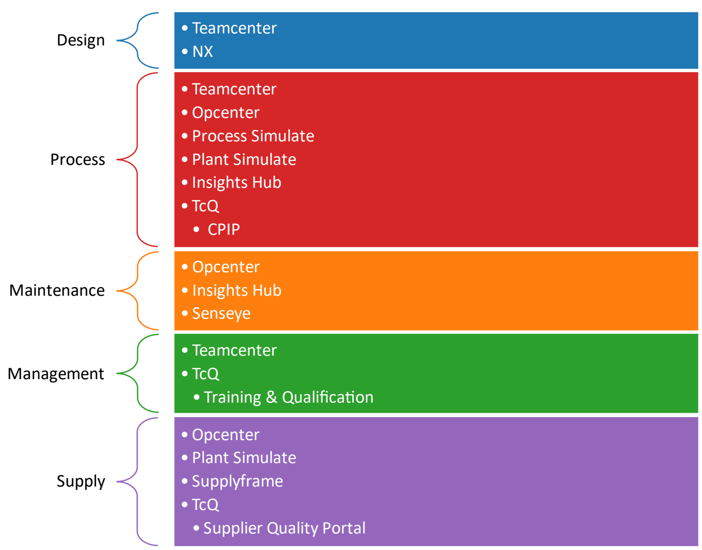

Figure 5.4: List of Siemens solutions to satisfy HQM pillars.

These same sources can be utilized to autofill the checklists as previously mentioned, depending on what the deliverables and checklists for a specific event are entailing. For example, there is a checklist item regarding if a requirement was met about the ability of the rocket bodies within the FF lab to withstand the pressure output by the robots' grippers. Currently, the responsible party would have to read that question and go searching for the sensor output from the cell and determine whether the parts are surviving the assembly process. Then they would need to reenter Tc and answer the question. With autofill capability, this sensor value could be directly pulled from IH. And, creating a rule or event, depending on whether the necessary value is being met, could be turned into a string to be written into TcQ inside the owning question. This process would be similar to any of the listed solutions and can be accessed similarly to what was explained in Chapter 4 with the addition of a POST API to write into Tc. And, to better align TcQ holistically with the ideal HQM model, this idea would make the information for almost all the metrics accessible across all solutions.

5.2.3 Usability Improvement

To achieve the final goal set, this process needs to be made more usable for the responsible parties. To do this, the app created attaches to the specific users Tc account, so that when they log in with the same Tc login, the deliverables and checklists that they are responsible for will be immediately accessible. Users can then complete their tasks within this app without ever having to enter Tc, at the same time keeping the source of truth inside the PLM solution. Then, users such as management or the quality team will be able to deep dive into the solution when needed and know that the data in Tc is still accurate. The interface that was created via Mx is shown in Figure 5.5, which also shows how that TcQ module is acting in the background.

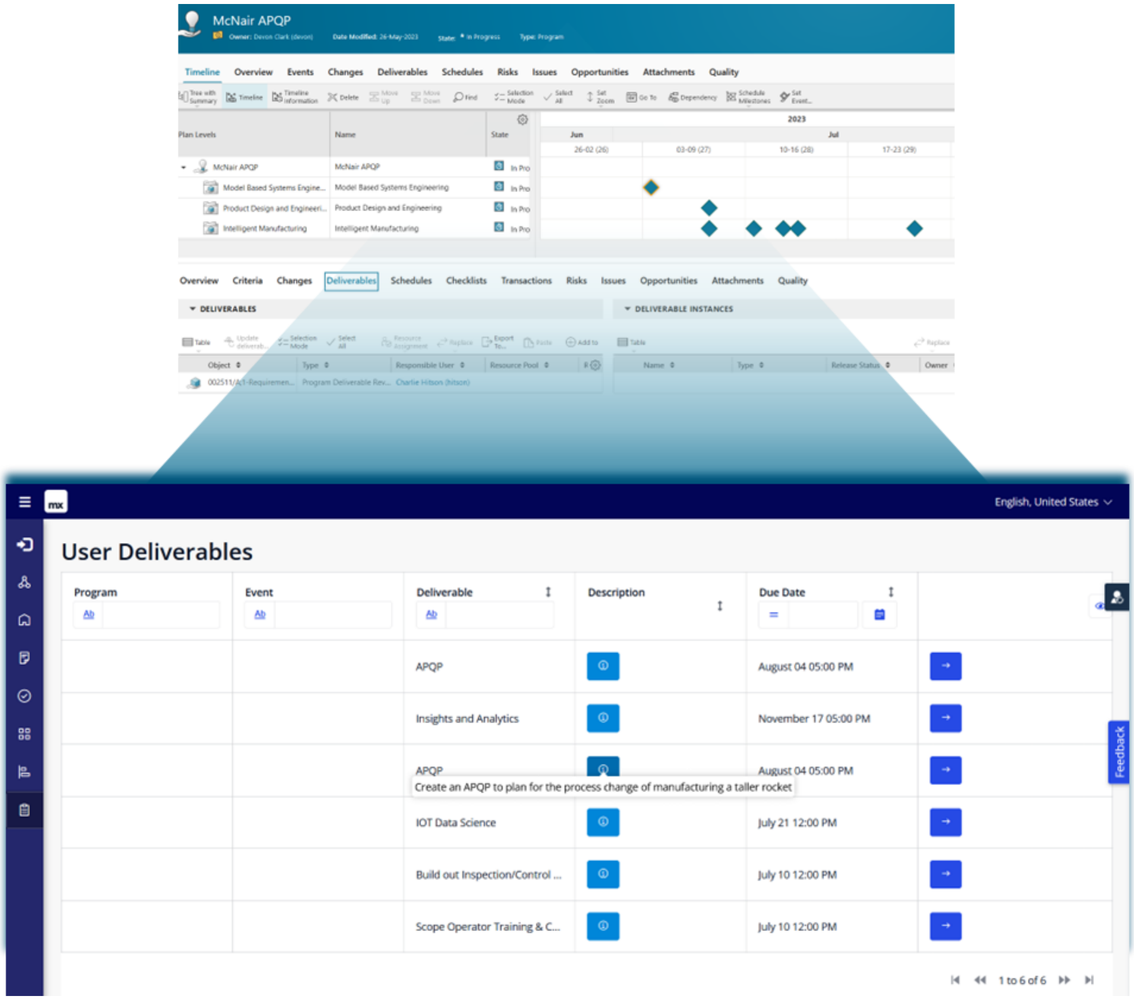

Figure 5.5: Mx interface created to improve usability for this industrial alignment.

5.3 Summary

To summarize this whole process, a Mx app was created to act as a face for the APQP TcQ module. This interface improves the usability for the employees responsible for specific tasks by making them more accessible. It also connects many Siemens solutions where the data can be utilized to autofill checklists. These solutions also cover the wide range of metrics within the HQM model to better align the tools. By improving the user experience and eliminating some degree of user error possibility, the overall QA process was improved for the TcQ Solution. This proves out the achievement of the three goals that are summarized in Figure 5.6. These are the same goals that the HQM model achieves showing the overlap of this alignment on the overall goals of this thesis.

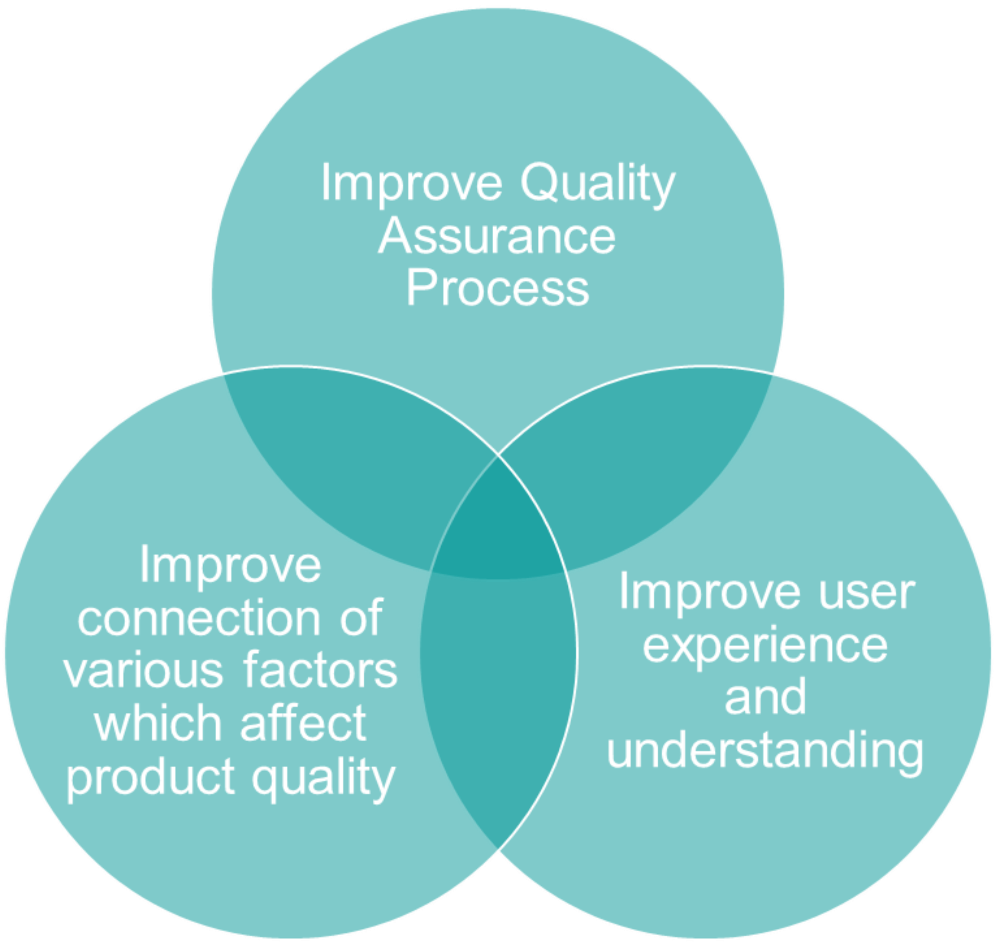

Figure 5.6: Summarized goals met by the HQM model and TcQ industrial alignment.

To continue to improve this solution alignment, many of the other TcQ modules that were mentioned could be mapped to eliminate gaps between themselves and the ideal HQM model. The steps and ideas contained in this chapter could also be repeated for other industrial solutions owned by companies other than Siemens. The conclusions and future work of this thesis will be summarized in Chapter 6.

Chapter 6 Conclusions and Future Work

6.1 Summary of Work

In this work a model was created to quantify the QA within a manufacturing facility. This model can act as a guide for QM to know which metrics and sub-themes are important to consider. It allows for CLQ capabilities through the data presented in the scores to deep dive into specific pillars and metrics causing point reductions. This gives a holistic view of the quality within a manufacturing firm.

To create the basic structure of the model an extensive literature review was conducted to determine common topics and crucial metrics. Once the papers were read, they were grouped into five pillars: Design, Process, Maintenance, Management, and Supply. These groups were determined by the author as common threads throughout many of the papers and how they were related to quality. Then, from within these papers crucial metrics were obtained. These metrics were either commonly researched throughout many of the papers or were included in legacy papers in the field of quality. Meaning they were papers cited often in this field. To add a level of complexity to better determine impact factors, the metrics inside of the pillars were grouped into sub-themes. And as cost is a crucial component for any industry and a common concept in the papers, a COQ calculation accompanies this model.

Once this structure was determined an AHP methodology was utilized to assign weights to these levels. The weights were informed through the input of industry professionals in the field of quality, giving this methodology and the results validity. The weights assigned here, were then integrated into the standard starting point instance of this complex model. Then, through a variety of methods, the metrics were standardized to allow for input into the model. To showcase the configurability of this model, two industry specific instances were created based off the input of a professional in the composite field and another professional in the pharmaceutical field, displaying how the base model can be tailored to a specific manufacturer to better analyze the quality within a facility.

The standard model was then implemented into the FF lab at the University of South Carolina in the McNair center. This was to show the process from start to finish for implementation in a real manufacturing facility. The metrics from this cell were gathered through a variety of sources and submitted into the base model to receive a generic score. An application was developed to display these calculations and concepts in a user-friendly fashion. Then, a specific instance for this research lab was developed, where the weights were configured and some inapplicable metrics were dropped. The results from both models were compared.

Finally, a true industrial QM tool was aligned with this HQM model, proving how this model can work alongside existing tools and how these concepts can be utilized to further improve existing tools and techniques in this ever-growing field. This model is a starting point for continued improvement.

6.2 Future Work

This thesis has room for future work and further improvement. The pillars in this existing model could be expanded to include other pillars such as sustainability and external factors. Sustainability is becoming an increasingly hot topic and, as such, needs to be considered when implementing quality solutions. External factors, such as brand damage from recalls or external failures, are also important for quality managers to consider when making decisions. Similarly, the existing pillars could be expanded to contain more out of the box metrics and allow for industry specific cases to be implemented.

The AHP methodology could be improved by increasing the amount of quality professionals surveyed and analyzing the consistency of their responses. The weighing ratios would be more accurate with the inclusion of machine learning to account for the fluctuation of everchanging impact factors. These suggestions would improve the model weights. It would also be interesting to include more industry specific generic models that could be more accurate from the first step, than the overall generic model.

These are just a few ways that this model could be improved in future work or new versions. As this work combines many disciplines found in manufacturing, it also represents the overlap of topics being researched in the FF lab. It is also a strong representation of the departments found in full manufacturing facilities.

6.3 Situation of Research

This HQM model encompasses many of the research topics found in the FF lab and was implemented in the current orientation that began with the early work of (Kircaliali et al., 2020). The recognition of mechanical design features from (R. Harik et al., 2017) can represent the Design pillar and the complexity of these features. The image segmentation inspection in (Xia, Saidy, et al., 2021) is under the process umbrella. This pillar also contains process improvement works such as the VC from (Xia et al., 2019) and robotic calibration through motion capture cameras (Kirkpatrick et al., 2023). The Maintenance pillar has within it the multi-modal data to monitor robotic health (Saidy et al., 2020) and potentially predict maintenance events. On top of works inside of the pillars, the live data integration found in this model is reminiscent of the ideology that a digital twin is reliant on data from the manufacturing facility (Xia, Sacco, et al., 2021). The AHP methodology utilized in this thesis was based on the work of (Harik et al., 2015). A major factor in this model was the inclusion of live data. The actual data is visible within the published dataset by (Harik et al., 2024).

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