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Continual process improvement under causal ambiguity

Doctoral dissertation

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Author´s Declaration

No portion of the work referred to in this dissertation has been submitted in support of an application for another degree or qualification of this or other university or other institution of learning.

Furthermore, this dissertation contains no material previously written and/or published by another person, except where appropriate acknowledgement is made in form of bibliographical references, etc.

Thomas Bernhard Ladinig
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Abstract

Abstract of dissertation submitted by:

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This study examines strategic, quantitative, and behavioral factors of continual process improvement in a complex, small-volume, batch production system of a premium car manufacturer's business unit. Operations management theories are linked to qualitative and behavioral analyses to increase their applicability and usefulness for practitioners in a multi-level and inter-disciplinary case study at the business unit. Practical applications of theories and scientific methods are hampered by causal ambiguity and bounded rationality, which make it difficult for management to fully understand the impact of their decisions on the system. A lens model, based on Social Judgment Theory, is applied to deal with imperfect decision making by visualizing the results of a discrete event simulation and a management judgment analysis. Another study, using concept mapping in combination with behavioral quality management, is conducted to map the conceptual domain of quality linkages within the business unit.

The results of both analyses visualize the conceptual domain as well as cause and effect relationships of a set of factors within the business unit and the preferences of management towards them. This behavioral approach can facilitate decision making regarding improvement project selection and can prevent errors in group decision making due to issues related to behavioral operations management. The case studies revealed substantial differences in the preferences of the management team and lack of alignment with the business unit's competitive priorities. By combining concept mapping, judgment analysis, and the results of the simulation, a mutually acceptable action proposal was created to select the most efficient and effective improvement activities to enhance quality and flexibility - the two competitive priorities of the business unit.

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List of Publications and Author´s Contributions based on the “CRediT - Contributor Roles Taxonomy”

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Co-Author:

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1. Introduction

The need for a more practical focus in operations management (OM) research has been pointed out in several papers and many new concepts were explored to emphasize the human aspect and practical relevance in OM in the recent past. Samson and Whybark (1998) called out for more attention on the "soft issues" in operations management and new fields emerged to focus on behavioral operations in management (Gino and Pisano, 2008; Croson et al., 2013) and in operations research (White, 2016). Furthermore, Schmenner and Swink (1998) and Schmenner et al. (2009) pointed out the bias towards rigor and theory at the cost of relevance and understanding of real management problems.

This research aims to ensure the usefulness and applicability of existing OM theories for managerial problems by applying specific concepts to strengthen links between theory, behavioral operations, and implementation on the process-level and below (group and individual). These methods are applied at a business unit (BU) of a multi-national automotive OEM during a project to re-design and improve its whole production system. They were developed to deal with imperfections of human judgments and visualize them to be integrated into a framework for policy- and decision making specifically tailored to the needs of the BU. In an OM context, they can be used to make better decisions regarding the design and improvement of production systems, especially in complex and dynamic areas with a high degree of causal ambiguity, which gives the study a high degree of external validity and generalizability as well.

1.1. Background and Project Description

The small-volume production BU of the automotive OEM is an internal supplier for various exterior body parts of premium sports cars (doors, bonnets, side panels). It has grown organically over the past ten years with a drastic increase in variety of products and consequently, an increase in complexity. However, the support systems, administration, and the production system design did not grow alongside to cope with higher complexity and dynamics of the new system. High process variability, a scattered material flow and quality issues increased the instability of the system and "firefighting" became the daily business of most people of the BU. Therefore, management decided to invest in an expansion of the factory building and a full production system re-engineering with a completely new material flow, logistics and production processes. The focus of the project was to optimize all production processes and connect them into an efficient value stream with increased productivity, faster throughput times and better quality. This meant that all support processes (maintenance, quality assurance, manufacturing planning and control, etc.), as well as the organizational design had to be improved and adapted as well.

The project started with an extensive planning phase conducted by an inter-disciplinary team of experts and operations management researchers to develop the first layout and system design for the new factory expansion. Data from the old system was gathered to develop new processes that would fit into the new design to create a fully integrated production system. A discrete event simulation (DES) analysis was carried out to test the new system, processes and logistics concept regarding material flow, throughput time, storage capacity, production capacity and process performance. After several improvement cycles and re-designs, the system and processes were ready to be implemented and tested on the new shop floor. However, due to the limited resources of the small-volume BU, the implementation of a multitude of new processes alongside the new production system became a serious issue for the project team.

1.2. Motivation and Objectives

It was critical to identify the most important processes that should be implemented and improved first to reach the goals of the production system based on the underlying strategy and competitive priorities of the BU. The main problem was causal ambiguity within the production system and cause and effect relationships were difficult to assess and understand to properly allocate resources towards the most important processes. The goal was to use scientific methods and theories to improve operations on the process level of the BU by giving more and better information for decision making regarding process improvement activities. Behavioral, strategic, and operative factors are included in the analysis to make it more practical and relatable for management to ultimately make mutually acceptable decision.

Behavioral operations and causal ambiguity are highly related because they both deal with imperfect decision making due to bounded rationality and unclear cause and effect relationships. This study builds on the latest and most significant developments in research on causal ambiguity (e.g. King, 2007) and behavioral operations (e.g. Bendoly et al., 2010) and expands it into a holistic concept for highly valuable practical application of OM research. The methodologies applied in this study can deal with bounded rationality and causal ambiguity simultaneously to create visual support for decision makers based on their own judgments and the results of the simulation analysis. This level of transparency can facilitate the creation of mutually acceptable action proposals as a result of this OM intervention, which increases the relevance of the results and research in general (White, 2016). The goal is to create an action proposal for the selection and management of continual improvement activities within the new production system based on the results of behavioral analyses and OM tools (in this case a DES).

The thesis is centered around two individual research papers and is structured as follows. Chapter two gives an overview about the strategy and competitive priorities of the BU and ties it to theory, behavioral OM/OR, and causal ambiguity. The third chapter describes the methodologies of the lens model application based on Social Judgment Theory (SJT) and concept mapping as used in the two research papers, respectively. The results of both analyses are discussed and integrated in chapter four.

2. Theoretical Framework and Literature

To deliver desired results of improvement activities on the process level it is first necessary to analyze and develop strategies, theories, and competitive priorities to ensure that the scientific methods are suitable for the production system. This chapter gives an overview about the identification of competitive priorities in general and for the business unit (BU), focused on Theory of Production Competence (Cleveland, et al., 1989). It starts with the underlying theories of this study and how they can be used to guide the management of a continual improvement process (CIP) to increase firm performance. Furthermore, it contains a top-level analysis of strategy and drills down to the quantitative and behavioral factors of operations management on the shop floor of an organization. The reasoning behind it is the need for a well-developed framework without conflicts between different theories to facilitate practical application of this OM intervention at the production system of the BU. At the end of the chapter, the role of causal ambiguity is discussed when managers make judgments and decisions, and how they can cope with uncertainty about cause and effect relationships.

2.1. Identifying Competitive Priorities and Organizational Capabilities

To decide what to do and how to do it, a group of managers should focus on three aspects when identifying the most critical competitive priorities and processes. First, strategic aspects ensure the alignment of manufacturing decisions with the strategy of the firm (Skinner, 1969; Anderson et al., 1989; Schmenner and Vastag, 2006). Quantitative aspects are critical to analyze and find policies and processes with the highest potentials for improvement to increase the performance of the company (Zantek et al., 2002; Li and Rajagopalan, 2008). Finally, behavioral aspects must not be overlooked to make sure that the whole management team understands and mutually agrees upon decisions, and to prevent conflicts between people of different functional and hierarchical areas (Hammond, 2007; Hämäläinen et al., 2013). Theoretical concepts and solutions can be successfully applied on the micro-level only if all three aspects are aligned in a logic and consistent manner and all (or most) conflicts are resolved between and within organizational levels.

2.1.1. Strategic Aspects (Factors are Strategically Relevant)

To highlight the path from theory to practical application it is necessary that managers understand how they can integrate a theory into their strategic decision-making processes. One factor is the combination of the product structure and process structure that defines the nature of the production system according to the product-process matrix (Hayes and Wheelwright, 1979). Another classification can be made based on relationship between the variability of demand and throughput time (Schmenner and Swink, 1998). Competitive priorities, for example, can be identified based on the classification of production systems (job shop, flow, batch, etc.) and process variability (Schmenner and Vastag, 2006). Factors like flexibility, product performance (quality) and reliable delivery are becoming more important with a higher percentage of job shop or batch production in a production system, especially, if there is also a high degree of process variability.

Pursuing the right goals based on a specific business strategy and production system is critical for the success of a manufacturing company and is measured and analyzed based on the Theory of Production Competence. *Production competence* is the capability of manufacturing systems to prosecute a market specific business strategy according to Cleveland et al. (1989). They were on the forefront to numerically assess production competence and found proof that it has a positive impact on firm performance, if manufacturing strategy and business strategy are aligned, which was the original thought of Skinner (1969). To follow the underlying reasoning behind these calculations it is important to start at the very top of organizational decision making, namely the strategic planning process. A business strategy defines how a company should compete in the market and which *competitive goal* should be pursued. The four most general competitive goals are quality, delivery, flexibility, and cost. It is highly important to decide which of these goals should be selected as *competitive priorities* based on the underlying business strategy (Vickery et al., 1997). Top-management defines competitive priorities based on company strategy and sets the *performance dimensions* on which the production system is assessed (Schönherr and Narasimhan, 2012). Competitive goals and priorities can be expressed in various performance dimensions to measure performance relative to competitors (adaptive manufacturing, cost effectiveness of labor, delivery performance, logistics, production economies of scale, process technology, quality performance, throughput and lead time, vertical integration) as mentioned by Cleveland et al. (1989). A plants' performance in those dimensions compared to its main competitors is referred to as *organizational capabilities* (in this case OM capabilities), or how capable a production system is in those dimensions. High organizational capabilities are critical for performance dimensions, which are based on the firm's competitive priorities. Alignment is necessary to ensure efficient and effective resource allocation to develop relevant capabilities based on competitive priorities. A firm can only have high production competence if they have high capabilities in their selected competitive priorities. This implies a fit between OM capabilities and competitive priorities based on a viable business strategy to achieve higher firm performance (Schönherr and Narasimhan, 2012).

Figure 1 depicts the four general competitive goals and related performance dimensions to be selected based on the BU's strategy. All performance dimensions were mentioned in the literature (Cleveland et al., 1989; Vickery et al., 1993; Schmenner and Vastag, 2006) to be relevant components of production competence. Each component was measured on a seven-point Likert-scale regarding its value to the overall business strategy ("+++" meaning that the dimension is critical for the company and its strategy; "- - -" meaning that the component is completely disregarded as a competitive factor; "Ø" meaning neutral). In the BU, quality issues are at the center of management attention and flexibility (lead times and manufacturing throughput times) is critical to complete a multitude of orders in batch production for a wide range of products. These are also the competitive priorities of the BU and the overall strategy is focused on the production of many different products, in small quantities, with short lead times and flexible labor and equipment to minimize initial investments. High quality requirements and a wide product range result in increased dynamics and complexity in the management of the production system and information about process performance becomes critical to control the system. In small-scale production there are almost no economies of scale and production costs are high due to low quantities of specialized products. Focus on quality conformance and throughput time make quality and flexibility competitive priorities of the BU with critical performance dimensions related to those priorities. This is also supported in the literature, since high process variability and batch production systems are typically characterized by a higher focus on the competitive goals of flexibility and quality (Schmenner and Vastag, 2006). Usual performance dimensions for those competitive priorities are advanced processes, quality performance, effective labor, cross-training, low inventory and fast throughput times, and the ability to frequently change the product mix.

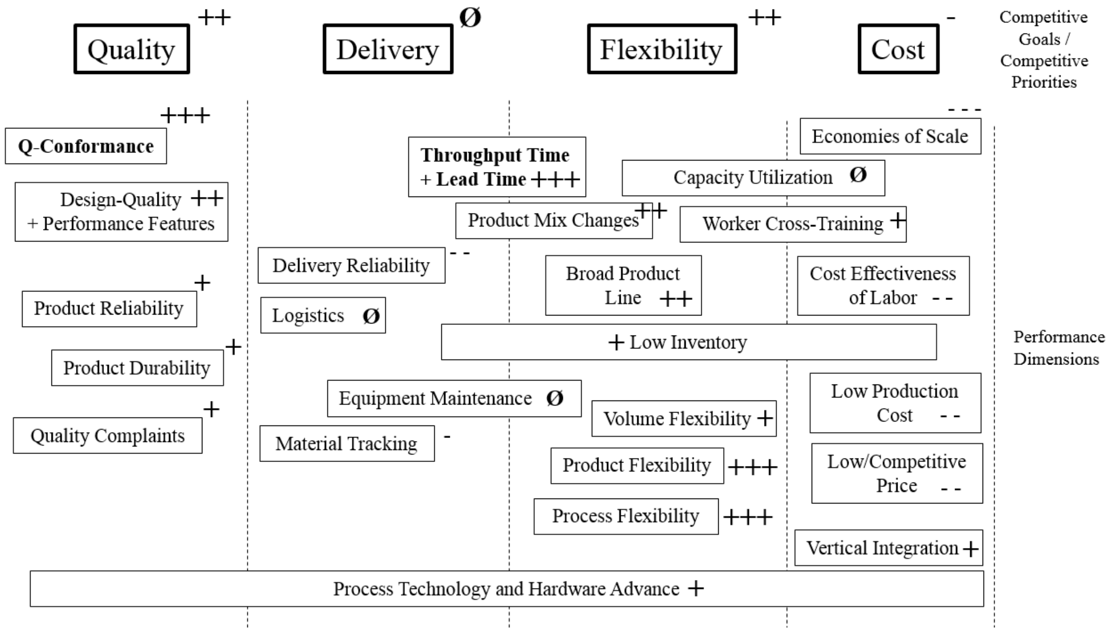


Figure 1: Competitive goals, priorities, and related performance dimensions of the BU. *Source: Own elaboration.*

2.1.2. Quantitative Aspects (Factors are Measurably Relevant)

Once the strategic aspects are clear the focus can shift towards a tactical level to analyze the highest potentials and to improve the most critical processes, which are measurably relevant for the firm. Cleveland et al. (1989) calculated production competence by multiplying the relative performance of each dimension (competitive capabilities) with its weight (competitive priority). Higher priorities get a higher weight and thus, are more important for the calculation of production competence of a firm. Firms with high OM capabilities in their respective competitive priorities have the highest production competence. The measurement of production competence was correlated with overall firm performance measures and a significant relationship emerged as shown in Cleveland et al. (1989) and Schmenner and Vastag (2006).

Using mathematical models, simulation analysis and other scientific methods can significantly improve decision making on a tactical level based on strategic decisions and macro-level theories (Luoma, 2016). The goal is to identify processes and policies that best fit strategic needs and macro-level theory based on a quantitative analysis about competitive priorities and critical processes.

2.1.3. Behavioral Aspects (Factors are Mutually Perceived to be Relevant)

The third and final aspect of the assessment of critical organizational capabilities and competitive priorities is based on the cognitive systems (experience, judgment, and understanding) of the management team, which is often overlooked when it comes to practical application of theories and models. Especially improvement projects, which require collaboration between different functional areas, can only be successful if identified capabilities are also mutually perceived and understood by the management team to be relevant for the production system. Individual managers might not understand the results of strategy development and quantitative analysis thoroughly and fail to identify their role and the contribution of their department to successfully complete an improvement project. This gap between the strategy, quantitative calculations, and understanding or judgment of individual managers and the whole management team should be closed so all sides can benefit when theoretical work is successfully applied at the shop floor.

A balanced score card (Kaplan and Norton, 1996), for example, can set strategically relevant targets, but the tactical question to select the most important improvement activities might not be as comprehensible for some people. Therefore, Dhir (2001) deliberately included judgments of the management team and compared them to his mathematical model to assess the decision problem holistically with the input of the management team. This increased the understanding of management regarding the model and the outcomes of the analysis, which positively influenced the acceptance and application of the results regarding the most important factors for a manufacturing system design. The integration of the cognitive system with the environmental system (or management judgments and scientific model) can ensure that everybody can accept the results and tactical decisions made by the whole management team.

Another problem arises when judgments and decisions are not transparently integrated into the decision task, which can cause conflict between people of different functional areas. Managers might be biased towards process improvement activities within their functional area and allocate more resources to their processes, which might not be the most beneficial for the overall production system. On the other hand, less motivated and engaged managers might want to shift attention away from their departments despite high potentials for improvement of the overall manufacturing system found in their processes. All these points can seriously endanger the successful application of theories, models, and calculations despite the correct identification of strategically relevant capabilities, priorities, policies, and processes.

2.2. The Role of Causal Ambiguity in Decision Making and Firm Performance

People in organizations need to make decisions based on strategic, quantitative, and behavioral aspects. However, manufacturing systems are characterized by increased complexity and dynamics, which makes it difficult for managers, or groups of managers, to fully understand the impact of their decisions on the overall system. Hammond et al. (1975) emphasize *causal ambiguity* as the reason why people have difficulties to acquire knowledge and understand relations within complex systems. They define causal ambiguity as a result of numerous probabilistic, interrelated, and interdependent variables, which make it impossible to find clear causal relationships among the variables to understand a complex system. Lippman and Rumelt (1982) describe causal ambiguity as the degree to which decision makers understand relationships between inputs and results, and the concept is also used in the Resource Based View (Barney, 1991), to characterize inimitable resources as a source of sustainable competitive advantages. As observed in the BU of the automotive OEM and based on an extensive literature review, causal ambiguity can emerge from three sources when managers make group decisions in complex systems with the help of scientific methods.

The first source was the inherent complexity of the manufacturing system due to, for example, dynamics, interconnectedness, or uncertainty, and how people dealt with these issues when making judgments and decisions. Mukherjee et al. (1998) mention detail complexity, or the presence of too many variables to comprehend problems in their entirety, and dynamic complexity, when distance and time make cause and effect difficult to establish. At the BU, managers of one department changed processes and were not aware of the effects their decisions had on the whole system or on other departments and, often, their solutions were not sustainable. For example, an improvement of the material tracking system was initiated by the logistics department, which was not entirely feasible for the manufacturing and quality departments. Many iterations were necessary to make the system work for all departments and the project was delayed without any benefits for the whole BU until the new processes were fully implemented. Despite substantial planning efforts of a cross-functional project team, nobody could fully conceptualize the entire system with all interfaces and dependencies. At the end, it turned out that manufacturing process improvements were necessary to streamline processes first to make them more suitable for the new material tracking system. Many resources were invested into the material tracking improvement project, while it could have been much more beneficial for the entire BU to improve manufacturing processes first. Wrong prioritization, in principle, could have been avoided by using models or experiments to predict the future state of a system given a set of input variables (Kelton, et al., 2015; Luoma, 2016). Then, cognitive processes such as learning and thinking can help people to make sense of causal relationships based on their experience and judgments (Hammond et al., 1975).

As production systems become more dynamic and complex, so do the scientific methods used to model and analyze those systems, and it becomes difficult for management to understand methods and results intuitively. This gap between management's understanding and the actual results of the scientific work might be significant and it was a second source of causal ambiguity. Dhir (2001) addressed this issue in the context of interaction between management and model builders, or anyone who is utilizing scientific methods in organizations for that matter. By including the management team and their individual judgments into the scientific method, the understanding of management can be increased, and sources of disagreement and misjudgments can be identified. Dietvorst et al. (2015) proved that people tend to avoid, or distrust results calculated with the help of models and algorithms and rely more on their own heuristics and judgments, although the results of the models were better on average. It was difficult for the researchers (the author and an external consulting company) to convey a lot of information, coming from countless hours of complex model building, to management is a short amount of time. This resulted in misunderstandings and managers often, especially in the early phases of the project, superseded results from the model with their own judgments and experiences, which are generally prone to many errors and biases (Bendoly et al., 2010).

The third source lies within the judgment patterns of various team members and in the way how they transferred tacit, complex, and interconnected knowledge within the team to ensure coinciding judgments to make cohesive group decisions. This problem of intra-firm causal ambiguity is one cause of silo-thinking, varying decision patterns, which are not synchronized towards a common strategy, and may lead to conflicts between people of different functional areas. Appelt et al. (2011) identify several measures of individual differences in judgment and decision making, like risk attitude, cognitive abilities, motivation, and personality, which can all be causally ambiguous for other group members. Some members of the management team are more motivated and willing to take risks, therefore drawing attention of improvement activities towards their departments, even when it might not be the most beneficial actions for the BU. People also understand complex problems differently and could decide to not fully disclose their real intentions based on their personality, for political reasons, or based on interpersonal conflicts. It might be hard to follow the real intentions of people and the underlying reasons why they go in a certain direction, which can increase causal ambiguity among team members and impede their ability to make good decisions as a team. Zollo and Winter (2002) and King (2007) measure intra-firm causal ambiguity and the development and transfer of dynamic capabilities to reduce this source of causal ambiguity. Knowledge transfer, joint decision making and the commitment to these decisions becomes increasingly difficult if a management team cannot, or is not willing to, consolidate their knowledge to reduce causal ambiguity for the whole group (Hammond et al., 1975). The human aspect of management, decision making, and collaboration has become increasingly important to bridge the gap between individual, subjective judgments and actions, and a common understanding about the environment, based on models and mathematical analysis of the system (Hämäläinen et al., 2013).

The problems of causal ambiguity within complex systems, scientific representation (models) of these systems, as well as causal ambiguity between the knowledge and judgments of individuals in a group, make it difficult for a management team to make sound decisions about major issues regarding the performance and improvement of a production system. These three sources lead to *linkage ambiguity* or, in other words, differences between perceived and measured resource-performance linkages that are difficult to resolve. Beleska-Spasova and Glaister (2013) analyze linkage ambiguity in export management by using structural equation modeling and a questionnaire to assess differences between perceived and measured importance of different factors on export performance observed for British export managers. Their study analyses intra-firm causal ambiguity and ways to reduce it to increase firm performance. In general, causal ambiguity has been a focus in strategic management to assess *inter-firm* causal ambiguity (Powell et al., 2006; Reed and DeFillippi, 1990) in the context of the Resource Based View - RBV (Barney, 1991). Causal ambiguity can lead to difficulties to understand how complex and valuable resources are used efficiently and effectively and thus, can be utilized to protect resources against imitation by competitors. This results in a *causal ambiguity paradox* saying that inter-firm causal ambiguity increases firm performance because it makes resources harder to imitate by competitors, but it also makes it harder for the focal firm’s management to use these resources, therefore reducing firm performance (Lippman and Rumelt, 1982). King and Zeithaml (2001) and King

(2007) explore these phenomena and find that the positive effect of efficient and effective usage of resources within the firm outweighs the detriments of imitation between firms. Therefore, firms should strive to reduce causal ambiguity in general, even if it results in facilitated imitability for its competitors, for example, by hiring people from high-performance firms to copy their processes. However, a barrier for imitation still exists if a company is capable to collectively control and decrease intra-firm causal ambiguity as a result of efficient usage of internally developed decision support systems.

The purpose of this research is also to find ways to facilitate common understanding of different decision makers within the BU. This is done by reducing linkage ambiguity from all three sources to increase the quality of holistic decisions and the commitment of the management team. To achieve these goals, it is important not only to understand and analyze the dynamics of the environmental system (production system, supply chain, etc.), but also the cognitive system (judgment patterns) of the decision makers, because misalignment between the scientific methods and the organizational decision-making processes can destroy the results on both sides (Luoma, 2016). Therefore, a behavioral approach has been selected to develop a decision framework based on recent trends in behavioral operations (Bendoly et al., 2010) to integrate classic OM methods with behavioral analyses.

2.3. Causal Ambiguity and Behavioral Operations

Causal ambiguity is aggravating precise decision making in complex and dynamic environments and forces decision makers to rely on their judgments to assess the situation and make informed decisions. As a result, behavioral issues emerge which further increase the difficulty to make good decisions. Zhao et al. (2013) emphasize the fact that consumers, workers, and managers are all human actors in operations systems and supply chains and are subject to judgment and decision biases when facing uncertainty and complexity. This requires the development of alternative OM models that consider realistic human behaviors and judgments through experimental research. Gino and Pisano (2008) also mention that a behavioral perspective can lead to improved identification of appropriate management interventions and is a main area for research in behavioral operations (BO).

Bendoly et al. (2010) provide an excellent overview of four of the main bodies of knowledge in behavioral operations and the issues that arise in relation to them. The field of *cognitive psychology* analyzes imperfections in judgment and decision making of individuals, like heuristics and biases. Overconfidence and algorithm aversion (Dietvorst et al., 2015) are only two examples why people fail to make accurate decisions due to overestimating their own, or human ability in general, to plan and forecast in complex situations. To deal with these issues it is important to aid decision makers with transparent, understandable und applicable methods that enable them to make more accurate and objective decisions. *Social psychology* deals with the underlying forces that motivate decision makers to make the right decisions, like goals and feedback. Specific, measurable, and meaningful goals and appropriate, timely feedback can have a significant impact on performance of a team and the system in general. Linderman et al. (2003) found that goal specification has a severe impact on alignment and performance in Six Sigma projects. Strategic alignment, focused on competitive priorities and a clear action proposal to achieve certain goals, are critical to deal with issues coming from this field.

The third body is *group dynamics* and covers issues in group decision making, like group think and the Abilene Paradox. Sometimes groups can make decisions that are not mutually accepted by all members initially, but people shift their preferences to reflect the consensus of the group, which can cause conflicts when it comes to implementation. Even more conflict can arise from the Abilene Paradox (Harvey, 1974) when people do not shift their preferences, but their decisions still reflect the group consensus because of group pressure. These conflicts can result in a breakdown spiral where poor performance results in internal and external blame, which increases the pressure on the group, intensifying group think and the Abilene Paradox. This reduces the performance of the group even more, and more conflicts and blame cause even worse decisions being made by the group. Those decisions are not mutually acceptable for all members of the group, however, a visual representation of judgments of group members can help to shed light on deviations in judgments and individual preferences. This can reduce group think and the Abilene Paradox because deviating preferences are immediately visible for other group members and conflicts can be prevented by avoiding unintentional changes of preferences due to group pressure.

The final field is *system dynamics* and deals with the complexity in dynamic contexts, like nonlinearities, time delays and feedback processes. Complex and dynamic systems result in causal ambiguity and systematic dysfunctional behavior (Sterman, 1989) due to misperceptions of feedback structure and feedback dynamics. Separation of cause and effect due to time delays can make it difficult for decision makers to understand the feedback structure within the system and they can misjudge the effects their decision have on the overall system. Also, the magnitude of feedback (feedback dynamics, like accumulation or growth) can often be misinterpreted by decision makers and the final effect might be drastically underestimated. Here, simulation can be specifically helpful to increase the understanding and awareness of decision makers about the causalities and feedback loops within complex and dynamic systems (Bendoly et al., 2010).

Causal ambiguity forces people to exercise their judgment which, in turn, is prone to behavioral issues of people making decisions in difficult environments. The argument is that relevant applied research in behavioral operations should deploy methodologies which reduce most of the behavioral issues described in the literature. Transparency is needed to unveil sources of disagreement and potential conflicts to avoid disorders in group decision making. A clearly defined and articulated research methodology is needed, and future users should be included in the computations and research to increase their knowledge and prevent them from falling back into their habits of using heuristics and biases. Cause-and-effect relationships towards specific goals should be clearly articulated to make sure that people can follow the right path towards goal achievement based on the company’s competitive priorities. Without a suitable support system to deal with imperfect group decision making, bounded rationality, and causal ambiguity in dynamic systems it becomes increasingly difficult to make precise decisions about complex issues.

3. Research Question and Methodology

Causal ambiguity and behavioral issues of operations management result in increased difficulty to make complex decisions. New systems are needed to support managers making these decisions, considering all possible inputs available to them, and to researchers conducting in-depth empirical studies. This chapter deals with the integration of behavioral analyses and OM/OR tools to develop decision frameworks for the BU to select the most efficient improvement projects and design choices. It defines the research problem and the desired outcomes in the first part and the proposed methods to achieve these goals in de second part. The topics and methodologies of both papers are outlined to give an overview about the application and the desired contributions of both.

3.1. Research Problem and Objectives

It is critical for any company to adapt to changing internal and external factors through efficient and effective improvement of key processes. Companies can use a variety of improvement methods as frameworks for process improvement to increase performance of their production systems. Total Quality Management (TQM) is one of the oldest and most known management systems for quality improvement and integrates a holistic, quality-focused philosophy from product development, to manufacturing, until customer service, where quality should constantly be improved; see Martínez-Lorente et al. (1998) for an overview and origins of the term. It is described as an integrated management philosophy that builds on three principles: customer focus, continual improvement, and teamwork (Dean and Bowen, 1994). The two most common modern methods that were developed based on the TQM philosophy are Six Sigma (Hahn, et al., 2000), and Kaizen / lean thinking / lean management (TAhB Academy, 2016). Six Sigma was introduced by Motorola and is a customer-focused effort to reduce defect rates and process variability to achieve a six-sigma level of process stability, meaning only 3.4 defects per million opportunities (Kumar and Gupta, 1993). Lean management is used by Toyota and is focused on constant reduction of "waste" (non-value adding tasks) in processes, therefore, resulting in an increase in efficiency and productivity through "lean" manufacturing systems based on just-in-time production (Shah and Ward, 2007).

Continual process improvement activities are at the heart of the previously described improvement methodologies. The selection of improvement projects and activities has been a major focus in the literature and is key for the successful application of improvement methods (Zantek et al., 2002; Kumar et al., 2008; Li and Rajagopalan, 2008; Chakravorty, 2009; Büyüközkan and Öztürkcan, 2010; Filho and Uzsoy, 2014). The problem of selecting the optimal set of improvement activities with limited resources is well established in the literature. However, multi-disciplinary approaches addressing the integration of hard and soft OM/OR are not very prominent and most apply either the one or the other. In this thesis this gap is filled by adding new methodologies from other disciplines to the tool kit of OM/OR. The call to conduct more research regarding the "soft issues" of OM/OR is answered without neglecting the hard facts and quantitative computations needed to ensure robust results.

This work introduces integrated concepts to help management with improvement project selection and decision making for global projects under causal ambiguity. The applied methodologies combine qualitative and quantitative factors for the selection of continual improvement activities in the BU. They are applicable for all improvement methods that use continual improvement cycles (Six Sigma, Lean, TOC). They also tie the selection process to the unit's strategy and competitive priorities to achieve a consistent framework from top-level theory to actual application on the shop floor. The goal is to apply new concepts to reduce the previously mentioned issues of causal ambiguity and complexity. Support systems are introduced to aid decision makers in the complex production system of the BU within the two exploratory case studies of the research papers. Their applicability was studied within the BU to ultimately help management to improve the overall design of the production system and its critical processes.

3.2. Design and Methodology of the Case Studies

Both case studies include a behavioral and quantitative aspect to deal with the previously mentioned issues of causal ambiguity. Both use inputs of the experts of the system to include their opinions, expertise, and judgments for scientific analyses. They are visualizing the results of cognitive processes of the experts within the BU and create new inputs for decision problems they aim to address. The methodologies were selected to deal with difficulties resulting from causal ambiguity as mentioned in chapter two. The first methodology is a lens model, a tool of Social Judgment Theory (SJT), visualizing human judgment to compare it against quantitative analyses of an environmental system in which these judgments are made. The second methodology is concept mapping to create a visual interpretation of a subject matter based on the inputs of an expert team to help them categorize and visualize areas of improvement in a complex system.

3.2.1. Social Judgement Theory and The Lens Model

Social Judgment Theory (SJT) is used to understand human judgment within an ecological context (Cooksey, 1996), or to analyze attitude changes of individuals based on judgmental processes and effects (O'Keefe, 2016). The first point emphasizes the representation and understanding of individual decision patterns in various scenarios and judgment tasks to better describe the outcome of a judgment processes within a given context. The latter focuses more on influencing decision patterns and individual attitudes using persuasive communication to change positions towards various criteria. However, both focus on the cognitive processes, like experts understanding of complex systems, or the level of involvement and attitude towards certain questions, that determine individual judgments and how individuals perceive possible solutions to decision problems.

Most decision problems include many different input factors (or "cues") with complex probabilistic relationships, which make it difficult to assess causalities in the system and to assign weights or ranks to various solutions for specific problems. SJT is analyzing differences between causal relationships within the environment based on several input factors and how decision makers are using those factors as cues for their judgments. These causally ambiguous relationships are at the center of individual judgments and are highly dependent upon the judge's cognitive processes (Hammond et al., 1975). SJT aims to describe the outcome of cognitive processes when the decision makers are facing complex situations and causal ambiguity with the results pointing outwards from an individual. It is not particularly concerned with inwards pointing stimuli, coming from the environment, but is rather focused on the cognitive processes and the results of the judgments in relation to the environment ("what really is" compared to "what a person thinks there is"). Therefore, both, the environment, as well as the judges can (and should) be assessed in the same way based on the principle of parallel concepts (Brunswik,1952; Brunswik, 1956). Data can be analyzed with scientific models and calculations on the *surface* for the environmental system, and in the same way inferred inputs (cues) can be analyzed in the *depth* of the user's cognitive system. This distinction between surface and depth, and given and inferred, is critical for SJT, because it lays the foundation for the study of the differences between them. These differences lie hidden in *zones of ambiguity*, where causal ambiguity makes it impossible to simply analyze what is inside the black box. However, the relation between the impact of the given inputs and the utilization of the inferred inputs, as perceived by the individual, can be assessed using the lens model.

The lens model is based on the principle of parallel concepts (Brunswik, 1956) and describes the differences and similarities of an ecological system (production system) and the cognitive system (judgments) of the decision maker with the same types of constructs. It represents causally ambiguous processes on both sides in the same way and can therefore be used to study and analyze cognitive systems of individuals in relation to the environmental system. These processes describe the mediation of uncertain information within the environment through various observable input indicators (cues) and the usage of those cues by the management to achieve reasonably accurate inference about a matter of interest (Hammond, 2007). The results can be used by a management team to make more informed and cohesive decisions for complex problems. The method itself facilitates cooperation between the management team and model builders, which is also one reason why it is preferred over other methods and theories (Dhir, 2001). These levels of transparency and involvement also facilitate the creation of a well-defined and mutually acceptable action proposal, which should be the goal of any OM/OR intervention (White, 2016).

The focus of this study is to use the lens model approach to expand production competence of the production system based on effective and efficient implementation of jointly made decisions to improve operations based on a continuous improvement process (CIP). Extending organizational capabilities without additional investments into capacity is more efficient and can result in sustainable competitive advantages (Vastag, 2000; Ryall, 2009), especially for small-volume production systems with less available resources. To allocate the required capacity to successfully execute complex improvement activities, it is often necessary to build teams of different experts to focus on a single major project. This means that it is important to find improvement projects with the highest potential benefits for the production system (Büyüközkan and Öztürkcan, 2010; Filho and Uzsoy, 2014), as well as the right team composition, methodology and implementation plan to successfully complete the project.

The lens model can be used to describe the outcome of cognitive processes and how judges cope with causal ambiguity in decision tasks based on their preferences, experience, attitude, and the inferred variables. It can also equally represent the outcome of a scientific analysis based on some given variables, like the results of a simulation analysis. Figure 2 depicts the application of the lens model methodology in the first research paper. Throughput times are analyzed as the criterion (dependent variable) with a regression analysis based on data coming from a discrete event simulation on the left side of the lens model. The impact of different cues, or different improvement activities, is analyzed to define the most important activities to reach previously defined competitive goals of the BU. On the other side of the lens model, the same cues are analyzed within the judgment analysis to create the same type of information about the cognitive systems of all judges to be compared with the results of the regression analysis. The differences and similarities between the results are then analyzed to create an action plan based on the information created on both sides of the model.

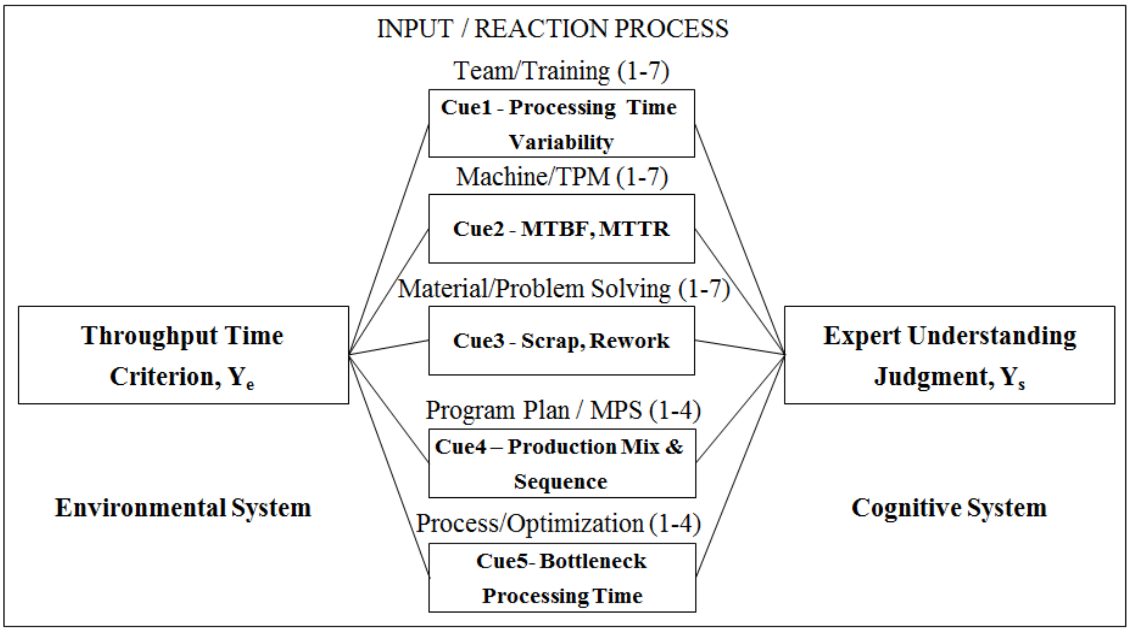


Figure 2: Lens model application with defined criterion and cues.
Source: Own elaboration.

3.2.2. Concept Mapping and Structured Conceptualization

Trochim (1989) defines the methodology as: “Concept mapping is a structured process, focused on a topic or construct of interest, involving input from multiple participants, that produces an interpretable pictorial view of their ideas and concepts and how these are interrelated”. This methodology has a similar characteristic of inputs and outputs as those used in the lens model. It takes inputs from the cognitive systems of a team of experts and, through quantitative computations, visualizes results in an intuitive way to make them more usable and understandable for practitioners. The output of the analysis, one or more concept maps, is a structured, labelled, and weighted set of clusters representing the conceptual domain of a problem.

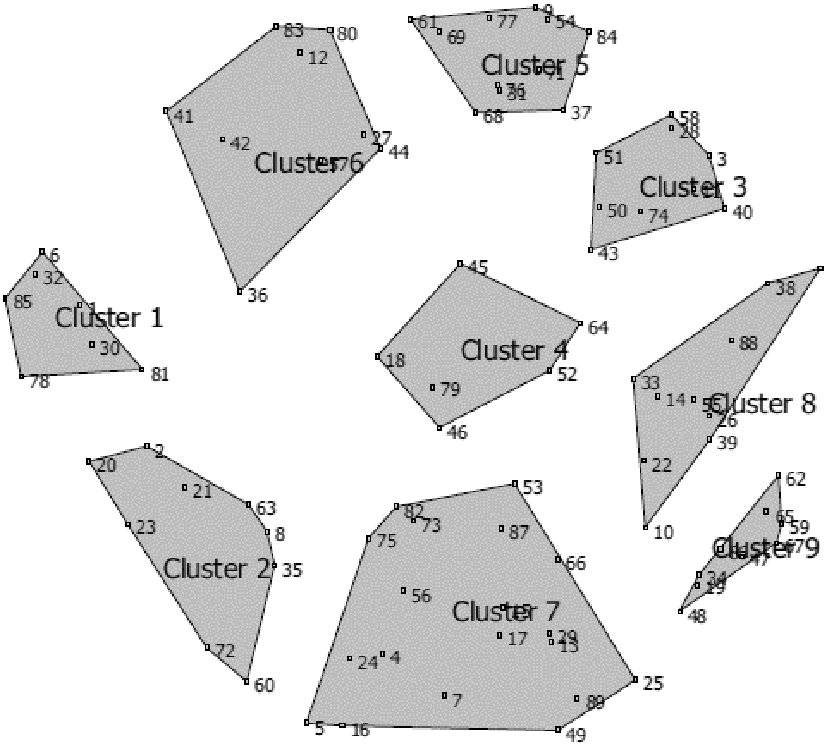


Figure 3: Illustrative example of a hypothetical concept map with 89 statements.
Source: Trochim and McLinden (2017).

Figure 3 depicts a hypothetical concept map with 89 statements as an illustrative example (Trochim and McLinden, 2017). Statements that represent the conceptual domain of a construct of interest are gathered by the participants to define the scope of the analysis (usually through brainstorming or similar techniques). These statements are then grouped by the participants to select similar statements to form groups of related points. A point cloud is created where the distance of statements/points of related groups is shorter compared to others that were not that frequently grouped together by the participants. Clusters within the point map are created to label accumulations of points in a meaningful way to be able to interpret the map. Points, and later clusters of points, can then be weighted by the participants (e.g. Likert-Scale) to find the most important clusters to be improved as seen by the participants and experts of the production system.

Structured conceptualization is a way to transform tacit knowledge of individuals about a complex and causally ambiguous system into usable information for the improvement of this system. This was done by analyzing quality issues of the production system in the case study of the second paper to address the second competitive priority of the BU – quality and quality conformance. The expert team of the BU named 41 statements related to problems that affected quality performance of the production system with different connections and relations between those problems. A concept map was created to find clusters of related problems to define improvement activities in a more efficient and effective way using a structured approach based on tacit knowledge of the team of experts. The results were then used to create a causal loop diagram to assess causal relationships between points and clusters. Based on Trochim (1989), one of the most important and difficult steps in planning is the initial conceptualization, which ultimately determines the success of all following steps in a project. The idea of the methodology applied in the second research paper is the utilization of the created concept map as an input for further causal analysis (e.g. causal loop diagram, fishbone diagram, etc.). This gives a tailored solution for specific problems and facilitates decision making based on better and more detailed understanding of complex systems. Similar to the lens model application, an action plan was developed based on the results of the concept mapping methodology and the causal loop diagram after calculating the weighs and relative importance of each cluster, and analyzing casual relationships between points and clusters, respectively. The BU could improve clusters of problems with specific solutions to increase quality performance of the production system with the help of the information created in the case study of the second paper.

4. Theoretical and Practical Results and Implications

The last chapter deals with the development of an integrated action proposal for the management of the BU to summarize the results of the research papers. It summarizes the lens model approach and compares it to a traditional approach of managerial decision making and OM interventions. The action proposal of the concept mapping study is added to the decision framework of the lens model analysis to create a holistic picture for resource allocation and improvement project selection. The goal is to increase the alignment and commitment of the management team to ultimately facilitate practical application of the results generated by the analyses. From a theoretical point, the inter-disciplinary and multi-level approach is described in more detail with a focus on how this approach can be beneficial for applied research and theory development in the future.

4.1. Development of an Integrated Action Proposal

Action proposals support a causal link between a course of action and its consequences and can be used to justify how certain solutions, based on theoretical research and models, lead to an anticipated and desired outcome on the process-level of a production system (White, 2016). Friend and Hickling (2005) point out that OR-interventions and models rarely solve organizational problems directly and if they were to be relevant, useful and meaningful for practitioners, they need to be embedded in action proposals, or commitment packages, as they call it. Therefore, this method can be used, in combination with the lens model methodology, to reduce causal ambiguity between the management's understanding and the design, calculations and results of the model itself (Ladinig et al., 2020).

A commitment package, as developed by Friend and Hickling (2005), is an action proposal that defines a set of immediate actions and future decisions to achieve incremental progress in a continuous planning process. It defines what actions must be taken immediately, or if more exploration is necessary, based on time and uncertainty of the decision areas. This means that some decisions should only be made if uncertainty is below a certain level and if there is not enough time for further exploration. It also leaves future decision space for deferred choices and contingency planning if there is still enough time to analyze further choices or to reduce uncertainty by doing more research. Note, that this is only one isolated concept out of the whole framework to assist decision makers in a continuous planning process but is an excellent tool to summarize the results of the lens model methodology. It can also be used synergistically with continuous improvement cycles based on Six Sigma or Lean and is designed to work in environments with high uncertainty and causal ambiguity where judgments are needed to make complex decisions (Ladinig et al., 2020).

4.1.1. Results of the Lens Model Analysis and Action Proposal

The results of the lens model analysis include all three previously defined aspects of the identification of competitive priorities and processes. The strategic aspects to define the criterion (manufacturing throughput time) and the cues (Figure 2) were considered based on the Theory of Production Competence and were important performance indicators for the BU. The simulation and regression analysis dealt with quantitative aspects of identifying competitive priorities and improvement choices. Finally, behavioral aspects were considered as well by using judgment analysis to include the management team during the research project and their experiences as an input for a holistic analysis. The ladder graph of Figure 4 shows the results of both sides of the lens model analysis. The indifference of the management team can be seen on the right side and they could not mutually agree on a single-most important cue with a significant margin. The simulation on the other hand generated clear results to focus on a specific factor with the highest potential for improvement of throughput time (Ladinig et al., 2020).

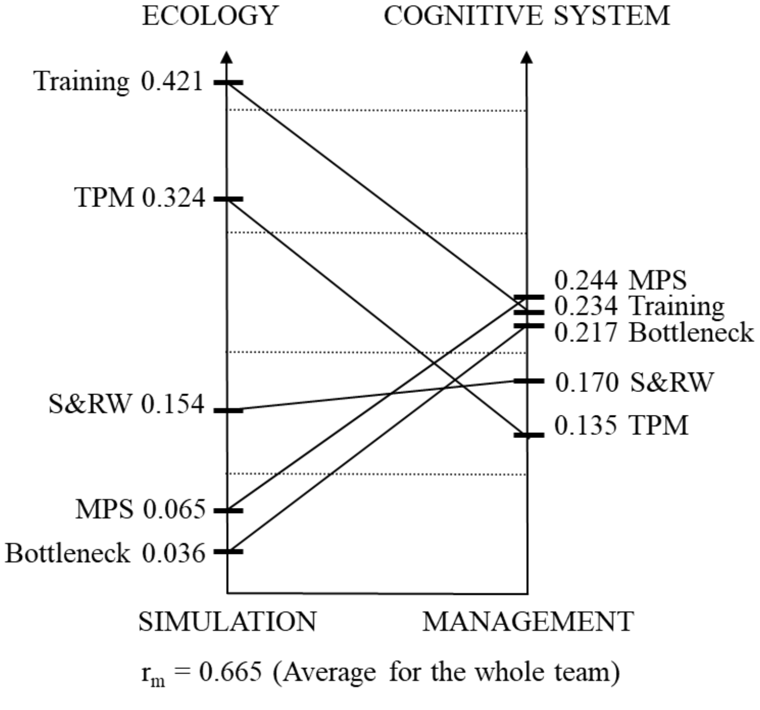
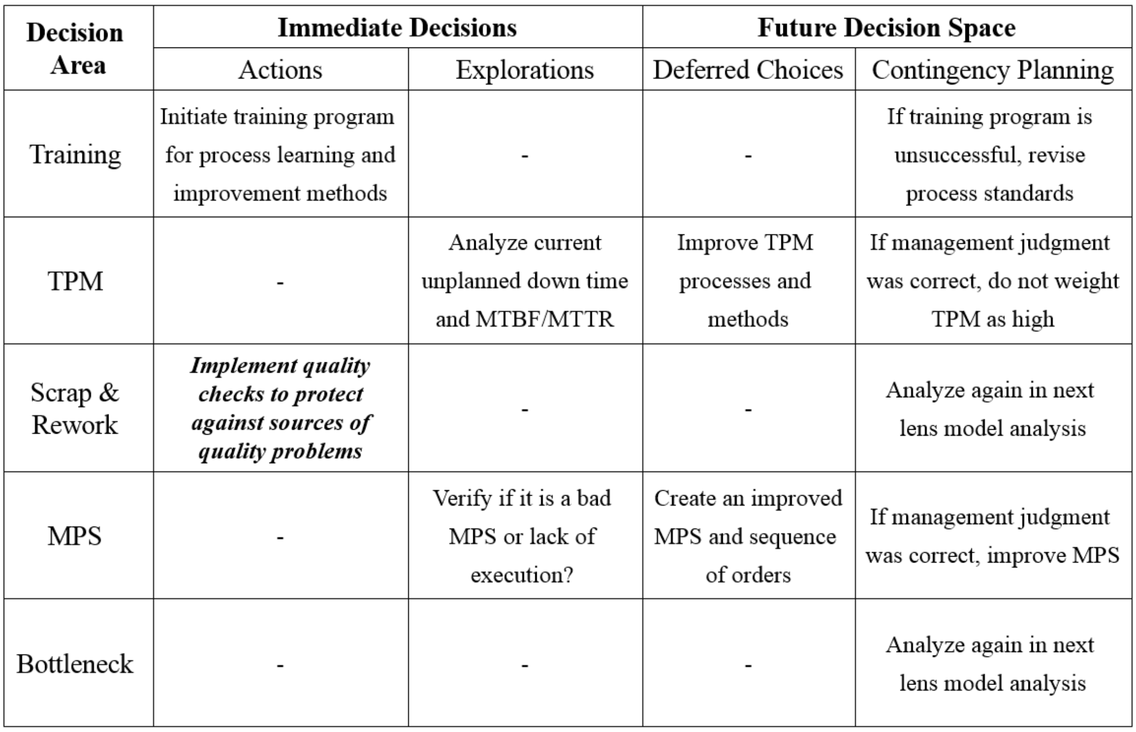


Figure 4: Ladder graph from de lens model analysis depicting the results of both sides.
Source: Ladinig et al. (2020).

By combining the results of both sides, it is possible to create an action proposal including the results of both analyses coming from the simulation and the management team as seen in Figure 5. An immediate action that should be taken based on this research is to initiate a training program to improve manual processes and to reduce processing variability. Stable and improved processing times had to be the number one priority of the BU and it was implemented through an extensive production preparation process where all manual processes were trained, improved, and standardized. Also, a new internal audit system should be created to confirm adherence to the new standards by the workers and test the new standards to achieve the desired effects. This allows the management team to continually revise standards if necessary and gives them a better overview about the desired and actual performance of the workforce based on training effects for the new processes. This continual improvement cycle for training, standardization and process improvement was the new main priority for the BU and a clear focus for resource allocation (Ladinig et al. 2020).



Decision Area	**Immediate Decisions**		**Future Decision Space**	
	Actions	Explorations	Deferred Choices	Contingency Planning
Training	Initiate training program for process learning and improvement methods	-	-	If training program is unsuccessful, revise process standards
TPM	-	Analyze current unplanned down time and MTBF/MTTR	Improve TPM processes and methods	If management judgment was correct, do not weight TPM as high
Scrap & Rework	***Implement quality checks to protect against sources of quality problems***	-	-	Analyze again in next lens model analysis
MPS	-	Verify if it is a bad MPS or lack of execution?	Create an improved MPS and sequence of orders	If management judgment was correct, improve MPS
Bottleneck	-	-	-	Analyze again in next lens model analysis

Figure 5: Commitment package, or action proposal as a result of the lens model analysis. *Source: Ladinig et al. (2020).*

Allocation of resources into improvement of TPM and master production scheduling (MPS), on the other hand, was deferred and required further investigation, data collection and analysis. Those were the two processes were the management team deviated from the DES and at least one side valued it as a top-priority and the other mostly neglected it. This makes both processes good candidates for further explorations and differed choices in Figure 5, as it is obvious that no consensual decision could be made based on the lens model analysis. In this case the continual improvement cycle starts again with a “plan” or “define” stage in the future and no resources should be deployed without a clear understanding about the potential benefits of those processes. Also, no further resources were assigned to the bottleneck optimization process since it was the lowest ranked of the top-group for the management team and the lowest overall in the DES. Contrary to the Theory of Constraints, there was no immediate concern to closely monitor and improve the bottleneck until other processes had been improved (Ladinig et al. 2020). The action defined for scrap and rework led to the second paper and case study.

4.1.2. Results of the Concept Mapping Analysis and Action Proposal

The concept map (Figure 6) combines similar problems into clusters of statements (ranked by their perceived importance) and shows connections and importance ratings. This visualization method is based on expert knowledge and aims to reduce causal ambiguity in decision making regarding quality management (Ladinig and Vastag, 2020).

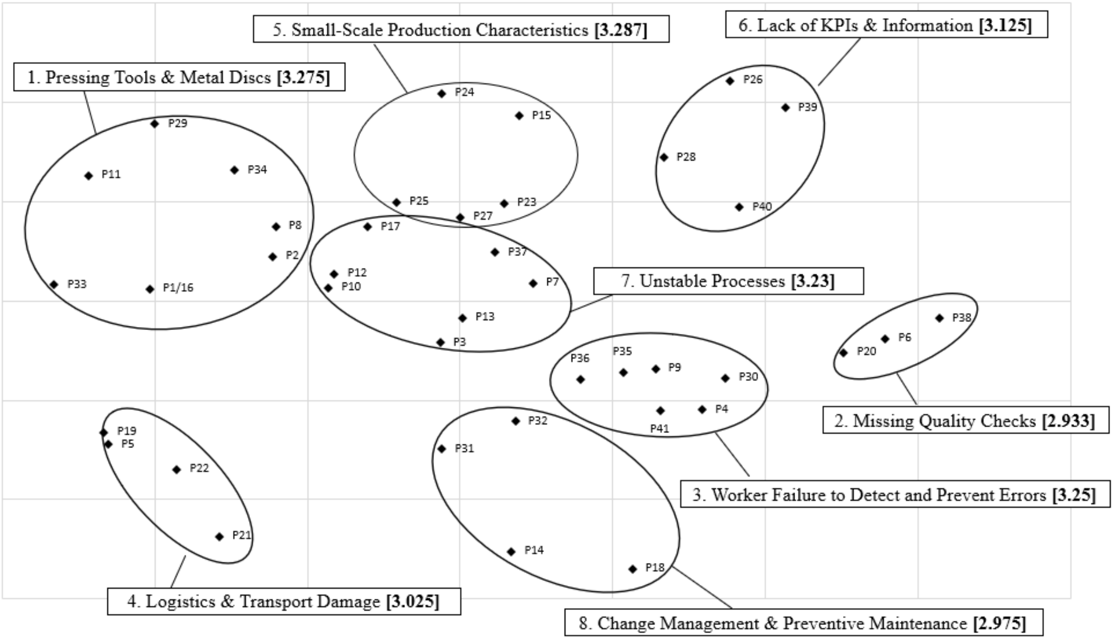
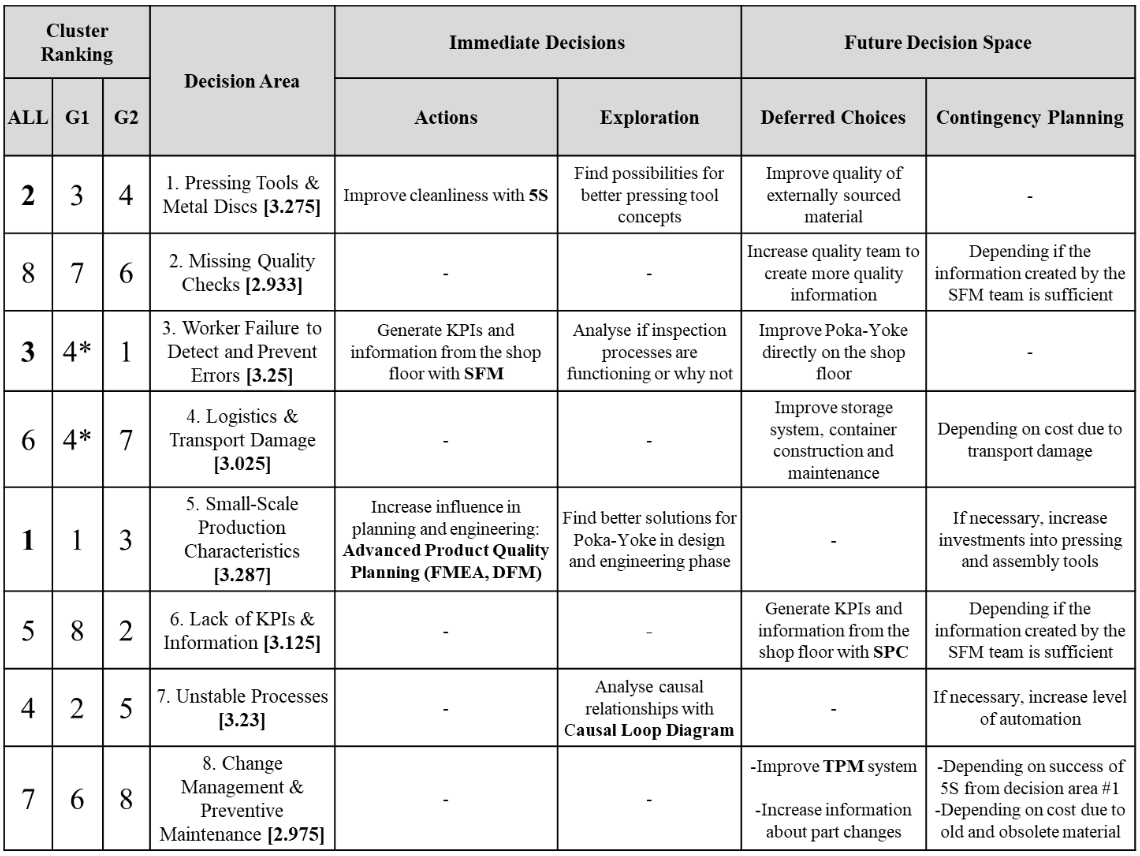


Figure 6: Concept map of quality issues with eight clusters.
Source: Ladinig and Vastag (2020).

Product quality in the production of premium sports cars is of utmost importance and has been identified as a competitive priority of the production system, therefore complying with the strategic aspect of the identification of critical process improvement activities. The structured conceptualization approach, two-dimensional visualization, and weighting of the results based on mathematical computations ensures that the requirements for the quantitative aspects are met as well. By using brainstorming to define the conceptual domain of a problem, with inputs coming from the experts of the production system, it is assured that the behavioral aspects are considered as well to fulfill all requirements for the identification of competitive priorities.



Cluster Ranking			**Decision Area**	**Immediate Decisions**		**Future Decision Space**	
ALL	**G1**	**G2**		**Actions**	**Exploration**	**Deferred Choices**	**Contingency Planning**
2	3	4	1. Pressing Tools & Metal Discs **[3.275]**	Improve cleanliness with **5S**	Find possibilities for better pressing tool concepts	Improve quality of externally sourced material	-
8	7	6	2. Missing Quality Checks **[2.933]**	-	-	Increase quality team to create more quality information	Depending if the information created by the SFM team is sufficient
3	4*	1	3. Worker Failure to Detect and Prevent Errors **[3.25]**	Generate KPIs and information from the shop floor with **SFM**	Analyse if inspection processes are functioning or why not	Improve Poka-Yoke directly on the shop floor	-
6	4*	7	4. Logistics & Transport Damage **[3.025]**	-	-	Improve storage system, container construction and maintenance	Depending on cost due to transport damage
1	1	3	5. Small-Scale Production Characteristics **[3.287]**	Increase influence in planning and engineering: **Advanced Product Quality Planning (FMEA, DFM)**	Find better solutions for Poka-Yoke in design and engineering phase	-	If necessary, increase investments into pressing and assembly tools
5	8	2	6. Lack of KPIs & Information **[3.125]**	-	-	Generate KPIs and information from the shop floor with **SPC**	Depending if the information created by the SFM team is sufficient
4	2	5	7. Unstable Processes **[3.23]**	-	Analyse causal relationships with **Causal Loop Diagram**	-	If necessary, increase level of automation
7	6	8	8. Change Management & Preventive Maintenance **[2.975]**	-	-	-Improve **TPM** system -Increase information about part changes	-Depending on success of 5S from decision area #1 -Depending on cost due to old and obsolete material

Figure 7: Commitment package as a result of the concept mapping analysis.
Source: Ladinig and Vastag (2020).

Several tools and methods of quality management have been defined based on the results of the concept mapping analysis to be implemented at the business unit. The 5S methodology (“Sort, Set/Straighten, Sweep/Shine, Standardize, Sustain” a method of Lean Manufacturing to improve workspace conditions and cleanliness) should be implemented, especially for metal disc and pressing tools for cluster one (second-highest rating in Figure 7, with 3.275 out of 5). Advanced Product Quality Planning (APQP) should be implemented to increase the influence of the production system regarding product manufacturability and error prevention for specific production processes. This was the outcome of the analysis for the highest-rated cluster (cluster one) to deal with issues related to complex small-scale production factors. The final tool to be implemented at the business unit was Shop Floor Management (SFM) to address issues of the third-ranked cluster containing problems due to worker failure to detect and prevent errors (Ladinig and Vastag, 2020).

This means that, for the first improvement cycle within the BU, two immediate decisions for specific sets of actions were made to improve two critical processes - one for each competitive priority. Resources were allocated accordingly, with the majority going into the execution of the immediate action plans, and the rest could be invested into further analysis of the other important factors that required more information. This ensured efficient and effective selection of improvement projects based on the strategy of the BU, measurable indicators, and judgments of management.

4.2. Increasing Alignment and Commitment of the Management Team

The difference between regular approaches to translate strategy into the right action, by using a balanced score card (Kaplan and Norton, 1996), for example, and the lens model approach is shown in Figure 8. On the left side, the strategy and competitive priorities are developed top down by the top-management of the BU and relayed to other departments to take the necessary actions to reach the BU's goals. This is countered, however, by specific factors from each department that might cause conflicts when it comes to making coherent and mutually acceptable policies. Logistics, production, or quality departments (to name a few; many other departments could also play an important role) could have conflicting individual goals, which they might prioritize higher than overall BU goals. Tools and methods are needed to reduce the principal-agent conflict, like appraisal systems, or a balanced score card, to make people act in the best interest of the BU. Additionally, there is causal ambiguity and bounded rationality, which makes it even harder to make the right decision to reach BU goals based on its competitive priorities.

Support and additional information for decision makers can be spread throughout the organization on different organizational levels as indicated with the arrows for “consulting” and “simulation” in Figure 8. Managers with different sources of information can use it to pursue varying goals and make decisions based on a different understanding. Without transparency and mutual understanding, it becomes exceedingly difficult to make concise group decisions, especially when considering causal ambiguity and bounded rationality. In this case, department managers make ill-advised decisions based on biases and their own heuristics. Furthermore, they do not trust sources of information coming from analyses and calculations from other departments, because of algorithm aversion, as they did not participate in any analysis. Sources of disagreement cannot be identified, and conflicts arise because of decisions that are not mutually acceptable and targeted towards reaching common BU goals. The top-management of the business unit, therefore, cannot be sure if decision makers of all departments are aligned towards the overall strategy as it was the case in this research and, for example, in King and Zeithaml (2001).

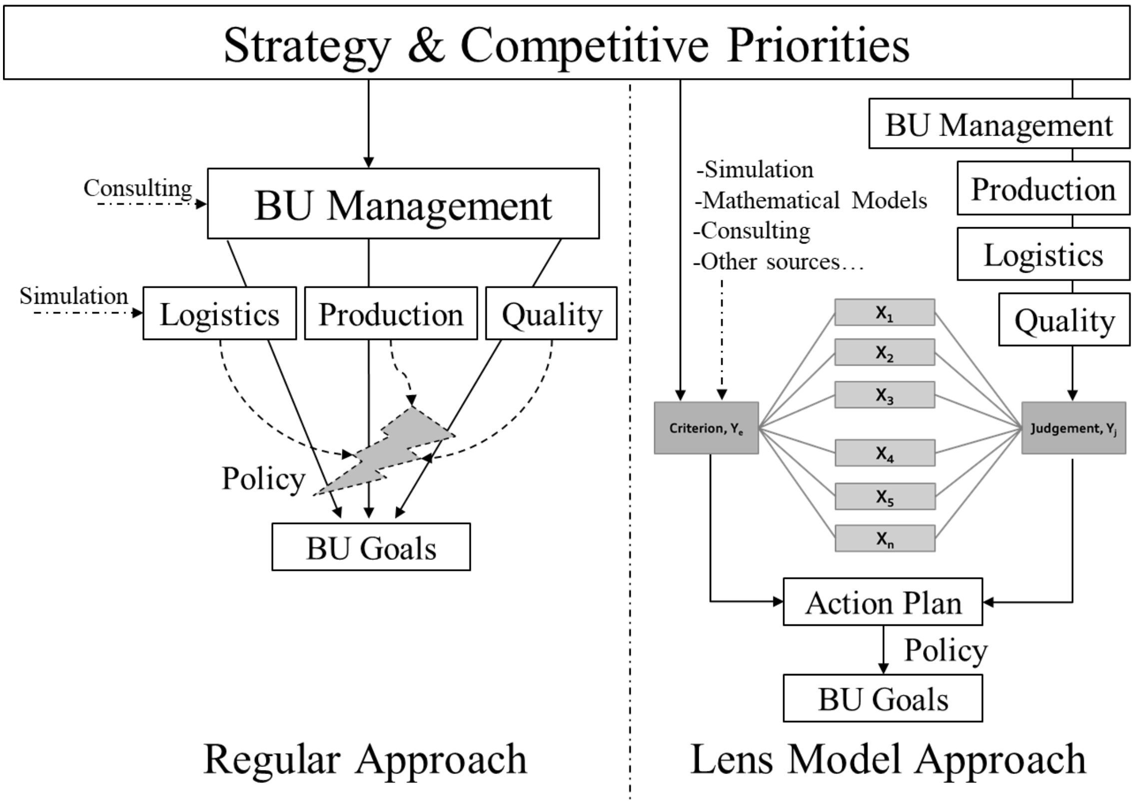


Figure 8: Comparison between regular policy making and lens model approach.
Source: Own elaboration.

The right side of Figure 8 depicts the policy-making process using the lens model methodology and starts with strategy and competitive priorities on top as well. In this case, however, all departments and the top-management of the BU participate in the judgment analysis where their preferences are made transparent and relatable for the rest of the group. This integration of judgments and the involvement of the management team ensures better understanding towards a matter of interest, therefore reducing the likelihood of conflicts and misunderstanding within the group. Also, causal ambiguity is reduced due to the left side of the lens model, giving essential information about the environment based on various methods, tools and calculations from consultants, researchers, or other sources of additional information. This also ensures a proper interface between the scientific work of researchers and application by practitioners as the model requires an analysis of the environmental side to be compared to the judgments of the management team. This integration also facilitates the reduction of the only remaining source of causal ambiguity (see Chapter 2.1.3), namely management's understanding of the methodology and results of the scientific work.

The clear interface for the practical application of scientific work is a crucial advantage of the lens model and facilitates implementation of scientific methods throughout the organization. It also increases the relevance of OR/OM interventions due to the clear input (environmental analysis on the left side of the lens model based on various research methodologies) and output (action plan). Therefore, it is to be hoped that it can also increase the value and relevance of various other OM/OR applications in completely different settings.

4.3. Multi-Level and Inter-Disciplinary Connection of Theories

The application of an action proposal can be facilitated by a clear connection of theories over different organizational levels as shown in Figure 9. Three links are important to make macro-level theories (like the Theory of Production Competence) usable for line managers who ultimately make the operative decisions to improve certain processes. When such links are strengthened, it becomes easier for management to align with the overall strategy of the company and to follow recommendation from scientific analyses based on theory.

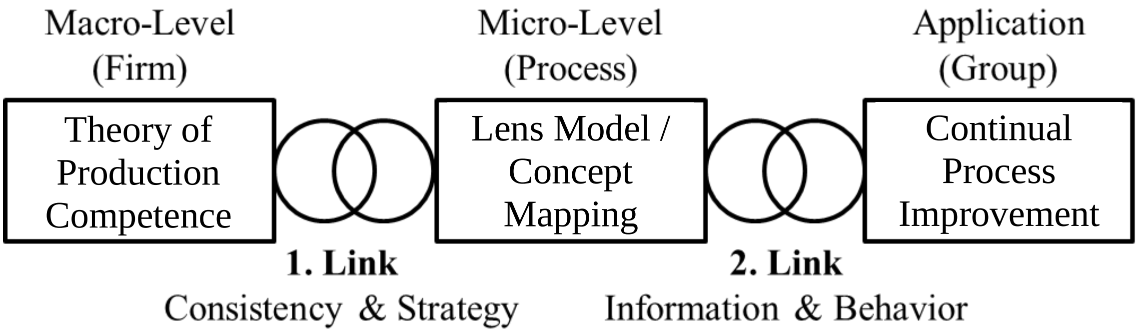


Figure 9: The main-links from macro-level to individual or group-level application.
Source: Own elaboration.

The first link ensures a consistent and logical flow of ideas and concepts from the macro-level to the micro-level, which is also tied to the strategy of the firm. For example, a firm can achieve competitive advantages if it can improve competitive priorities and production competence through the efficient and effective management of processes on the micro-level. Process management, on the micro-level, based on the lens model analysis is the driver to achieve macro-level goals defined by the macro-level theory. On the other hand, competitive priorities, defined on the macro-level, determine the processes to be considered in the lens model approach to ensure proper scope in the application of the methodology. The lens model can then be used on the process-level to find processes with the highest influence on competitive priorities and firm performance can be advanced by using continual improvement.

The second link transmits information from the process-level to the individual or group level to be applied based on the framework of continual process improvement. This is only possible if the information from the environmental system coincides with the cognitive systems (judgements and behavior) of the individuals, or groups, at least to a certain degree. If the management team cannot understand and agree upon the usage of the information, they will not be able to manage processes effectively and holistically with the overall strategy in mind. This link can be strengthened by analyzing the judgments of management and include them into the higher-level theories and concepts, to make sure that they agree with the strategy and the most important actions to be taken on the individual level. This is the second point to emphasize as a benefit coming from the lens model, – or concept mapping methodologies, as it allows a management team to follow the path from macro-level theory to practical application of the results. The correct scope is defined based on the top-level theory, as mentioned above, and it facilitates precise operative decisions making to select the most important factors based on micro-level processes and behavioral factors of the group, responsible for applying the results.

To summarize, the strategy and the understanding why it can be used to create competitive advantages for the firm are developed on the macro-level, which is then connected to the micro-level via the first link. Here, the information is created based on the higher-level strategy and theory to find the right processes that work best to achieve strategic goals via short- and medium-term actions. A strong second link connects this information to the individual judgments of the management team who can then put the strategy into action because they understand causal relations of their actions to achieve the main goals of the firm.

Rousseau (1985) already emphasized the importance of levels in organizational research. By focusing on the analysis of isomorphism between different organizational levels and scientific disciplines it becomes easier to break down macro-level theories to the individual or group-level to facilitate practical application. Composition models (e.g. the lens model) and multi-level theories can help to increase the usability of macro-level theories for lower levels of an organization and to avoid fallacies when conducting research aimed at multiple organizational levels. The management of competitive priorities in the Theory of Production Competence and in process management, for example, describe the same concept from different organizational levels and Social Judgment Theory (SJT) adds an inter-disciplinary aspect to it when it comes to individual understanding and judgement about decision making regarding improvement project selection.

Another example for the use of isomorphism between different organizational levels in an inter-disciplinary context is the analysis of causal ambiguity on the firm level, based on the Resource Based View (RBV), and on the individual (or group) level, based on SJT. Examining individual decision makers' understanding and knowledge of cause-and-effect relationships enables us to understand how firms can manage causally ambiguous resources with the help of SJT. This understanding, coming from SJT, can then be used to create causally ambiguous resources as a source of sustainable competitive advantages on the macro-level for the RBV (Barney, 1991). Causal ambiguity is a protection against imitation of resources, because it makes it difficult for competitors to understand and learn about cause-and-effect relationships that make the resources so effective and valuable, and to copy and use them to create the same effects and benefits (Ryall, 2009). However, this is also the case for the incumbent firm's employees (see chapter 2.2 and the causal ambiguity paradox), therefore, there must be something that enables them to understand and communicate more effectively than their competitors in order to be able to use these causally ambiguous resources to their maximum potential. SJT is focused on the analysis of the reasons of superior understanding and communication on the individual, - and group level and can draw inferences about the creation of inimitable resources on the firm level. This connects top-level theories and practical application from two different points of view, describing the same phenomenon in an integrated and comprehensive way.

5. Conclusion

Human judgment is characterized by systematic errors, biases, and misjudgments (Bendoly et al., 2010; Bazerman and Moore, 2009) that affect efficient and effective managerial decision making. Even with models and sophisticated calculations it is sometimes difficult for managers to understand, trust, and use additional information correctly (Dietvorst et al., 2015; Dhir 2001). In this research, some of these difficulties of decision making in complex and dynamic systems are attributed to causal ambiguity and it presented a way to reduce linkage ambiguity from several sources. The strategy of the BU was refined based on the Theory of Production Competence. Performance dimension were analyzed based on the BU´s competitive priorities to find the most important areas for improvement. The lens model and concept mapping helped to assess processes and related problems to define the most important improvement activities to increase organizational capabilities in the areas of highest strategic relevance to improve production competence of the BU. This method ensures that operative decisions made, based on the lens model and concept mapping results, are aligned with the strategy of the company and support goal achievement with a clear focus on competitive priorities, which, ultimately increases firm performance.

Causal ambiguity has been a matter of interest in social judgment theory (Hammond et al. 1975; Cooksey, 1996; Hammond, 2007) and in management theory (Lippman and Rumelt, 1982; Barney, 1991; King and Zeithaml, 2001; King, 2007) for a long period of time. This study aims to integrate both research streams in a synergistic way to maximize the value of information from OM interventions to be highly relevant for practitioners. Managers in complex production systems rely more than ever on good collaboration with their colleagues and with researchers and model builders to make sound decisions for difficult problems. This method is valuable even for production systems without extensive data collection of their processes and can be easily implemented in the decision-making processes of the management team. All managers are included into the decision-making process and valuable insights can be gathered by making all judgments available to top management. This was also observed by King and Zeithaml (2001) who reported a high interest of top managers regarding the perception of their colleagues and middle managers about resource-performance linkages, which was also the case in this research (Ladinig et al., 2020). They also find that the transfer and collaborative exploitation of resources and competencies can lead to increased firm performance, which is why this research aims to make this information available for the whole management team to reduce causal ambiguity and to facilitate knowledge transfer (see also Szulanski, 1996).

Furthermore, Bazerman and Moore (2009) name six strategies to improve managerial decision making: (1) use decision-analysis tools, (2) acquire expertise, (3) debias your judgment, (4) reason analogically, (5) take an outsider's view, (6) understand biases in others. This method facilitates number one, two, three and six by giving visual representations of the manager's judgment and of the whole group to make biases understandable and transparent for the whole team by using the proposed method. It is also useful for the second strategy because the whole management team is included in the process and they understand the results and insights of the model, and subsequently, the environmental system. This methodology does not fully conform to the fourth strategy, which emphasizes learning from two exercises, that have the same lessons and are related, to create more generalizable insights for the learners. However, looking at the problem from two sides, a behavioral and environmental, still gives some benefits regarding analogical reasoning from two different sources of information to maximize generalizability of results. Also, an outsider's perspective can be included when external experts participate in the judgment analysis. While it is still the management's job to use the information appropriately, the method increases the chances to successfully reduce problems in managerial decision making, like biases, bounded awareness and emotional influences as described by Bazerman and Moore (2009).

From another theoretical point of view Bromiley and Rau (2016) scrutinize causal ambiguity, as a necessity for imperfectly imitable resources, in their critical evaluation of the RBV. Both, the firm who possesses the resource and their competitors, must face the same level of causal ambiguity, so the resource cannot be easily imitated by hiring people of the firm with present competitive advantages (Lippman and Rumelt, 1982; Barney, 1991). The question they raised was how to use and measure something that is not understandable or imitable as a source of competitive advantages? While causal ambiguity is not directly measured, the lens model can be used to observe the effects it has on the judgment and decision making of the management team. If a management team understands better how to use a set of resources within the whole organization holistically, they can use these resources more efficiently due to better decision making, and the resources, as used by the company, cannot easily be imitated. The same argument was made by Samson and Whybark (1998) and Vastag (2000) who focus on soft issues and organizational capabilities to outperform competitors due to better decision making and usage of manufacturing inputs, investments, and choices.

SJT gives us an inter-disciplinary way of looking at causal ambiguity and its role in operations management from a technical and behavioral point of view. Valuable data can be integrated into decision support systems by including the experience, knowledge, and judgments of the management team into combined behavioral and OM research. Modeling, behavioral experiments, and analyses can complement each other and can be used to cross check findings as well as enhance the insights learned through traditional methods (Bendoly et al., 2006). Sources of causal ambiguity within the management team and between the team and its environment can be identified and analyzed to make better decisions on resource allocation in complex and dynamic production systems. It can also uncover misjudgments and potential sources of conflicts between people of different functional areas, and even within specific teams, that could eventually cause improvement activities to fail to deliver the desired results. A lot of research exists on the best way to improve production systems, Goldratt and Fox (1986) or Ferdows and De Meyer (1990), to name just two, but ultimately it depends on the judgment and alignment of the decision makers to go in the same direction and work together to achieve common goals. Production systems, or supply chains are, after all, complex social systems, where behavior of individuals, groups, or whole organizations is the central driver of operations and performance (Gino and Pisano, 2008). However, OM/OR research plays a critical role in this process to find causalities and new ways to understand and master causal ambiguity in an increasingly complex environments, like overly complex modern production systems (Ladinig et al., 2020).

This research analyzed causal ambiguity in two specific case studies and showed that several sources of causal ambiguity are present within the management team and their environment. However, additional research is necessary to get a more general picture about causal ambiguity in complex production systems and how it affects decision making in the long run for other dependent variables as well. This study differs from other studies of causal ambiguity, continual improvement project selection and judgment analysis (Beleska-Spasova and Glaister 2013; Büyüközkan and Öztürkcan, 2010; Dhir, 2001), because it includes judgments and simulation results in an operations management context from an intra-firm perspective for single cases. It confirms the findings of the other research regarding linkage ambiguity and adds to the literature by observing causal ambiguity even in relatively homogeneous groups of managers from the same company.

It also shows that integrated information from the DES and the judgments of the management team can be used to create holistic, mutually accepted action proposals to increase the relevance of OM interventions for practical applications (Ladinig et al., 2020). This method is designed to assist management in their decision process over several improvement cycles and longitudinal analyses are necessary to further study the effects this method has on the quality of the decisions being made in specific production systems.

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Research Paper 1

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Sensemaking Support System (S^3) for Manufacturing Process Improvement

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Sensemaking Support System (S^3) for Manufacturing Process Improvement

Production management teams often face unfamiliar situations where each team member must understand new phenomena individually before the team can make mutually understandable and acceptable decisions. Contradicting subjective judgments can distort the group's decision-making process because team members understand situations differently and are generally prone to behavioural biases. This paper presents the development of a sensemaking support system (S^3, S cube) for selecting improvement projects in a complex, small-volume batch production system of a premium car manufacturer. All phases of the sensemaking process are facilitated by making various sources of information available to a team of managers and experts to reduce conflicts regarding the selection of improvement projects. S^3 is based on a lens model which combines judgments of the management team with discrete event simulation and provides visual representations of the differences and misjudgments related to various improvement options. The results – that can easily be generalized to many similar settings – indicate different understanding and lack of coherence within the management team which prevents them from defining mutually acceptable actions. This is countered with the creation of an action proposal, summarizing, and visualizing causal relationships, and connecting them to improvement options to improve performance of the production system.

Keywords: sensemaking support system, lens model, manufacturing process improvement, automotive industry, discrete event simulation, judgment analysis

1. Introduction

Based on a true story, Norman Maclean's (1992) book *Young Men and Fire* describes the events of a deadly fire disaster happening in Montana when several fire jumpers were dropped to deal with a small wildfire that they expected to have under control within a short timeframe and would not impact a surface area larger than 100 acres. Unique characteristics of the terrain, unknown to the firefighters, however, caused the fire to increase rapidly and turn towards their direction, which did not make sense to them and served as the basis for Weick's (1993) analysis about their sensemaking processes during the incident. Surprised by the turn of events they failed to communicate properly because everybody had a different understanding of what was happening, and all responded differently to this dire situation. They failed to formulate a mutually accepted action plan and, in the end, almost all the first responders died or suffered major injuries and the fire spread upon an area of 4,500 acres.

A similar situation, albeit not as catastrophic, was observed by the authors within a small-volume job shop production system of an automotive OEM and serves as an example of the applicability of Weick's sensemaking framework in operations management. Managers, assigned to deal with stagnating manufacturing performance, initially were inclined to use the methods they were familiar with from large-scale production. However, none of the improvement projects initiated led to significant performance gains, which did not make sense for management, and the ‘fire’ kept spreading endangering the survival of the business unit. Managers needed to find different explanations for situations at the new production system. Many failed and still made decisions based on old misconceptions because they expected to be able to work in the same way in the small-scale production system and that the same measures and actions would lead to the same results based on their own individual experiences. This led to two problems. First, decisions made in the old mind-set were generally counter-productive or sub-optimal because of the different characteristics of the production system, and second, decisions clashed with those of other managers and led to conflicts or at least missing support and understanding from their colleagues.

After several years and several failed attempts to improve specific parts of the production system, like material tracking and reduction of work-in-progress materials, or preventive machine maintenance, management realized that they would need a different approach to develop action plans for future improvement activities at the business unit. The question was how to aid managers within their sensemaking process in this unfamiliar situation to reduce distortions in a team’s decision-making process due to subjective and biased decision-making methods of individuals.

In this paper, a sensemaking support system (S^3, S cube) is introduced to help management to make sense of a new and not very well understood production system and to define proper improvement activities based on Six Sigma and continuous process improvement, or Kaizen. A lens model methodology (Castellan, 1972; Cooksey, 1996) is used to contrast cause-and-effect relationships between different input variables, or cues, and manufacturing throughput time for all weekly production orders. The results of a discrete event simulation (DES) model are compared to the results of a judgment analysis questionnaire, measuring how the same cues are perceived by management. S^3 uses the results of DES to visualize cause-and-effect relationships based on a regression analysis to create, label, and categorize cues to determine inputs and transformations. This creation and labelling of cues (please note that we use the word ‘cue’ synonymously with the inputs of the simulation analysis and the choices given in the judgment tasks) is one integral part of the sensemaking framework. We then perform a judgment analysis based on a questionnaire to develop a visual representation of the judgments of the management team. This facilitates further steps of the sensemaking process, namely the interpretation of cues by individual managers and their communication to form a mutually accepted action plan. The goal is to make differences and similarities of perceived and measured resource-performance linkages visible to the management team and support their sensemaking process.

The following exploratory case study showcases an application of S^3 within the production system to aid sensemaking and define actions for efficient and effective improvement of processes to reduce manufacturing throughput time – a competitive priority of the production system. The production system is characterized by high complexity, causal ambiguity and a general lack of holistic insight into the system, which makes it difficult to identify and assess improvement projects efficiently. A major problem of the business unit was that the production system grew at a rapid pace, but processes and control systems did not grow alongside to cope with increased dynamics and complexity. There was a lack of employee training, missing preventive equipment maintenance (TPM), the quality management system needed an upgrade; all while the overall value stream had to be improved as well. All major processes had to be analysed, improved and aligned with the overall strategy of the unit, but there were not enough resources to do it simultaneously. An efficient, effective, and mutually agreeable action plan was needed to prevent wrong prioritization, misalignment of different departments and misunderstanding between people of different functional areas to improve the most important processes to increase manufacturing performance.

The remainder of this paper is organized as follows. Section 2 gives an overview about the literature on continual improvement, sensemaking and the lens model. Section 3 describes how the lens model can be used facilitate sensemaking when it is unclear which actions should be taken to improve specific processes for increased manufacturing performance. Section 4 describes the environmental system and the main variables (cues) and processes that influence the performance of the production system in terms of throughput time reduction. The simulation model and the judgment analysis are described in section 5 and the results and findings are discussed in section 6.

2. Literature Review

Continual improvement in manufacturing is still a highly relevant topic (Li, Papadopoulos, and Zhang 2016) and many factors are important when making decisions regarding improvement projects in organizations. In general, the commitment and active participation of management, a long-term plan, and the application of tools and techniques are critical for the success of any lean programme (Netland 2016). Careful planning of lean and continual improvement actions is highly important because misalignment or missing strategies can have a severe impact on the success of a lean programme (McLean, Antony and Dahlgaard 2015) and the stress levels of people on the shop floor (Stimec and Grima 2019). Knol et al. (2018) found that especially for advanced lean enterprises, leadership is a critical success factor when organizations start to manage more different improvement projects with increased complexity.

All this means that management needs a very detailed and precise plan to manage several improvement projects in alignment with the company strategy and the support of the shop floor levels of the organization. Consequently, if managers find it hard to make sense of new situations in a different and less well-known production system, and their decisions are not aligned towards a common goal, it becomes very difficult to achieve the desired results. Managers often tend to fall back on subjective decision-making methods and heuristics which can be detrimental to the overall selection process of improvement activities. Kirkham et al. (2014) found in their study that almost 90% of the large organisations analysed were almost always successful when solely applying objective methods, while less than 70% reported the same results when combining objective and subjective methods. The S^3 can detect subjective misalignments based on the results of objective analyses and improve group decision making by reducing subjectivity and biased judgments.

The S^3 provides managers crucial information about their environment and their own judgments to aid them in their sensemaking processes when entering new and unfamiliar systems. Maitlis (2005, p.64) defines sensemaking as ‘process of social construction in which individuals attempt to interpret and explain sets of cues from their environments […] sensemaking allows people to deal with uncertainty and ambiguity by creating rational accounts of the world that enable action’. Most authors define several steps within the sensemaking process. We use five key activities as summarized by Seidel et al. (2018) for our study. Sensemaking starts with chaos (Weick et al. 2005) and a trigger event (Weick 1995) characterized by disruptive ambiguity and outcome uncertainty which usually leads to a situation when nothing seems to make sense. Maitlis and Christianson (2014) define several triggers. First, triggers can be the results of unexpected events that disrupt people’s understanding of the world in a significant way for them to question their ability to understand the environment in which the event took place, for example, the realization that a fire is not behaving as expected. Also, organizational crises as a result of significant exogenous forces or questioning of self-identity can act as triggers. Furthermore, planned change interventions which are anticipated and planned by organizations to change organizational identities and processes can trigger sensemaking

At the second step, people begin to construct intersubjective meaning by noticing and bracketing cues which might have caused the trigger event to occur. For example, when process improvement activities do not bring the desired results people start questioning their understanding of cause-and-effect relationships and begin to look for possible input factors and explanations for the failed intervention. Managers in our production system expected to use the same, familiar methodologies that always worked based on their previous experiences and sooner or later realized that this was not the case (trigger event). They needed to look for different inputs and different processes to improve and communicate their intentions with their colleagues to find a mutually acceptable action plan. This search for different cues is difficult and complex and could be improved with a support system to create sense in a planned and guided process.

The third step in the sensemaking process is the labelling and categorizing of newly found cues to form diverging opinions and knowledge for new and ambiguous phenomena. Experiences must be labelled and categorized to put them into new perspectives. This means that sensemaking is retrospective and experiences are compared to previous observations (Weick et al. 2005). A DES can be used to define cues, label them, and put them into categories when selecting the input parameters for the simulation and regression analysis.

The fourth step, after the sensemaking has been triggered, cues are identified, and labelled, is about presumption and action. People start to anticipate outcomes based on latest experiences and cue inputs in this new environment and begin to act in different ways to create more inputs. In other words, the actions they take are the inputs for further cue generation, interpretation, and labelling, thus, resulting in a continuous sensemaking processes. The DES can be used in this context to create further information to predict outcomes, in this case for manufacturing throughput times, in the real environment based on the results of the regression analysis. People can then act based on their new knowledge and incrementally increase their level of understanding for new phenomena. The difference between decision making and sensemaking is that in sensemaking the broader conceptual framework in which the decision-making environment is formed. Decisions are only part of the process to create cues to further promote future sensemaking.

The final step in the process is about the social aspect of sensemaking and it is accomplished through discussions to formulate a common view of new phenomena. This includes the knowledge and judgments of all the people involved in the sensemaking process and forms an organizational view of things in a new setting. S^3 facilitates this process by visualizing the cue selection process and judgments of individuals and compare them to their peers. It calculates weights for each cue given by the preferences of participants of the judgment analysis and serves as the basis of discussion of differences and similarities. If a group of people, in this case the management team, can find mutually understandable and acceptable outcomes of their combined sensemaking processes, decisions can be taken, which ultimately lead to action and the creation of further inputs for the sensemaking process. The lens model unites all the previously mentioned steps by visualizing the results of the DES based on the identification, labelling and categorizing of cues and by providing information about potential outcomes for ambiguous situations. It furthermore visualizes the judgments of people to be compared with the results of the judgment analyses of all participants to each other and to the results of the DES as a basis for communication and action.

The lens model has been used for various applications to visualize judgments and support sensemaking processes of managers for complex judgment tasks or behavioural analyses. Dhir (1987) used the lens model to understand consumer behaviour in the hospitality industry and found that consumers are not fully aware about their own judgments and preferences – for example, due to preference uncertainty and attribute conflict (Fischer et al. 2000). The lens model provides a representation of their judgments and helps restaurant managers to better understand and adapt to individual customer preferences. Other applications are found in healthcare (Thompson et. al. 2005), where the lens model is used to analyse decision processes about a patient's status in critical care, or in education (Haigh et. al. 2013), where it is used to improve judgments about teacher's readiness to teach. It is also used as a judgment capturing tool to give insights into production strategy and policies (Ebert et al. 1985).

The lens model is based on Brunswik's (1952) work and a tool of social judgment theory. The reason why it is preferred over tools from other theories is its strongly descriptive approach. It facilitates recommendations solely based on the decision maker's own judgments. Dhir (2001) compared this theory to various other theories (decision theory, multi-attribute utility theory, analytic hierarchy process, information integration theory, etc.) in a manufacturing setting and concluded that social judgment theory and the lens model can be best used to develop judgment and decision aids because of its descriptive nature to obtain an unfiltered model of individual judgment processes. Most other theories mentioned, on the other hand, are highly prescriptive and indicate how rational decision should be made or why they are made which is not the purpose of this study.

3. Integrating the Lens Model into a Continuous Improvement Process

Figure 1 depicts a typical univariate lens model in a stochastic environment. The distal variable or criterion variable Y_e is the dependent factor in the environment or ecology to be judged by the decision makers. In this paper, it is manufacturing throughput time, or the time to produce all weekly production orders for a given product mix, which is influenced by independent factors (x_k), or cues. The left side of the model depicts the true state of the ecological system, or how the distal variable will behave based on the inputs. The right side describes how decision makers use the cue information to make judgments about the true state of the system. Their judgment Y_s is then compared with the true state Y_e to calculate the correlation between their estimates and the true state, which is called *response validity*, or *achievement index*, $r_\alpha = r_{Y_e Y_s}$. This gives an indication about the performance of the decision makers and their ability to understand how the criterion will behave under different conditions.

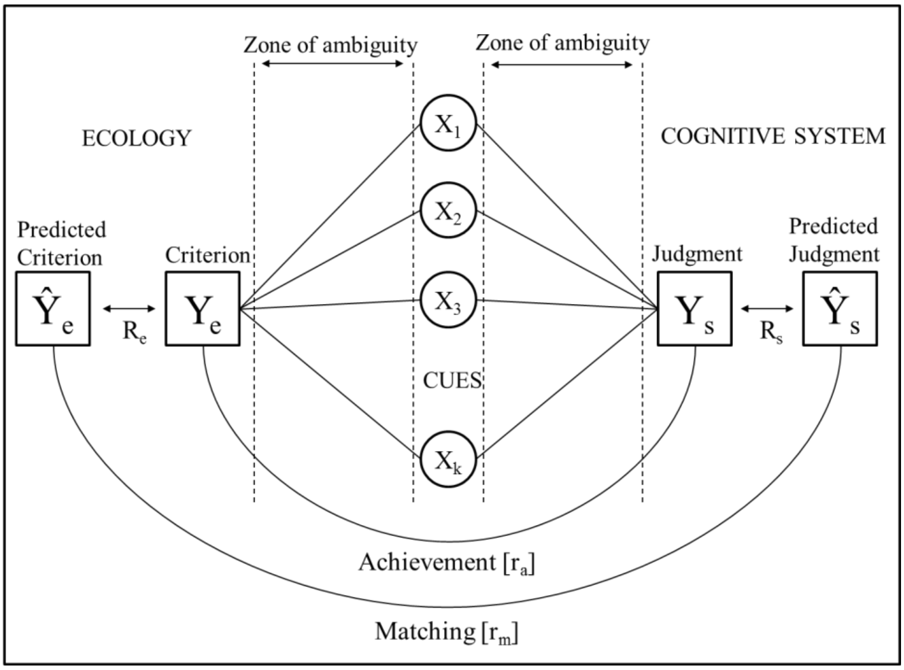


Figure 1. Univariate Lens Model.
Source: Authors representation of Cooksey (1996) and Castellan (1992).

In a stochastic environment, however, the true state must be predicted using some sort of model. In this research, it is a simulation model based on the processes and value stream of the production system. $\hat{Y}_e$ is the predicted criterion variable and the environmental predictability can be calculated ($R_e = r_{Y_e \hat{Y}_e}$) with throughput time as the dependent variable and the cues as the independent variables. The same process is applied on the right side of the lens model to analyse how judges are utilizing different cues with the help of a questionnaire. R_s is the consistency of the judge's cue utilization based on different cue input profiles, that is, how coherent is their assessment of cues towards the distal variable ($R_s = r_{Y_s \hat{Y}_s}$). The correlation between the predicted ecological state and the predicted judgments is called the *matching index* $r_m = r_{\hat{Y}_e \hat{Y}_s}$, or how similar the expected judgments are, compared to the expected environmental state.

To visualize judgment processes, it is important to calculate the weight of each input variable given by the judgments of the management team by using a non-additive model of polynomial form (see appendix) as described in Hammond et al. (1975, 281-282) and Cooksey (1996, 178-180). They use algebraic transformation of the regression model and separate weight and function form for each cue to visualize the results of all judgments. The method is called '*range method'* and the results give an indication about the preferences of individuals based on their judgments. The highest weight represents the highest preference of the judge towards a cue factor with function forms showcasing judgments related to higher and lower performance levels, respectively (Figure 2). This method visualizes how managers are using uncertain and intersubstitutable cue information in causally ambiguous situations based on their judgments. The same method can be applied to visualize the regression results of the data generated by the DES. Weights and function forms are computed for both, the DES, and the judgment analysis, and is the foundation of S^3 to make decisions regarding the selection of improvement activities for different processes.

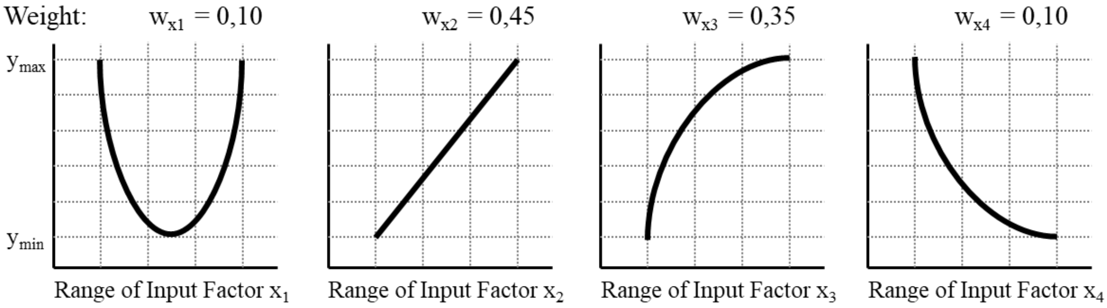


Figure 2. Illustrative Example of Visualizing Weights and Function Forms.
Source: Authors representation of Dhir (2001).

Previous research has shown that process performance can be significantly improved by the adequate use of continuous improvement methods (Hahn et al. 2000). However, it also shows that there is no guarantee that any kind of operational excellence can be achieved if certain factors are not available to generate the desired outputs (McLean, Antony and Dahlgaard 2015). The success of improvement projects depends on the experience of team members and their abilities to identify and solve problems (Easton and Rosenzweig 2012). Companies are sometimes spending billions of dollars for process improvement (Swink and Jacobs 2012) and it is critical to ensure proper allocation of scarce and expensive resources. The management of a production system needs a holistic understanding about causal relationships between all processes within the system to be able to properly identify the most beneficial improvement projects. Too many projects without enough capacity increase the risk of failure for all projects and can be a reason why Six Sigma or Kaizen do not yield the desired returns (McLean, Antony and Dahlgaard 2015). S^3, introduced in this paper, is used to guide an improvement process to select the most beneficial improvement projects to increase performance based on competitive priorities by following a stepwise approach adapted from Dhir (2001).

(1) *A trigger event initiates a sensemaking process about a criterion variable* which is ambiguous in terms of resource-performance linkages, in this case, manufacturing throughput time and its influencing factors.

(2) *Define, label, and categorize* what factors influence this variable in terms of management judgments and for building the model of a system. Different key performance indicators (KPIs) and related process improvement options were selected as cues to analyse their impact on throughput time within the system. All KPIs selected for this analysis could potentially be improved to reduce throughput time by initiating an improvement process. However, due to high expenses and limited resources, it was necessary to decide and mutually agree upon the priority of process improvement options.

(3) *Calculate and visualize* weights and function forms (Figure 2) as perceived by the management team and based on the results of DES. The questionnaire is used to analyse judgments of the management team. The key question was how the management team, based on their experiences and knowledge, utilizes KPIs as cues within their cognitive systems to make decisions regarding throughput time improvements. For the left side of the lens model, DES is used to predict throughput time reduction within the production system when different processes and KPIs are improved.

(4) *Use the results and analyse how decision makers utilize cues compared to each other and to the DES*. The results of both analyses, from the environmental system and the cognitive systems, are visualized to make both results comparable to be discussed within the sensemaking process. The overall weights and function forms can be determined for each cue to select the most important KPIs and processes for improvement. Also, differences and similarities (matching index) can be assessed and discussed to make a mutually acceptable decision and to mitigate subjective influences of individuals.

4. System Design and Variables

4.1. Production System Overview and Value Stream

The production system consists of three departments that contain all production processes from metal disc to final assembly of all core products like doors, side panels, roofs, bonnets, and hatches for premium sports cars. The first department is the component production, where metal components are pressed, and laser cut out of aluminium or stainless-steel discs. The second department contains all the assembly processes where the final assemblies are put together from two to five main-components. The third department is called ‘finish’ and it is responsible to ensure proper quality of the final product. This department is also the bottleneck of the system based on the results of the DES and has the highest utilization rate of all processes. There is also an Operations Management department within the small-volume production segment, responsible for launching new projects and to ensure continuous smooth operations of all running projects throughout their life cycle. In addition to the small-volume batch production segment, the business unit contains four other segments, which are: quality management, logistics, fixture construction and tool making. Also, many projects are running at the same time, like new product implementation into the existing production equipment, improvement projects for existing processes, and implementation of new processes, which creates a matrix structure of the organization as depicted in Figure 3.

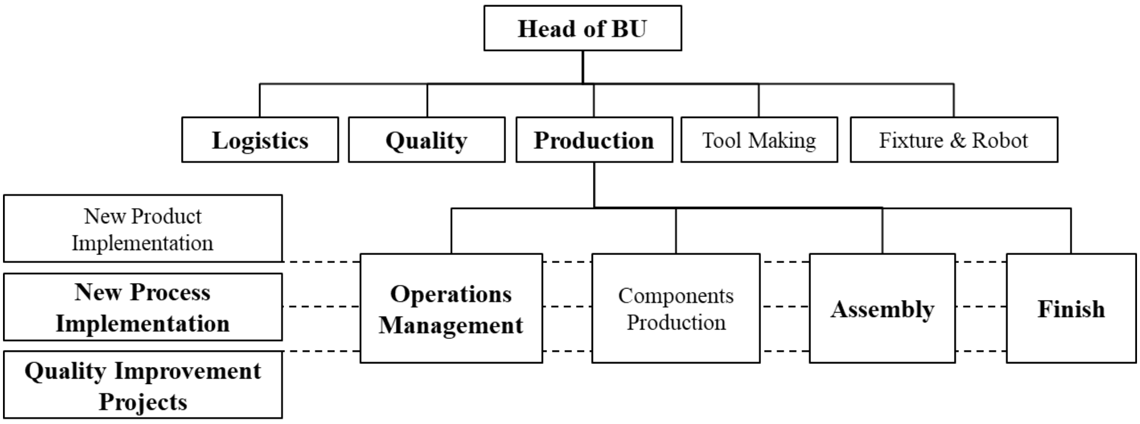


Figure 3. Organizational Structure of the Business Unit (BU).

In this complex environment of many interconnected processes and projects, the head of the unit must allocate resources properly to all ongoing projects. The key-actors and decision makers of the management team, including project managers, are coming from the highlighted departments (bold text in Figure 3), and those are the ones who will be included in the judgment analysis. Projects can be managed by production ramp-up managers for new product implementation, industrial engineering for quality and process improvement projects, and production system planners for new process implementation. With a lack of control and signalling tools as well as feedback loops, it was critical for the top-management of the business unit to rely on mutual understanding, joint decision-making and unified actions to reach the unit's goals based on a collectively developed action proposal.

The production system is simulated from the components supermarket to the finished goods inventory. The value stream design, as depicted in Figure 4, is focused on ensuring a stable and balanced material flow between each supermarket based on the theory of Swift, Even Flow (Schmenner and Swink 1998; Schmenner 2015). This is also the basis of the DES and the judgment analysis.

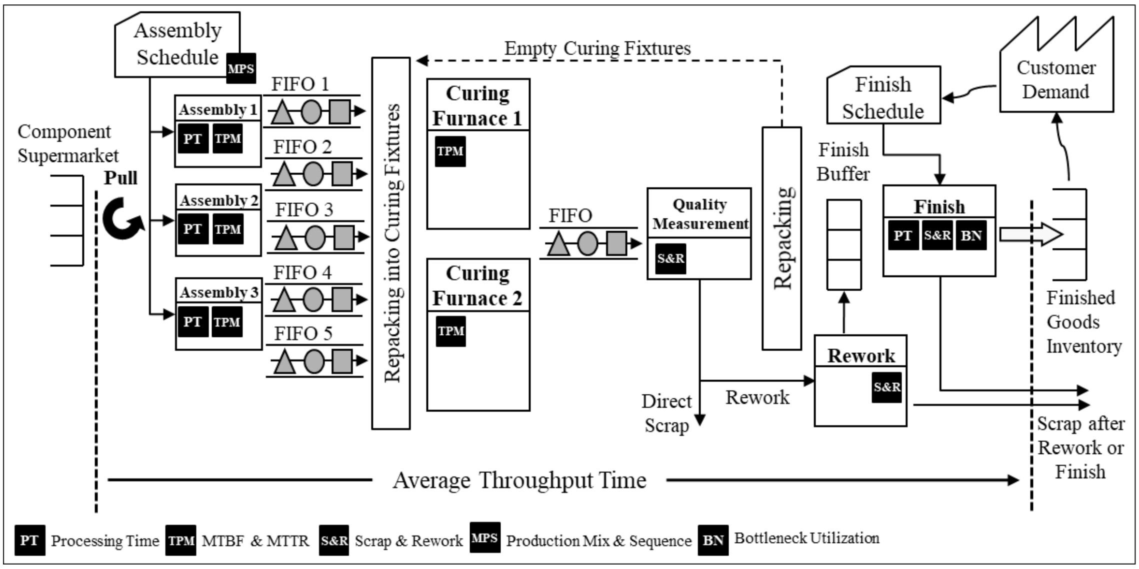


Figure 4. Value Stream of the Production System.

4.2. Inputs (Cues), Improvement Options and Performance Levels

Five KPIs were defined as cues with help of and inputs from the management team. Each input is connected to a reaction process to improve KPIs if they are not satisfactory. If so, a specific process improvement option is selected to bring the KPI back into the desired range by improving the appertaining reaction process. Management could decide where to intervene and how much resources should be invested into a process improvement option, which results in different performance levels for all reaction processes and ultimately different ranges of KPIs. The higher the investments into improvement activities for a process, the higher the performance level of the reaction process and the better the range for the input variable will be, which, in turn, will influence throughput times. Performance levels and expected values of each cue, as depicted in the complete list of cues in the appendix, were defined with the current measurements within the production system and feedback from management about what was 'normal', or what could be achieved for a ‘good/bad’ week. For example, machine down time for the average level was defined by log files coming from the maintenance department. The upper and lower values for all the other levels were then defined by the management team and cross-checked with past log files. The following is a list of the five KPIs to be considered in the lens model analysis with their specific reaction processes and performance levels.

Cue 1: Processing Time Variability and Training (Level 1-7): Processing time variability based on varying worker performance for manual tasks was the first KPI to be considered in the analysis and was selected by the production department of the production system. Workers were not fully trained for all manufacturing processes according to the defined standards, did not have the required qualification profiles, and lacked understanding of basic process improvement methods. Therefore, the project team concluded that a reaction process called ‘training’ would be the most appropriate to improve this KPI as learning and training is a major tool to reduce process variability (Zantek et al. 2002). Training only influences processes with a significant amount of manual operations, which can be found in the assembly systems and the finish department marked with ‘PT’ in Figure 4. The range of the KPI is determined by the distribution of tact times for the completion of one product and is dependent on the performance level of the training process. The higher the performance level of the training process, the lower the dispersion (or spread) and the overall completion time of manual tasks will be until they reach the defined, standardized processing times with high reliability.

Cue 2: Mean Time Before Failure (MTBF), Mean Time To Repair (MTTR) and Total Productive Maintenance (TPM) (Level 1-7): Machine processing times at the assembly systems and curing furnaces cannot deviate much, but machines can have unplanned downtime, therefore, MTBF and MTTR can be defined as another set of indicators (again required by the production department to be included in the analysis). The underlying concept of those measures is total productive maintenance (TPM), introduced by Nakajima (1988), which is used as the reaction process for the MTBF and MTTR indicators. The right maintenance policy is critical to maintain high levels of availability and performance at an optimal cost level and has become a significant profit contributor in modern production systems (Faccio et al. 2014). Again, high performance levels of the TPM reaction process tend to improve related KPIs and has an impact on overall throughput times of the system.

Cue 3: Scrap, Rework Rates and Problem Solving (Level 1-7): If product quality is not within the given range, a problem-solving process is triggered to deal with quality problems. Scrap and rework mostly result from changing part quality discovered at the quality measurement, rework, and finish departments (see ‘S&R’ marks in Figure 4). A problem-solving team of experts and engineers is needed to improve the quality of products and processes. A high-performance level can only be achieved with enough investments into quality analysis and improvement to deal with complex problems. It is then possible to sustainably and efficiently reduce scrap and rework rates and ultimately improve throughput rates and throughput times (Johnson 2003) with a sophisticated problem-solving process. This process was selected by the quality department of the production system and all KPIs were critical for the managers of this department.

Cue 4: Production Mix, Sequence and Master Production Scheduling (Level 1-4): Master production scheduling (MPS) based on the manufacturing planning and control framework by Vollmann et al. (2004) is the process for the fourth input: production mix and sequence, as requested by the logistics department. It aims to create an assembly schedule to achieve an optimal product mix and sequence for the assembly stations to ensure proper replenishment and inventory levels at the finish buffer. Based on Jonsson and Ivert (2015), the balancing between capacity and demand is used to define performance levels for the MPS. A very low performance level of the MPS process means that the production sequence and mix are completely random and unbalanced, which results in long throughput times. No demand or capacity restrictions are considered at this level and the production plan is not capable of balancing both factors due to a sub-optimal MPS. The basic production plans for all higher levels of this reaction process, from levels two to four, is based on an optimized MPS considering capacity, demand, sequence, and product mix issues. Nevertheless, as analyses within the production system have shown, there were up to ten deviations per week from the production plans due to planning errors, from a total of 25 production orders every week. The performance levels of the MPS process are therefore based on the number of deviations of the production plan compared to the optimized plan to analyse the effect of bad planning on average throughput time. This means that for a level four process, there is no deviation from the optimized MPS. The lower levels were then simulated by changing the sequence of the production plan for up to ten production orders to deviate from the optimal MPS based on real examples experienced at the production system. Planning errors due to low performance levels are introduced artificially and randomly to simulate different levels of planning performance.

Cue 5: Bottleneck Utilization and Business Process Optimization (Level 1-4): The fifth cue is the bottleneck's processing time compared to the processing time of the second slowest process, or, the difference of utilization levels of the two processing units with the highest utilizations (Hopp 2011). Business process optimization of the bottleneck was used as a reaction process to achieve balanced and improved flows of materials as requested by the operations management department. Sophisticated process optimization will accurately analyse potential bottlenecks and ensure a balanced production based on the concepts of Drum, Buffer, and Rope (Goldratt and Fox 1986) or the theory of Swift, Even Flow (Schmenner and Swink 1998; Schmenner 2015). With low performance levels, processing times and utilization levels will vary, causing the whole production system to suffer from unbalanced process design due to a lack of focus on the bottleneck. The finish department was identified to be the bottleneck process under normal circumstances with an average utilization of over 80%. The process with the second-highest utilization was the curing furnace with only about 60% of utilization for all weekly production orders, given the product mix used for the DES. Shift models, worker cross-training, dedicated machines for special product families, or different routing options can help to balance the throughput time for each process as shown in Johnson (2003). A mix of worker cross-training with more finish stations, an increase in capacity, as well as improvements in processing times were used to optimize the bottleneck process towards utilization rates like those of the curing process.

Each of the main inputs of the model has an impact on the overall throughput time of the production system in terms of supply chain management (Hopp 2011), manufacturing throughput times (Johnson 2003), or other capacity, variability and inventory trade-offs within process management (Klassen and Manor 2007). Therefore, these five KPIs are used as input factors (cues) for the lens model application as depicted in Figure 1. Filho and Uzsoy (2014) use a similar set of input variables for their simulation analysis of cycle time in a flow shop. The reduction of variation due to quality, quantity and timing is also a critical factor in the theory of Swift, Even Flow (Schmenner 2015), with the other factor being throughput time.

5. Simulation Model and Judgment Analysis

Each cue of the lens model is divided into certain performance levels on an ordinal scale representing different ranges of values for each KPI. Different scenarios of production system configurations were created to obtain the input data for the questionnaire and the

DES. This was done by randomly assigning performance levels to each cue, based on viable and concerted ranges, to create different production system profiles with varying strengths and weaknesses based on the cues with higher or lower performance levels, respectively. 20 input profiles were created randomly to simulate trade-offs and present them to the management team for the judgment analysis. The set of profiles was checked for plausibility, variety of profiles, and orthogonality. Where necessary new profiles were created randomly to replace unsatisfactory ones. At the end, the Pearson product-moment correlation coefficient was used to calculate the correlation between all pairs of factors to test for orthogonality of the input profiles. The highest correlation was found at $r = -0.368$ between factors three and four. The t-value for the highest correlated pair was 1.677, which lies under the critical t-value of 1.734 at 0.1 level of significance for 18 degrees of freedom. This means that there is no significant correlation between all pairs, thus making the profiles orthogonal. All scenarios (input profiles) were simulated for 25 runs to obtain a data set for throughput times from the DES. Management was asked to rate the same profiles in the questionnaire to obtain their judgments for the same scenarios and the cues they mostly utilized to make their decisions.

Group	Code	Name	Function	Age	Exp.[1]	In BU	Edu.[2]
Group 1 Top-Management & Innovation	TOPMGR1	Top-Manag. 1*	Head of BU	45-50	2 - 4	2 - 4	Eng. + IE
	NPIMGR1	New Proc. Implement. Manag. 1*	Project Head	55 +	12 +	2 - 4	Eng.
	NPIMGR2	New Proc. Implement. Manag. 2	Project Supervisor	30-35	4 - 6	6 - 8	Eng.
Group 2 Production Management	PROMGR1	Production Manag. 1	Head of Production	40-45	4 - 6	< 2	Eng.
	PROMGR2	Production Manag. 2*	Head of Production	40-45	< 2	8 - 10	Eng.
	PROMGR3	Production Manag. 3	Line Manager	45-50	10 - 12	2 - 4	Eng.
Group 3 Logistics Management	LOGMGR1	Logistics Manag. 1*	Head of Logistics	40-45	2 - 4	2 - 4	Business
	LOGMGR2	Logistics Manag. 2	Line Manager	35-40	< 2	4 - 6	Logistics
	LOGMGR3	Logistics Manag. 3	Project Supervisor	25-30	< 2	2 - 4	Logistics
Group 4 Quality Improvement	QUAMGR1	Quality Manag. 1	Line Manager	35-40	< 2	2 - 4	Eng.
	PRIMGR1	Proc. Improv. Manag. 1	Project Supervisor	30-35	4 - 6	4 - 6	IE
	PRIMGR2	Proc. Improv. Manag. 2	Project Supervisor	35-40	2 - 4	< 2	IE

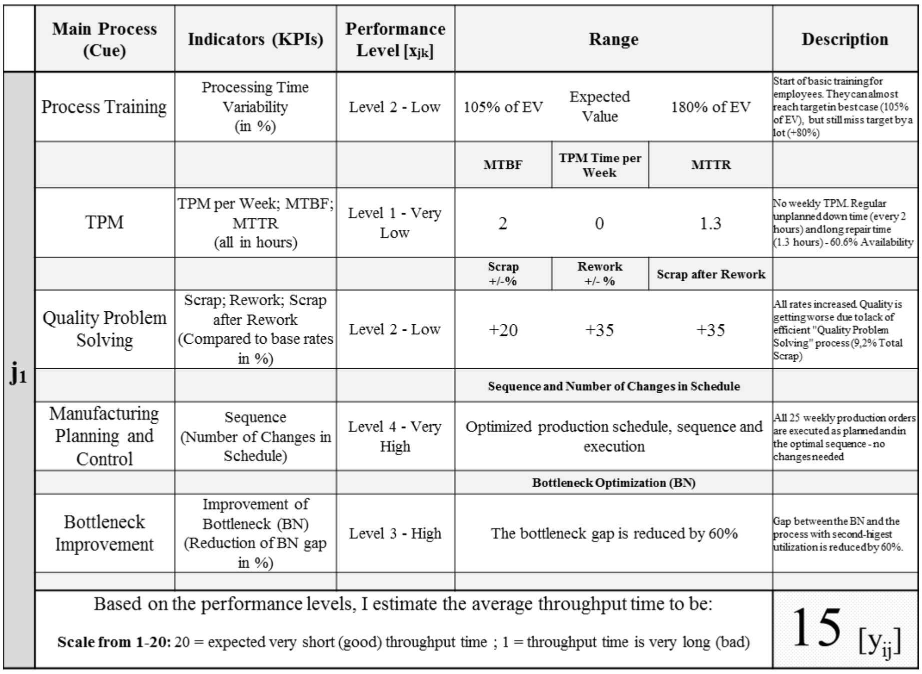
[1] Work experience (number of years in current funcion and level)

[2] All with masters degrees in Engineering (Eng.), Industrial Engineering (IE), Business or Logistics

Table 1. List of Participants and Functions (*Top Decision Makers).

The judgment analysis was conducted to develop a pictorial representation of the expert's mental models to be compared with the results of the simulation model. The judges are members of the management team, from production and logistics department, but also production system planners, process engineers and other members of the business unit with in-depth knowledge of the production system, who decide on how to run the system in terms of improved throughput times. 17 experts were identified, who were qualified to participate in the survey – of whom twelve completed the questionnaire under the guidance of the authors. Five people were considered as the top decision makers with the highest level of involvement in making decisions, of whom four responded to the questionnaire (asterisk in Table 1). Consequently, we are confident that all relevant characteristics of the problem domain were captured.

Each expert received the same questionnaire with the set of 20 different input profiles and was asked to rate each profile and its expected performance regarding throughput times from a scale from 1 to 20, with 1 meaning that the expert is estimating very long (bad) throughout times and 20 meaning that the expert is estimating a significant reduction of throughput times. Each profile was presented to the participants in form of a ‘profile card’ (Table 2), so they could rearrange the cards and have a better overview over the whole set of profiles. 20 profiles represented the upper limit participants could handle in terms of complexity and time to complete the questionnaire, so this number was selected by the authors. The most important information on the cards were the different performance levels for each process and KPI. The ranges and an additional description were also visible, and the list of all ranges was given to the participants as well (appendix). Before the actual rating of the input profiles, an a priori assessment was conducted, and the participant could assign a total of 100 points to each of the five processes to represent their preferences before the actual judgment analysis. The comparison of the a priori assessment with the actual judgment analysis gives an indication about the consistency of the judges and the difference between a simple assessment and a causally ambiguous judgment task.



	Main Process (Cue)	Indicators (KPIs)	Performance Level $[x_{jk}]$	Range			Description
j1	Process Training	Processing Time Variability (in %)	Level 2 - Low	105% of EV	Expected Value	180% of EV	Start of basic training for employees. They can almost reach target in best case (105% of EV), but still miss target by a lot (+80%)
				MTBF	**TPM Time per Week**	**MTTR**	
	TPM	TPM per Week; MTBF; MTTR (all in hours)	Level 1 - Very Low	2	0	1.3	No weekly TPM. Regular unplanned down time (every 2 hours) and long repair time (1.3 hours) - 60.6% Availability
				Scrap +/-%	**Rework +/- %**	**Scrap after Rework**	
	Quality Problem Solving	Scrap; Rework; Scrap after Rework (Compared to base rates in %)	Level 2 - Low	+20	+35	+35	All rates increased. Quality is getting worse due to lack of efficient "Quality Problem Solving" process (9,2% Total Scrap)
				Sequence and Number of Changes in Schedule			
	Manufacturing Planning and Control	Sequence (Number of Changes in Schedule)	Level 4 - Very High	Optimized production schedule, sequence and execution			All 25 weekly production orders are executed as planned and in the optimal sequence - no changes needed
				Bottleneck Optimization (BN)			
	Bottleneck Improvement	Improvement of Bottleneck (BN) (Reduction of BN gap in %)	Level 3 - High	The bottleneck gap is reduced by 60%			Gap between the BN and the process with second-higest utilization is reduced by 60%.
	Based on the performance levels, I estimate the average throughput time to be: **Scale from 1-20:** 20 = expected very short (good) throughput time ; 1 = throughput time is very long (bad)						15 $[y_{ij}]$

Table 2. Input Profile with Judgment y_{ij} in Form of a ‘Profile Card’.

The weights and function form, as judged by each member of the management team, could be calculated based on the ratings of each profile and the regression model. Performance levels for each cue were the independent variables and profile ratings the dependent. The results gave a visual representation of the cognitive system of the judges and the mutual preference of the management team to be compared with the results of the DES. The DES was modelled after the value stream design of the production system with all process steps, master product data (bill of materials) and routing based on Figure 4, using the Tecnomatix Plant Simulation software by Siemens. All input profiles were modelled, and 25 simulation runs were executed for each profile to acquire a large enough sample size for the regression analysis to calculate weights and function forms for the environmental system. The average throughput time over the whole product mix was the output of the simulation and the dependent variable of the regression analysis to assess the impact of performance level changes of each cue on throughput time. All input profiles could be simulated by changing the levels of each parameter in the simulation, for example, processing time variability, unplanned machine down time, and various production schedules. The production at the assembly stations was simulated based on the assembly schedule with the previously defined ranges for processing times. A specially coded logic in Tecnomatix Plant Simulation for the repacking stations and the curing furnace was applied to simulate the selection of the next batch to be cured at the furnaces based on the arrival from the FIFO-lines and the availability of curing fixtures. Scrap and rework rates were applied before and after the finish stations and at the rework station. A higher quantity of products had to be produced to compensate for quality losses affecting the overall manufacturing throughput times of the system. Twelve finish stations were simulated individually based on the finish schedule taking parts from the finish buffer with an initial starting level of WIP materials. Machine down breaks were also simulated randomly based on the probability of a break down and the average duration. A TPM break in the middle of the week was set to simulate TPM times defined by the performance levels of the TPM cue.

The results were validated by comparison with real-life data and by following each part through the value stream as modelled in the simulation. Furthermore, the simulation was used to plan and validate processes of the real shop floor of the production system in a different project. Other outputs of the simulation were the log files of each process, which product type was processed when and where, and the number of parts/containers coming into each station and out of it. The functioning of the simulation model could be validated with the help of the log files and the real-life data.

The cue performance levels for each cue as independent variables and the average throughput time as dependent variable were then used as input data to conduct curvilinear regression analysis for testing the fit of the regression model of throughput time. To compare the results of each profile, the production system was simulated for one week of production (seven days) without a warm-up period to better reflect the changes of the dependent variable for each profile. The regression model captured the dependence of the output variable with a relatively high degree of accuracy, with an adjusted R-square of .935 (see appendix for more details), with most of the input variables being significant at the 0.01 level. The regression model of the DES was visualized in the same way than the regression models for each judge based on the results of the questionnaire to obtain weights and function forms of all cues and to compare both sides of the lens model.

6. Comparing the Results on both Sides of the Lens Model

6.1. Judgment Analysis - Weights, Function Form and Causal Relationship

The judgment analysis was performed to explore judgment patterns and subjective preferences of each team member based on their knowledge and experience. The management team was divided into four functional groups: (1) Top-management and process innovators, (2) production management, (3) logistics management, (4) quality improvement, with each group containing three members.

The first group included the head of the business unit (TOPMGR1) and the two most important project managers (NPIMGR1/2), responsible to manage the re-engineering and implementation of all new processes. Two of the top decision makers are based in this group and both were foreign expats; appointed and sent to the business unit by the headquarters of the corporation – the top-manager for a longer period and the project manager for the duration of the project. Both had been working at the business unit for more than two years when the judgment analysis was conducted. The second group consisted of the former head of production (PROMGR1), with a lot of experience coming from the foreign headquarters as well; and the current head of production (PROMGR2), who was relatively new at this position, but also a top decision maker and a local manager within the business unit for a long time. Together with a third production line manager, this group was responsible for the training, TPM and scrap and rework KPIs, as well as the overall functioning the production system. The third group consisted of two logistics managers with LOGMGR1 being the head of the logistics department and the only local female top decision maker of the management team. These two were the only managers from the same group with relatively similar judgments and were responsible for the production planning and training processes. The last group included a quality manager and two process improvement coordinators responsible for improving product and process quality. This group had no top decision maker, but all members were heavily involved in defining and implementing improvement projects with a focus on scrap and rework, bottleneck improvement and training.

The weights and function forms were computed based on the judgments of each manager as depicted in Figures 5a-d. The results within the groups indicate that there was a general lack of agreement within each group and within the whole team. Only a few pairs of managers had similar judgments and they came from different functional areas and different groups. The results also indicate that the participants relied on different cues for their judgments. It was not possible for the management team to identify a single most important cue for throughput time of the production system due to linkage ambiguity within the systems and within their judgments. Although all participants were experienced managers, familiar with the production system, and routinely made decisions regarding improvement activities, there was a general lack of agreement and common understanding. Many managers were biased towards the process which is most critical in their functional role, for example, scrap and rework for the quality manager – QUAMGR1.

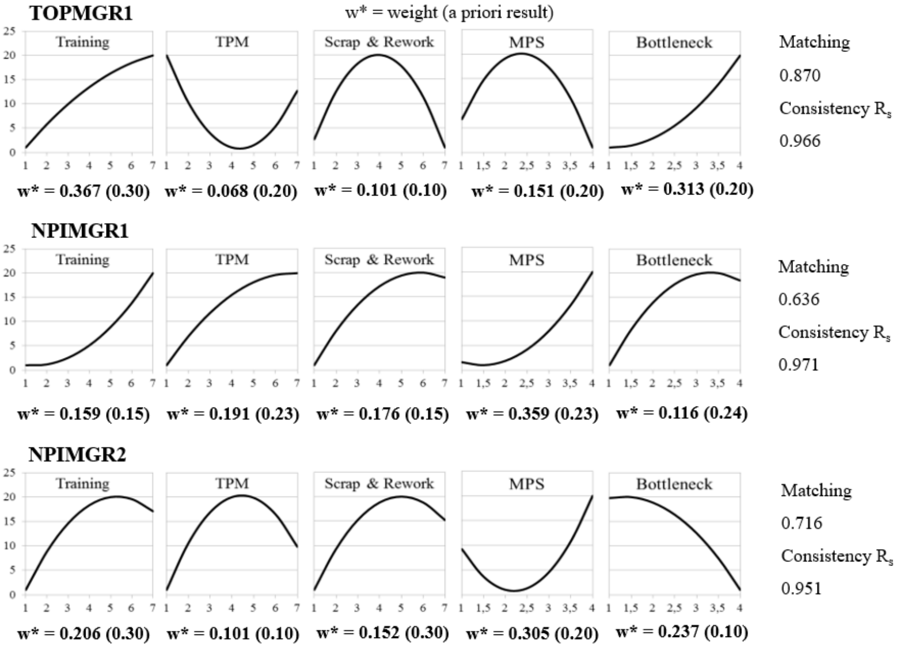


Figure 5a. Weights and Function Forms of Group 1, Top-Management, and Innovators.

A lack of focus on specific cues made it very difficult to rate profiles consistently based on the a priori assessment, which resulted in substantial differences between the weights of the a priori results and the actual judgment analysis. Those, who clearly prioritized one or two cues, generally could achieve higher consistency with their a priori assessment, because they only focused on specific cues when rating the profiles which made it easier to cope with the complexity of the judgment task. One reason for high variance was, most likely, the absence of a clear and holistic manufacturing policy to align decision making of all managers. This also resulted in judgment errors for some managers and they misjudged some profiles which caused high deviations from their a priori assessment; see LOGMGR2 for the TPM cue, for example. Misjudgements, or overlooking of alternatives can always happen in complex judgment and decision tasks and this method can detect, and point towards them, to re-evaluate some alternatives.

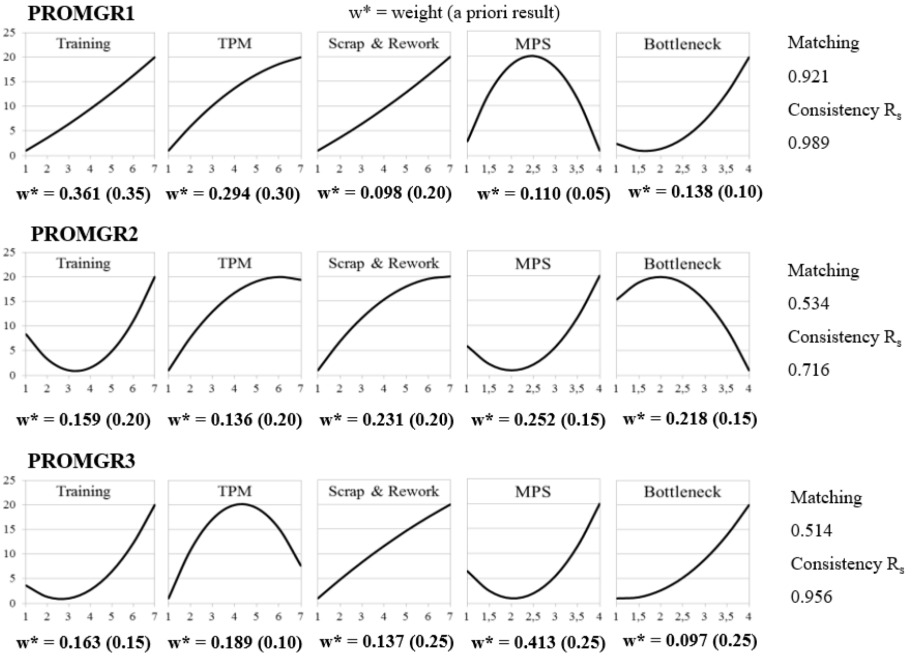


Figure 5b. Weights and Function Forms of Group 2, Production Management.

Function forms also play an important role in the judgment analysis as they depict the changes of perception of managers for different cue levels. It is important to note, however, that the function form should always be considered in relation to the weight because of the characteristics of the range method. The range method always calculates the graph between the minimum and maximum judgments over the whole range of cues and the weights are separated from the function form. A function form of a cue with a lower weight should not be emphasized as much as one with a higher weight because of the higher impact of the latter. Some of the function forms are strictly negative linear, which could mean that the participant thought of that cue as highly negative for throughput time, for example the MPS cue for LOGMGR3. The reason for that is that the manager completely disregarded this specific cue in favour of other inputs, which resulted in a very low weight of .02 for the MPS process. Other managers, however, also had negative function forms with high weights for some cues, which means that they truly had a negative perception about specific cues in terms of throughput time reduction.

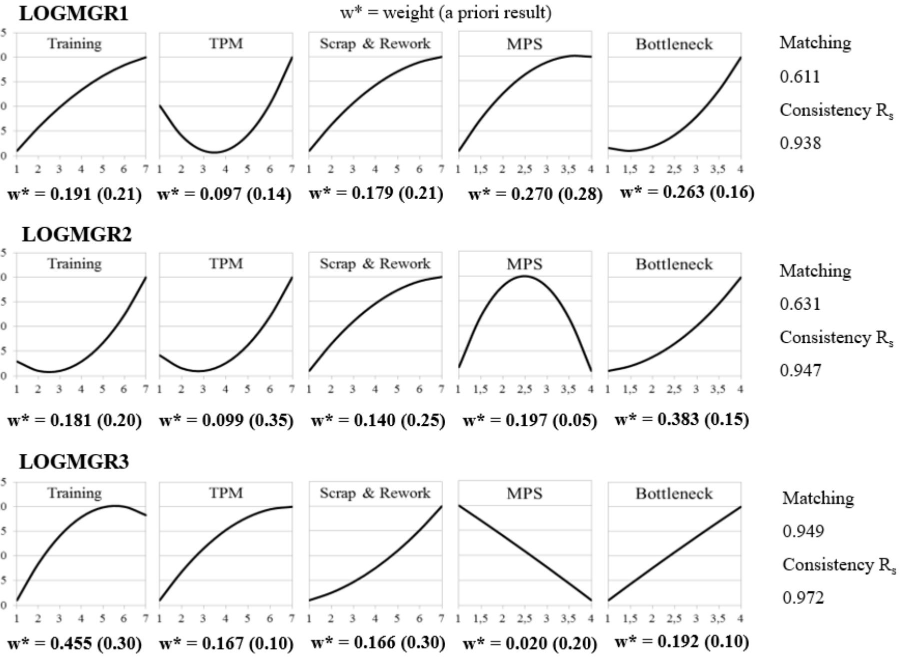


Figure 5c. Weights and Function Forms of Group 3, Logistics Management.

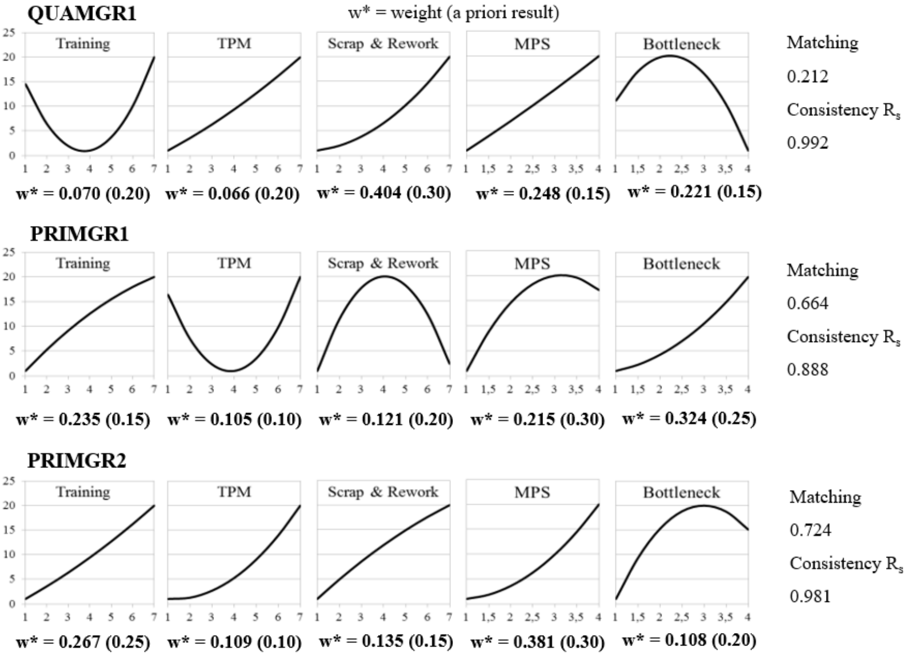
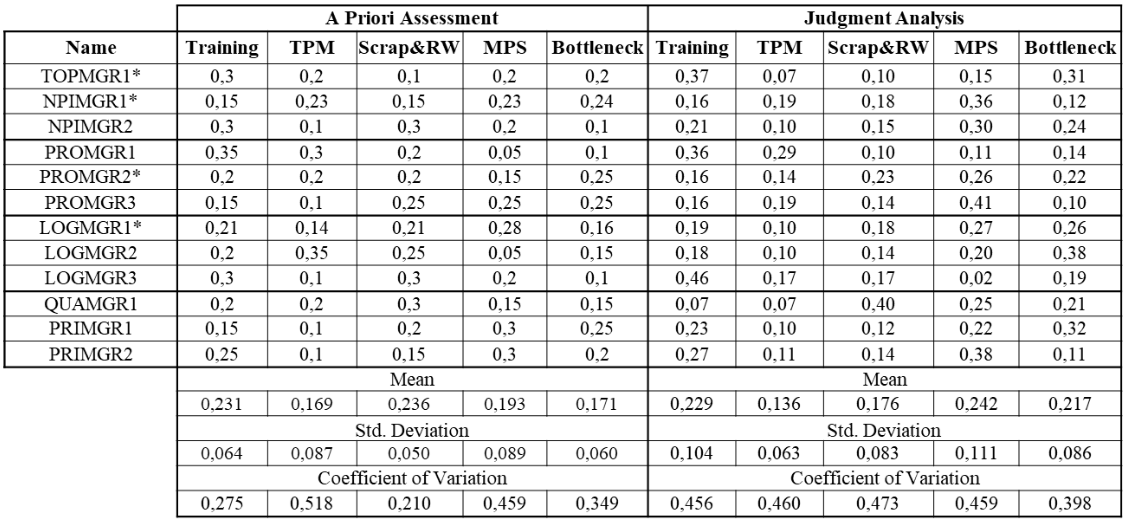


Figure 5d. Weights and Function Forms of Group 4, Quality Improvement.

Table 3 summarizes all results for the whole management team. This showcases the general lack of consensus among the management team with no clear priorities among the variables as every manager chooses to rely on different cues. The aggregate group preference lies in the MPS process with only a minor lead over the training process and bottleneck optimization for the judgment analysis. The team seems to agree only on the TPM process to be the least relevant process for throughput time, which is somehow counter-intuitive. The only explanation by the authors is that TPM is the least appealing and intuitive process among all cues so the participants sub-consciously devalued the impact of this input on throughput time. The equipment was also relatively new, which led to assumptions that there would not be as much unplanned downtime as initially simulated. In the a priori assessment it came in last in terms of relative weights as well, but not by the same margin as was the case in the judgment analysis and there were outliers in both assessments. Scrap and rework had a relatively low weight as well, because of the nature of the small-volume batch production system, characterized by a low quantity of high-value products being produced. In this case, the influence of scrap and rework is higher on quality costs than on throughput times which is intuitive and was also reflected in the judgments of the management team.



	A Priori Assessment					**Judgment Analysis**				
Name	**Training**	**TPM**	**Scrap&RW**	**MPS**	**Bottleneck**	**Training**	**TPM**	**Scrap&RW**	**MPS**	**Bottleneck**
TOPMGR1*	0,3	0,2	0,1	0,2	0,2	0,37	0,07	0,10	0,15	0,31
NPIMGR1*	0,15	0,23	0,15	0,23	0,24	0,16	0,19	0,18	0,36	0,12
NPIMGR2	0,3	0,1	0,3	0,2	0,1	0,21	0,10	0,15	0,30	0,24
PROMGR1	0,35	0,3	0,2	0,05	0,1	0,36	0,29	0,10	0,11	0,14
PROMGR2*	0,2	0,2	0,2	0,15	0,25	0,16	0,14	0,23	0,26	0,22
PROMGR3	0,15	0,1	0,25	0,25	0,25	0,16	0,19	0,14	0,41	0,10
LOGMGR1*	0,21	0,14	0,21	0,28	0,16	0,19	0,10	0,18	0,27	0,26
LOGMGR2	0,2	0,35	0,25	0,05	0,15	0,18	0,10	0,14	0,20	0,38
LOGMGR3	0,3	0,1	0,3	0,2	0,1	0,46	0,17	0,17	0,02	0,19
QUAMGR1	0,2	0,2	0,3	0,15	0,15	0,07	0,07	0,40	0,25	0,21
PRIMGR1	0,15	0,1	0,2	0,3	0,25	0,23	0,10	0,12	0,22	0,32
PRIMGR2	0,25	0,1	0,15	0,3	0,2	0,27	0,11	0,14	0,38	0,11
	Mean					Mean				
	0,231	0,169	0,236	0,193	0,171	0,229	0,136	0,176	0,242	0,217
	Std. Deviation					Std. Deviation				
	0,064	0,087	0,050	0,089	0,060	0,104	0,063	0,083	0,111	0,086
	Coefficient of Variation					Coefficient of Variation				
	0,275	0,518	0,210	0,459	0,349	0,456	0,460	0,473	0,459	0,398

Table 3. Judgment Analysis for the Management Team (*Top Decision Makers).

The results in this analysis are consistent with the findings of Dhir (2001), where participants had substantial differences in their initial judgments, however, they could at least agree upon the two most important factors with a significant margin in a deterministic judgment problem. In our study, however, managers even within the same area had substantial differences in their judgments and a high degree of linkage ambiguity can be observed, even within a relatively homogeneous group.

6.2. Simulation - Weights, Function Form and Causal Relationship

The weight and function forms for the simulation analysis were computed in the same way as the results of the judgment analysis. All profiles were rated based on the averages of throughput times from 25 simulation runs with the best profile getting 20 points and the worst one point. The ratings were then used like the results of an additional judge in the judgment analysis, and function forms and weights were calculated accordingly. Figure 6 shows the results of the 'quasi judgment analysis' based on the simulation results to create a picture for the left side of the lens model.

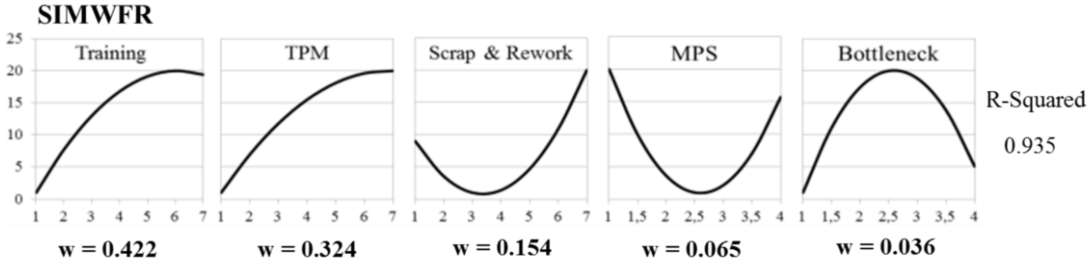


Figure 6. Weights and Function Forms Based on Simulation Results.

The simulation results decisively showcased the impact of the variables on throughput time for the environmental system on the left side of the lens model. Employee training was the most important factor for throughput time improvements because of the wide range of the input variable (see appendix). In the worst case, workers performed manual processes with only half the speed compared to the defined standards, while in the best case they could even improve on old standardized processing times with decentralized improvement on the operative level. This spread was a clear indication that employee training was critical for fast and stable processing of production orders, especially, because the modifier also affected bottleneck processing times at the finish department which is 100% manual and relies heavily on training. A unit-wide training program was the most promising decision to enable employees to improve their processes autonomously with good knowledge in standardized work and improvement methods.

The second-most important process according to the simulation analysis was TPM to reduce unplanned machine downtime and further decrease the variability on the shop floor. This process only affected automated process of the assembly systems and furnaces with relatively lower capacity utilization levels compared to the finish department. However, long downtime significantly affected the proper flow of products through the value stream and, at a certain level, the upstream processes could not supply the finish department efficiently. At low levels of the TPM process, the bottleneck shifted to the furnace process because the TPM modifier for automated processes did not affect the finish department. Machine breakdown occurred randomly and with varying impact on the system based on the current state of production and the duration of the downtime period. Manufacturing planning and control with the development of an improved MPS to optimize the sequence and flow of parts through the system had almost no effect on throughput times due to high WIP inventory which decreased the sensitivity of the system to a varying product mix and sequence. It was far more important to produce each order effectively than to plan and optimize the sequence of orders due to high variability in other processes. The least important process was bottleneck optimization because it was also overshadowed by other processes with higher variability.

Furthermore, improvements at the finish department became meaningless when the bottleneck shifted to the furnace process due to a bad TPM process, which affected only furnace, but not the finish department. High unplanned downtime reduced protective capacity at the non-bottleneck workstations and caused increased bottleneck shiftiness, which confirms the finding of Craighead et al. (2001) that bottleneck shiftiness can be reduced by placing more protective capacity before and after the bottleneck. This questions the TOC (Goldratt and Fox 1986) that a continuous improvement process should always focus on the bottleneck, and improvement of non-bottleneck resources is wasted, which is also supported by Filho and Uszoy (2014). They find that smaller improvements at all workstations had almost the same effect on cycle time as a large improvement activity at the bottleneck workstation, which is confirmed by our analysis.

6.3. Comparison of Results and Development of an Action Proposal

Both sides of the lens model have been analysed and visualized in the same way and can now be compared to find sources of agreement and disagreement for better communication within the sensemaking process. The ladder graph of Figure 7 shows the weights for all factors as calculated for the simulation analysis and the judgment analysis of the management team. The indifference of the management team can be seen on the right side and they could not mutually agree on a single-most important cue with a significant margin. The simulation on the other hand generated clear results to focus on a specific factor with the highest potential for improvement of throughput time and therefore, the average matching index was relatively low.

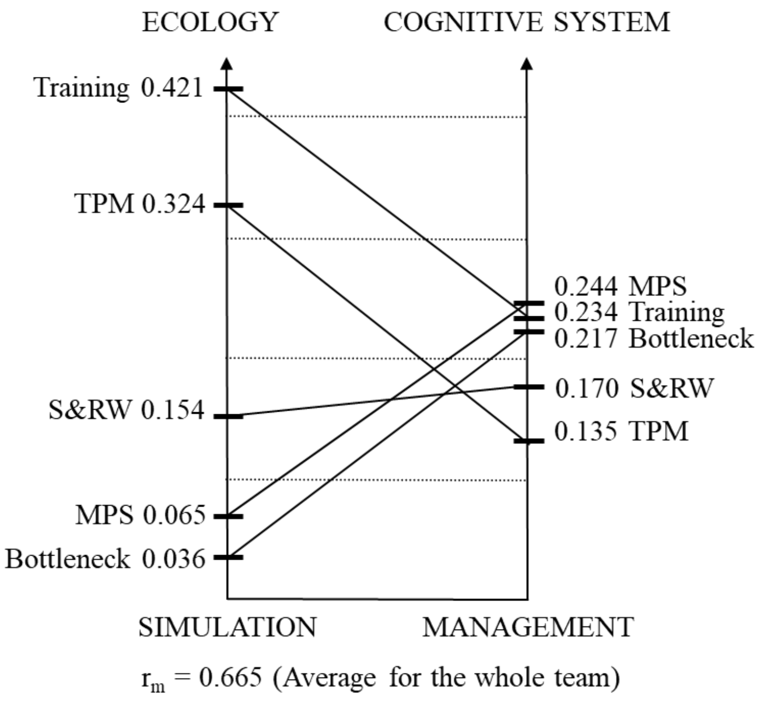


Figure 7. Comparison of Weights between Simulation and Judgment Analysis.

The training process was a clear winner for the simulation analysis and the management team agreed at least to some extent by giving this factor the second-highest weight, despite the large absolute difference in weights between both sides of the lens model. Scrap and rework were relatively even on both sides of the lens model but ranked differently. MPS and bottleneck processes did not influence the dependent variable as much due to the aforementioned reasons, however, the management team had them ranked in the top group of subjectively more relevant processes. While there might be various reasons for disagreement – attribute conflict and preference uncertainty (Fischer et al. 2000) for example – it shows that no clear causal relationship can be identified among the management team for the environmental system and only a few managers had some agreement with the simulation results as seen in Figure 8. The graph shows the weights for each factor for the three closest managers compared to the simulation; all three managers overvalued the bottleneck factor to the detriment of TPM. The goal of the lens model is to unfold these differences and make them visible for the management team to improve their group decision making.

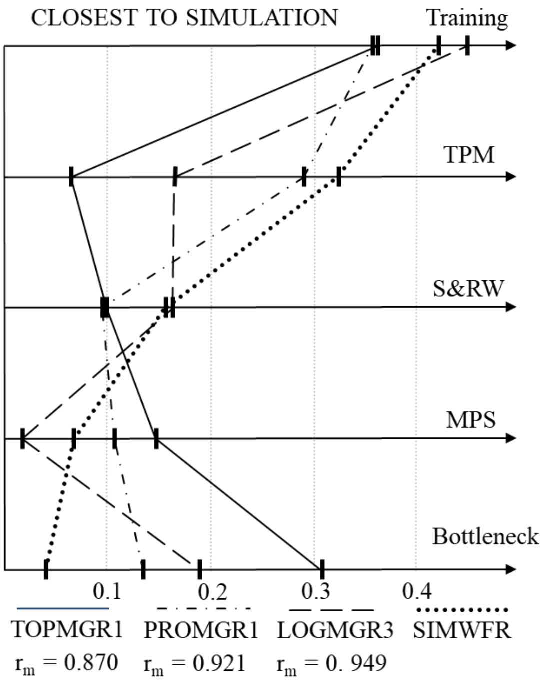
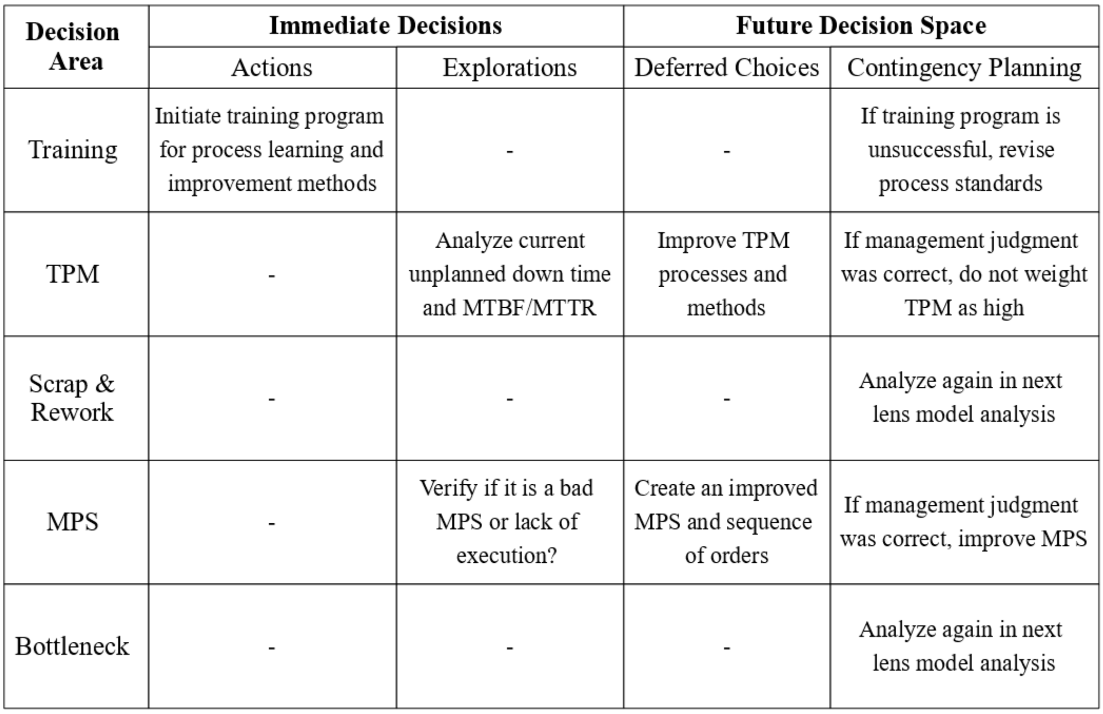


Figure 8. Highest Agreement based on Matching Index and Weights.

The differences in the weights for the TPM process were the most interesting, because they accurately reflected the real dynamics within the production system as observed by the authors. Only one participant, namely PROMGR1, weighted this factor above 0.2 in the judgment analysis, who was indeed the one who tried to initiate an improvement project for the TPM process during this research project. This process improvement activity, however, was never implemented due to a lack of support of the other managers and there was no mutually acceptable action proposal.

Action proposals support a causal link between a course of action and its consequences and can be used to justify how certain solutions, based on theoretical research and models, lead to an anticipated and desired outcome on the process-level of a production system (White 2016). Friend and (2005) point out that OM interventions and models rarely solve organizational problems directly and if they were to be relevant and useful for practitioners, they need to be embedded in action proposals, or commitment packages. This method can be used in combination with the lens model methodology because action is an integral part of the sensemaking framework (Weick et al. 2005).

A commitment package, as developed by Friend and Hickling (2005), is an action proposal that defines a set of immediate actions and future decisions to achieve incremental progress in a continuous planning process. It defines what actions must be taken immediately, or if more exploration is necessary based on time and uncertainty of the decision areas. This means that some decisions should only be made if uncertainty is below a certain level and if there is not enough time for further explorations. It also leaves future decision space for deferred choices and contingency planning if there is still enough time to analyse further choices or to reduce uncertainty by doing more research, as depicted in Table 4. Note, that this is only one isolated concept out of the whole framework to assist decision makers in a continuous planning process but is an excellent tool to summarize the results of the lens model. It can also be used synergistically with continuous improvement cycles based on Six Sigma or Lean and is designed to work in environments with high uncertainty and causal ambiguity where judgments are needed for decision making.



Decision Area	**Immediate Decisions**		**Future Decision Space**	
	Actions	Explorations	Deferred Choices	Contingency Planning
Training	Initiate training program for process learning and improvement methods	-	-	If training program is unsuccessful, revise process standards
TPM	-	Analyze current unplanned down time and MTBF/MTTR	Improve TPM processes and methods	If management judgment was correct, do not weight TPM as high
Scrap & Rework	-	-	-	Analyze again in next lens model analysis
MPS	-	Verify if it is a bad MPS or lack of execution?	Create an improved MPS and sequence of orders	If management judgment was correct, improve MPS
Bottleneck	-	-	-	Analyze again in next lens model analysis

Table 4. Commitment Package, or Action Proposal based on the Lens Model Results.
Source: Authors representation of Friend and Hickling (2005).

An immediate action that should be taken based on this study is to initiate a training program to improve manual processes and to reduce processing variability caused by assembly and finish workers. Stable and improved processing times had to be the number one priority of the business unit, however three of the four top decision makers (Table 3) viewed it not as a top priority according to the weights given in the judgment analysis. The lens model made these deviations transparent and specific managers could adjust their cognitive system by progressing in their sensemaking processes to adapt cue utilization for this specific problem. It is fair to assume that these misconceptions of key decision makers within the production system prevented actions to improve this critical input. With the help of the information generated by the lens model specific people could be convinced and the action was finally implemented through an extensive production preparation process where all manual processes were trained, improved, and standardized. This continuous improvement cycle was the new main priority for the unit and a clear focus for resource allocation. Allocation of resources into improvement of TPM and master production scheduling, on the other hand, was deferred and required further investigation, data collection and analysis. Those were the two processes where the management team deviated from the DES and at least one side valued it as a top-priority and the other mostly neglected it. This makes both processes good candidates for further explorations and differed choices in Table 4, as it is obvious that no consensual decision could be made based on the lens model analysis. In this case the continuous improvement cycle starts again with a ‘plan’ or ‘define’ stage in a future period and no resources should be deployed without a clear understanding about the potential benefits of those processes.

No resources were assigned to bottleneck optimization since it was the lowest ranked in the top group for the management team and the lowest overall in the DES. The quality solving process to reduce scrap and rework was also not a priority in terms of throughput time. Resources were allocated accordingly, with the majority going into the execution of immediate actions, and the rest could be invested into further analysis of other important factors that required more information. This ensured efficient and effective selection of improvement projects based on measurable indicators and management judgments. Relying on one source would potentially have led to a different allocation of resources without an exact classification of actions for each decision area.

Management generally trusted the results of the simulation analysis and accepted the action plan after pointing out the differences between the DES and their judgment analysis. They were involved right from the beginning of the analysis and the creation of the DES and could easily interpret the results of the judgment analysis to adjust their mental model. This way we could minimize subjective influences based on objective results and create a mutually acceptable action proposal.

7. Conclusion and Future Research Directions

There are many reasons why managers cannot or do not want to understand objective quantitative analyses. For example, complexity can create a gap between the model builder’s insights and a manager’s understanding of its results, as explained by Dhir (2001). Another point is that people are not particularly good at explaining the reasoning behind their judgments, which prevents effective communication and understanding between individuals. Dietvorst et al. (2015) found algorithm aversion, or a lack of trust into results of quantitative analyses if people have had bad experiences in the past. All these factors influence managers to still rely on their own subjective methods because they believe to already know the most important factor for improvement (Kirkham et al. 2014). The lens model confronts managers with their biases which is why it is so important that the analysis from the lens model method is purely descriptive to analyse factors deep within an individual's cognitive system.

The S^3 developed in this paper is not focused on decision-making based on precise mathematical calculations, but rather serves as a sensemaking tool to bring the management team closer together and empower them to define mutually acceptable actions to move forward and improve the production system. After a trigger event, a criterion variable (e.g. manufacturing throughput time, or behaviour of wildfires in certain terrains) is defined to be the centre point of the sensemaking process and the lens model analysis. The DES helps to define, label, and categorize inputs and generate insights into potential future states of the system and form presumption about the environment. Then the judgement analysis visualizes cognitive patterns of the management team and their preferences for cue utilization and rankings as a basis for communication. We exposed differences and similarities as a basis for communication and discussion to bring the management team closer together and facilitate exchange of ideas and knowledge. The action plan generated by combining both analyses is the foundation for future steps to create even more sense when the sensemaking process is repeated. In this ongoing process of sensemaking, action generates more inputs that can be included in future lens model analyses. That way knowledge and understanding can be continuously increased to make more sense of complex processes within the production system. More cycles in the sensemaking process are necessary to define, label and categorize different, and potentially better, cues and use the results of previous communication to integrate them into better models and create better action plans as the sensemaking process goes on, which is the goal for future research.

This method is valuable even for production systems without extensive data collection and can be easily implemented. Various other objective methods, for example pareto analysis, structural equation modelling, etc., can be used on the left side of the lens model to predict the true state of a system and can be compared with the judgment analysis on the right side to yield the same results. Future research can implement this method to test results of objective scientific methods and bring them into closer relation to the judgments of managers affected by this analysis. Another crucial part, left for future research, would be to test the effects of the cognitive analysis with the lens model methodology in comparison to just a ‘regular’ scientific intervention. This would empirically strengthen many ideas of behavioural OM/OR and the benefits of including the human factor in applied research in our field. In a broader sense, if we put academics fighting for rigor on one side and the practitioners living in the world of relevance on the other, our paper is an attempt to bridge the gap between the two groups. We hope that it will be followed by many.

The lens model methodology includes managers into the sensemaking process and valuable insights can be gathered by making all judgments available to top management. This was also observed by King and Zeithaml (2001) who reported a high interest of top-managers regarding the perception of their colleagues and middle managers about resource-performance linkages, which was also the case in this research because managers want to understand what their colleagues think. They found that the transfer and collaborative exploitation of resources could lead to increased firm performance; this is why this research aims to make this information available for the management team to improve mutual understanding. It shows that integrated information from the DES and the judgments of management can be used to create holistic and accepted action proposals to increase the relevance of OM interventions for practical applications. Samson and Whybark (1998) and Vastag (2000) emphasize focusing on soft issues and organizational capabilities to outperform competitors due to better decision making and usage of manufacturing inputs, investments, and choices. The sensemaking framework is one way to improve decision making within the production system and to help management acting in an organized, coherent way.

Kirkham et al. (2014) provide an excellent literature review of improvement project prioritization and conclude that limited empirical research has been conducted to understand improvement project selection processes. They find that objective prioritization methods, especially in a Six Sigma context, generally lead to better results, compared to subjective ones. We try to analyse and combine both methods to help to fill the gap in the literature and to create a deeper understanding of managerial sensemaking processes and the prioritization of improvement projects. A lot of research has been conducted on the best way to improve a production system, Goldratt and Fox (1986), or Ferdows and De Meyer (1990), to name just two, but ultimately it depends on the judgment and the alignment of the decision makers to go in the same direction and work together to achieve common goals of the production system. Production systems, supply chains or service providers are, after all, complex social systems, where behaviour of individuals, groups, or whole organizations is the central driver of operations and performance (Gino and Pisano 2008).

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Appendix

Appendix 1: Calculations of weights and function form of the lens model analysis.

The computations below were developed by, and are adapted from, Hammond *et al.*, (1975), with typographical errors removed. To visualize the judgment processes, it is important to calculate the weight of each input variable based on the judgments of each individual by using a non-additive model of polynomial form, as seen in equation 1.

Equation (1):

$$y_{ij} = \sum_{k=1}^{m} \left(b_{ik} * x_{jk} + b_{i(k+m)} * x_{jk}^2\right) + c_i + e_{ij}$$

where:

y_{ij} = judgment of the individual i for an input profile j (profiles with different values for cues to be ranked by an individual),

m = number of input factors, b_{ik} is the raw score regression weight for individual i on factor k's linear term,

$b_{i\,(k+m)}$ = regression weight for individual i on the quadratic term of factor k,

x_{jk} = value of input factor k on profile j,

c_i = constant term for individual i for input profile j.

In this equation, the function form and weight for each cue are not available and must be separated using the following transformation found in Hammond et al. (1975).

They define $f_k(x_{jk})$ as a function of x_{jk}:

$$f_k(x_{jk}) = (b_{ik} * x_{jk} + b_{i\,(k+m)} * x_{jk}^2)$$

They further define:

$$g_k = \frac{y_{max} - y_{min}}{f_{k\,max} - f_{k\,min}}$$

and:

$$h_k = y_{min} - g_k * f_{k\,min}$$

f_{kmax} is the maximum value of f_k over the range of factor k, f_{kmin} is the minimum value, y_{max} is the maximum value of judgment allowed, and y_{min} is the minimum value. A new function that ranges from y_{min} to y_{max}, can now be defined.

Equation (2):

$$F_k\left(x_{jk}\right) = g_k * f_k\left(x_{jk}\right) + h_k$$

By modifying the equation and substituting for $f_k(x_{jk})$ in equation 1 we get:

$$f_k(x_{jk}) = \frac{(F_k(x_{jk}) - h_k)}{g_k}$$

$$y_{ij} = \sum_{k=1}^{m} \frac{(F_k(x_{jk}) - h_k)}{g_k} + c_i + e_{ij}$$

or,

$$y_{ij} = \sum_{k=1}^{m} \frac{F_k(x_{jk})}{g_k} - \sum_{k=1}^{m} \frac{h_k}{g_k} + c_i + e_{ij}$$

or, equation (3):

$$y_{ij} = \sum_{k=1}^{m} w_k * F_k(x_{jk}) + C_i + e_{ij}$$

where:

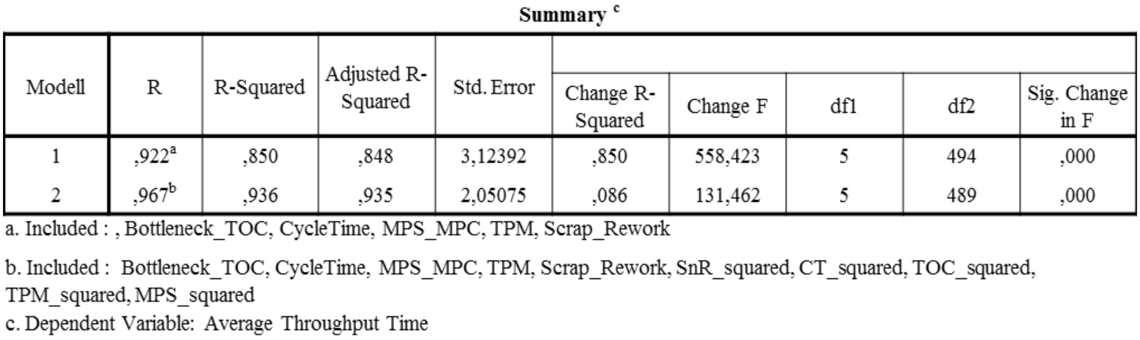
$$w_k = \frac{1}{g_k}$$

and:

$$C_i = c_i - \sum_{k=1}^{m} \frac{h_k}{g_k}$$

The ranges for all input factors k must be known to use this method and the cue weights as well as the function forms are calculated over the range of judgments (y_{min} - y_{max}), based on g_k. This method is called *“range method*” and it separates the weights w_k in Equation 3 from the function form $F_k(x_{jk})$ in Equation 2. The results give an indication about the preferences of the individuals based on their judgments. The highest weight represents the highest preference of the judge towards a specific input factor (cue).

Appendix 2: Results of the regression analysis (linear, nonlinear) of the DES.



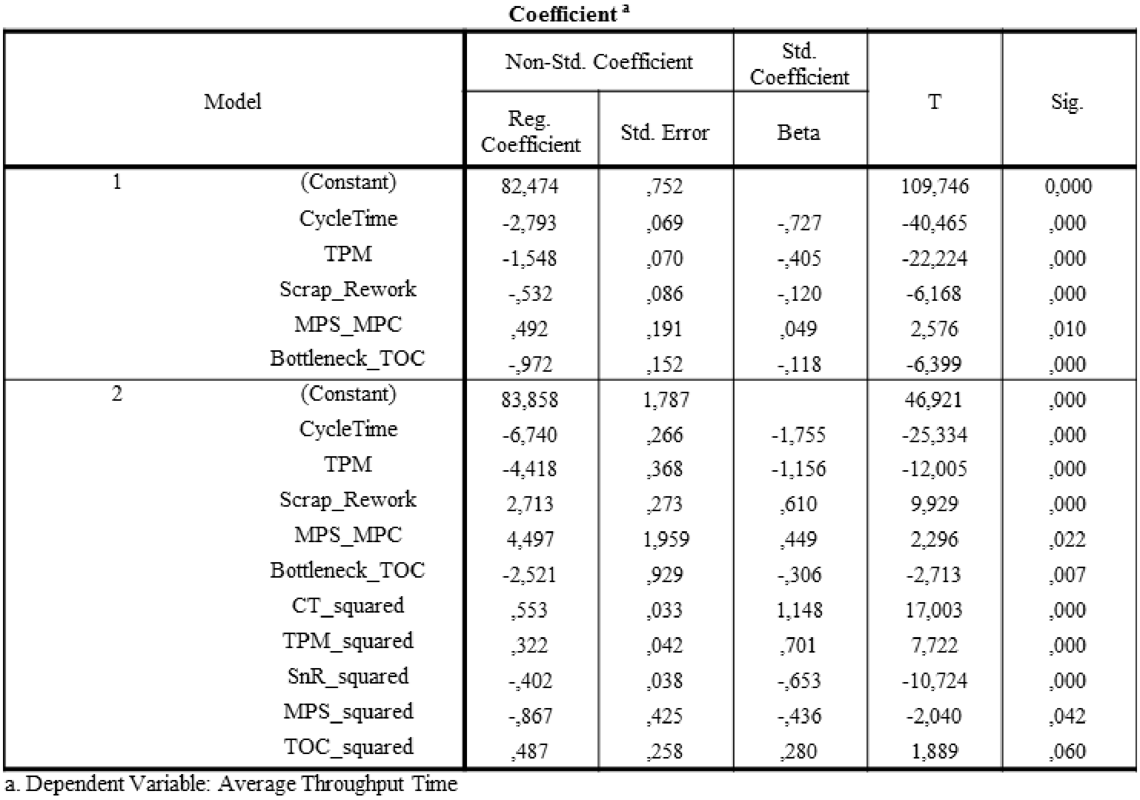
Summary [c]

Modell	R	R-Squared	Adjusted R-Squared	Std. Error					
					Change R-Squared	Change F	df1	df2	Sig. Change in F
1	,922[a]	,850	,848	3,12392	,850	558,423	5	494	,000
2	,967[b]	,936	,935	2,05075	,086	131,462	5	489	,000

a. Included : , Bottleneck_TOC, CycleTime, MPS_MPC, TPM, Scrap_Rework

b. Included : Bottleneck_TOC, CycleTime, MPS_MPC, TPM, Scrap_Rework, SnR_squared, CT_squared, TOC_squared, TPM_squared, MPS_squared

c. Dependent Variable: Average Throughput Time



Coefficient [a]

Model		Non-Std. Coefficient		Std. Coefficient	T	Sig.
		Reg. Coefficient	Std. Error	Beta		
1	(Constant)	82,474	,752		109,746	0,000
	CycleTime	-2,793	,069	-,727	-40,465	,000
	TPM	-1,548	,070	-,405	-22,224	,000
	Scrap_Rework	-,532	,086	-,120	-6,168	,000
	MPS_MPC	,492	,191	,049	2,576	,010
	Bottleneck_TOC	-,972	,152	-,118	-6,399	,000
2	(Constant)	83,858	1,787		46,921	,000
	CycleTime	-6,740	,266	-1,755	-25,334	,000
	TPM	-4,418	,368	-1,156	-12,005	,000
	Scrap_Rework	2,713	,273	,610	9,929	,000
	MPS_MPC	4,497	1,959	,449	2,296	,022
	Bottleneck_TOC	-2,521	,929	-,306	-2,713	,007
	CT_squared	,553	,033	1,148	17,003	,000
	TPM_squared	,322	,042	,701	7,722	,000
	SnR_squared	-,402	,038	-,653	-10,724	,000
	MPS_squared	-,867	,425	-,436	-2,040	,042
	TOC_squared	,487	,258	,280	1,889	,060

a. Dependent Variable: Average Throughput Time

Appendix 3: Performance levels and ranges for all input parameters (“cues”).

Main Process	Indicators (KPIs)	Performance Level	Range			Description
			Min.	Expected Value (EV) of Processing Time	Max.	
Training	Processing Time Variability (in %)	Level 1 - Very Low	110% of EV	EV for each product based on analysis	200% of EV	Employees cannot perform the manufacturing processes according to the defined standards due to missing of training.
		Level 2 - Low	105% of EV	EV for each product based on analysis	180% of EV	Start of basic training for all employees. They can almost reach the target in the best case (105% of EV), but can still miss target by a lot (+80%).
		Level 3 - Below Average	100% of EV	EV for each product based on analysis	150% of EV	Employees have had sufficient basic training and experience to reach the targets in the best case. Still up to 50% variability in the worst case.
		Level 4 - Average	95% of EV	EV for each product based on analysis	130% of EV	Additional training for employees. They start to improve processes up to 5% (95% of EV). Lower variability.
		Level 5 - Above Average	95% of EV	EV for each product based on analysis	120% of EV	Additional training and employees start to work according to the defined standards. Max 120% of EV in the worst case.
		Level 6 - High	90% of EV	EV for each product based on analysis	110% of EV	Training for a decentralized continual improvement process has begun. Employees know basic principles and take responsibility for their process.
		Level 7 - Very High	85% of EV	EV for each product based on analysis	95% of EV	Employees are experts in process improvement and standardization. They perform processes at the highest level without deviations.
			MTBF	TPM Time per Week	MTTR	
TPM	-TPM Time per Week -MTBF (Time to Failure) - MTTR (Time to Repair) (all 3 in hours)	Level 1 - Very Low	2	0	1.3	No weekly TPM. Regular unplanned downtime (every 2 hours) and long repair time (1.3 hours) - 60.6% availability.
		Level 2 - Low	2.3	0	1	69.7% availability. Long unplanned downtimes, several problems in each shift. Irregular, unplanned TPM activites whenever there is time.
		Level 3 - Below Average	3	8	1	75% availability - 8 hours of planned TPM per week. Slight improvement of downtime (every 3 hours). Faster repair time.
		Level 4 - Average	3.5	8	1	77.8% availability. Better TPM and improved availability.
		Level 5 - Above Average	4	6	0.9	81.6% availability - Improved TPM planning and processes. Reduced downtime, faster repair time.
		Level 6 - High	5	6	0.8	86.2% availability. Better maintanace and faster repair.
		Level 7 - Very High	6	4	0.6	90.9% availability - Just-in-time TPM processes. Optimized time effort and maximized benefit. Fast repair times.
			Scrap +/-%	Rework +/-%	Scrap after Rework	
Quality Problem Solving	-Direct Scrap -Rework -Scrap after Rework (Better / worse compared to current rates in %)	Level 1 - Very Low	+30	+50	+50	All scrap rates increased. There are almost no quality improvement activities at all. (10,2% total scrap rate).
		Level 2 - Low	+20	+35	+35	All rates increased. Quality is getting worse due to lack of efficient "Quality Problem Solving" process (9,2% total scrap).
		Level 3 - Below Average	+10	+20	+20	All rate slighty increased. Still bad quality due to low performance in quality problem solving (8,2% total scrap).
		Level 4 - Average	0	0	0	Current scrap rates (average for all products: direct scrap 5,5%; rework 15%; scrap after rework 11,6%; total 7,3%).
		Level 5 - Above Average	-10	-20	-20	Slight improvements in quality problem solving. Reduction of direct scrap: 10% , rework 20% (total scrap rates down to 6,3%).
		Level 6 - High	-20	-35	-35	Further improvements in problem solving. Total scrap: 5,7%.
		Level 7 - Very High	-30	-50	-50	Sustainable and efficient problem solving processes. Significant improvement in quality rates (total scrap: 5%).
			Sequence			
Manufacturing Planning and Control	-Sequece (Number of Changes in Schedule)	Level 1 - Very Low	Random sequence and schedule			No scheduling. Production orders are planned randomly without focus on capacity and demand.
		Level 2 - Low	Optimized production schedule with 10 deviations per week			Optimized production schedule (sequence, capacity, demand). There are still 10 deviation per week (out of 25 orders).
		Level 3 - High	Optimized production schedule with 5 deviations per week			Reduced deviations from optimized schedule (5 out of 25 orders not according to master production schedule).
		Level 4 - Very High	Optimized production schedule and sequence with 100% execution			All 25 weekly production orders are executed as planned and in the optimal sequence.
			Identification and Improvement of Bottleneck (BN)			
Bottleneck Improvement	Improvement of Bottleneck (BN) (Reduction of BN-gap in %)	Level 1 - Very Low	No information about BN and no improvement			The BN cannot be identified. There is no improvement activity at the BN. The BN is significantly slower than the other processes.
		Level 2 - Low	The bottleneck is identified and the gap is reduced by 60%			The gap between the BN and the process with second-higest utilization is reduced by 30%. Differences in utilization rates are reduced by 30%.
		Level 3 - High	The bottleneck gap is reduced by 60%			The gap between the BN and the process with second-higest utilization is reduced by 60%.
		Level 4 - Very High	The bottleneck gap is reduced by 100% - There is no difference in utilization			The gap between the BN and the process with second-higest utilization is reduced by 100%. The bottleneck operates with the same utlization rate.

Research Paper 2

Thomas B. Ladinig & Gyula Vastag (2020) Mapping quality linkages based on tacit knowledge, *International Journal of Production Economics* (under review, 2nd round after major revision).

Mapping quality linkages based on tacit knowledge

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Mapping quality linkages based on tacit knowledge

Abstract
A structured conceptualization method, concept mapping, is applied to visualize the conceptual domain of explicit and tacit quality linkages in a complex, causally ambiguous production system of a premium automotive OEM. Experts, intimately familiar with all facets of the conceptual domain, defined sources of quality problems and rated their impact on product quality. These inputs, formative measures for a latent construct, were used to create concept maps and clusters for the sources of quality problems. Differences and disagreements between subgroups were highlighted by pattern matching. The concept map and the preferred cluster solution, based on user-defined measures, served as inputs in the development of a causal loop diagram and an action plan for better resource allocation to specific improvement activities. The approach, using formative rather than the more commonly used reflective indicators, uses key informants and explanation building processes of high internal validity. In the spirit of the "proximal similarity model," the presented methodology is also highly transferable to similar settings of other automotive OEMs and beyond.

Keywords: Soft Quality Management, Concept Mapping, Knowledge Creation

1. Introduction

Lippman and Rumelt (1982) describe causal ambiguity as the degree to which decision makers understand input-performance linkages when creating and managing complex processes. In complex manufacturing systems with correlated stages, interdependencies, uncertainties and, consequently, with many sources of causal ambiguity, it is critical to identify quality linkages that affect the quality of the final product (Zantek et al., 2002). The authors observed issues related to causal ambiguity and quality linkages in a manufacturing unit of a premium automotive OEM – producing exterior body parts for luxury sports cars – with several correlated stages and various highly variable inputs per process (e.g., machines, materials). As product performance, in terms of quality, was a competitive priority for the business unit and for similar production systems (Schmenner and Vastag, 2006), management wanted to improve their understanding of factors affecting overall product quality. The goal was to identify the most important inputs and solutions to improve quality performance within the whole value stream of the production system.

Quality costs were high due to many required changes in machine parameters to ensure proper quality levels of a highly heterogeneous product mix with many changeovers and low batch sizes. Several attempts had been made to improve quality assurance and measurements to improve the overall quality within the system; yet a significant number of products had to be scrapped or reworked due to lack of knowledge and holistic insight into quality linkages. It was not clear to management which of the many factors, and what subsequent processes, had the most significant impact on quality. Data generated in one step of the process could not be linked to errors detected in the following steps and no decisions could be made to holistically improve quality over the whole value stream. All this resulted in a general lack of understanding of resource allocation towards the most efficient and effective quality improvement initiatives. It became extremely difficult for management to define policies without a clearer picture of quality linkages and issues that resulted in lower quality performance.

The authors decided to use a *structured conceptualization* methodology (Trochim and Linton, 1986), called *concept mapping*, to map the conceptual framework of quality and quality linkages within the system. The reasoning was that by creating a holistic picture of the problem domain, based on the tacit knowledge and experience of the engineers of the system, learning and understanding of cause and effect relationships could be facilitated. Concept mapping was chosen because it is more suitable to deal with causal ambiguity and it is more likely to create a more complete understanding of the system, as described in section 2. The goal was to use concept maps, consisting of all known quality issues, to ultimately select and plan quality improvement initiatives for the production system. Additionally, based on the results of the concept map, a causal loop diagram was created to further analyze casual relationships within the conceptual domain. Finally, the paper – using the results of concept mapping – presents an action plan for quality improvement to the management team of the business unit.

The structure of the paper is as follows: section 2 describes the literature on tools and principles of knowledge creation, process improvement and innovation, and gives an overview of concept mapping. Section 3 deals with the practical application of concept mapping and the explorative case study within the business unit. We summarize the results in section 4. Theoretical and practical insights are discussed in the fifth, and final, section of the paper.

2. Literature Review

One of the central drivers of performance in complex social systems, like modern manufacturing plants, or supply chains, is the behavior of individuals, groups, or the whole organization (Gino and Pisano, 2008). This is also the case for quality management (QM), where an increasing number of authors specifically investigate behavioral factors (soft QM) in their studies (Cho et al. 2017; Zeng et al. 2015). Soft factors, such as organizational learning and knowledge creation, are critical in most areas of operations management and, for that matter, in QM. The focus of how QM can enhance organizational learning and innovation (and vice-versa) is a central aspect of research in QM (Fundin et al. 2018; Asif, 2019; Dahlgaard et al. 2019) and the theoretical basis for our practical application.

2.1. Soft Quality Management and Organizational Learning

Mukherjee et al. (1998) defined two types of learning in an organization: conceptual and operational. Operational learning is focused on implementing and observing factors in an operative setting and drawing conclusions directly from experiences of problems in processes and solving those issues to achieve short-term goals. Conceptual learning, on the other hand, is more related to the assessment of cause and effect relationships and the design of abstract concepts. They concluded that conceptual learning is better suited to analyze more important factors of organizational learning and firm performance. The more valuable long-term goals are, for example, changing attention paid to measured variables and knowing the specific impact of factors on process variability and quality. This ensures more efficient and effective quality improvement based on a deeper and broader understanding of causalities compared to short-term operational problem solving. They specifically consider behavioral factors, organizational behavior, dynamic complexity, and ambiguity when comparing those two forms of learning in terms of quality improvement. A more conceptual focus is therefore necessary to explore quality linkages in complex production systems with causal ambiguity.

Choo et al. (2007) distinguish between two forms of learning, similar to Mukherjee et al. (1998): exploratory learning and exploitation learning. Exploitation learning, like operational learning, is focused on the application of methodological elements in an operative setting by using explicit knowledge. Exploratory learning is aimed at creating novel ideas and innovative solutions based on tacit knowledge and contextual elements (soft issues). While methodological elements contain metrics, tools, and stepwise problem-solving approaches to facilitate standardized and explicit quality programs, contextual elements include soft issues, like leadership, collaboration, and trust, to boost tacit knowledge creation through empowerment. More innovative solutions for quality problems based on tacit knowledge produce durable competitive advantages because they are difficult to imitate (Winter, 1987). This makes tacit knowledge a more valuable resource for a company, according to the resource-based view (RBV) of the firm (Barney, 1991), and should be the focus of learning and knowledge creation in QM.

Knowledge creation and dissemination of tacit knowledge from an individual to tacit knowledge of the group is called *socialization* in the knowledge creation framework of Nonaka (1991). While methods to create and disseminate explicit knowledge (e.g., simulation, regression, value stream maps, fishbone diagrams, etc.) are relatively straightforward, it is not so transparent with tacit knowledge. Anand et al. (2010) mention practices like brainstorming, or nominal group technique (Bartunek and Murninghan, 1984) for socialization of tacit knowledge in their study on the role of tacit knowledge in Six Sigma projects. They argue that it might be difficult to capture and apply tacit knowledge, especially in cross-functional teams that come together for a short-term project without significant cohesion and developed relationships among group members. It takes a substantial amount of experience and soft skills to facilitate tacit knowledge dissemination among group members in order to find and implement potential “winner” process improvements that could create long-term competitive advantages for the firm.

2.2. Soft Quality Management, Innovation and Process Improvement

Zeng et al. (2015) and Zeng et al. (2017) view small group problem solving and employee suggestions as important aspects of soft QM in that it allows for collective expertise in group decision-making and implementation of problem-solving plans. They claim that firms should promote employee participation in decision-making processes through empowerment and encouragement to ensure process quality, competency, and customer focus. Zeng et al. (2017) found that soft QM has a significant positive impact on hard QM and plays an important role in improved innovation performance, either directly or indirectly through improved hard QM. By promoting soft QM and the integration of worker experience, organizations can achieve higher innovation performance by finding different, and potentially better, solutions to existing problems.

One of the most important factors for the success of soft QM and its impact on innovation performance is the proactive behavior of people within the organization (Escrig-Tena et al., 2018). People need to understand the conceptual framework of quality based on strategy, tactics, processes, competitors, and organizational results to help align employee behavior and organizational objectives to promote innovation based on soft QM and organizational learning. (Dahlgaard et al. 2019) The work of Escrig-Tena et al. (2018) indicates that, while soft QM might not have a direct impact on innovation, it can create an infrastructure and atmosphere of empowerment and teamwork that allows employees to act and develop new ideas. Employees fully demonstrate proactive behavior only if they are well-informed about the firm, their work, and the problems they are faced with; thus, making it critical to create a conceptual framework for the environment they work in.

Not only the behavior and understanding of employees is important for finding innovative solutions in complex and dynamic areas, but also the thinking of management plays a significant role for performance improvement. Cho and Linderman (2019) analyzed the impact of managerial metacognition on process improvement practices and firm performance. While cognition is defined as the knowledge structure used to make a decision, metacognition is the higher-order process that controls the underlying knowledge structure. Usually, managers could potentially decide between multiple decision frameworks and different kinds of information to formulate responses to different problems. Cho and Linderman (2019) use the level of understanding of the usage of different kinds of information as a variable to define the metacognitive experience of managers. Also, the conscious focus on important information and re-evaluation of usability and applicability of different kinds of information are indicators of managerial metacognition. This conscious thinking and understanding of how knowledge should be used and the search for different kinds of information can help management adapt to rapidly changing environments in order to create a competitive advantage for an organization. A holistic awareness of the conceptual domain is critical to reach higher levels of managerial metacognition to find innovative solutions and to change management's perception of specific problems and potential solutions.

2.3. Concept Mapping

To facilitate tacit knowledge creation and innovation in causally ambiguous production systems, we apply *concept mapping*, to create a 2D representation of the problem domain as seen by a management team and a team of experts. We holistically analyze quality linkages in the small-volume, batch production system of an automotive OEM that faces high degrees of variability and causal ambiguity. Previously, concept mapping has been used extensively in program management, for example, to assess the conceptual framework of staff's views of a supported employment program for persons with severe mental illness (Trochim et al., 1994). In an operations management context, however, it has been used only very scarcely – for example, to show how management views the benefits of acquiring an ISO 14001 environmental certification and contrasting it with the views of experts (Vastag and Melnyk, 2002). The methodology is still highly popular in many scientific fields, as a recent special publication dedicated to it was issued

(Trochim and McLinden, 2017).

By creating a visual representation of the conceptual framework of a problem, the applied methodology facilitates proactive behavior to make knowledge explicit and usable for an organization. Concept mapping increases the understanding of employees and includes them in the improvement process. It furthermore facilitates innovation and managerial metacognition by unveiling potentially novel approaches due to the holistic methodology of mapping the conceptual domain in its entirety.

One of the most difficult and important steps in planning is the initial conceptualization, which ultimately determines the success of all following steps. Concept mapping can be used whenever a group of people should develop a conceptual framework for evaluation or planning, and the content of the maps is entirely determined by the group. Each map is a pictorial representation of the group's thinking, displays their ideas regarding a specific topic, and shows relationships between those ideas and their relative importance, based on the methodology developed by Trochim (1989). The methodology consists of six steps followed in this study:

Step 1: Preparation - This step includes the selection of participants and the definition of a focal point of the conceptualization.

Step 2: Generation of Statements - Statements should be created based on a "prompt" to represent the conceptual domain of the topic of interest. This part is very similar to a traditional brainstorming approach and as many statements as possible should be created to ideally represent the entire conceptual domain of the topic. As many different statements as possible should be generated and there should be no criticism regarding the legitimacy of statements as long as they fit into the previously defined area of focus.

Step 3: Structuring of Statements - In this step all statements are sorted and ranked by the participants. Unstructured card sorting can be used to sort statements and put them into clusters. Response scales (Likert) are used to rank the importance of statements.

Step 4: Representation of Statements - Three tasks are necessary to graphically represent the conceptual domain based on the similarity matrix from step three. The first task is the creation of a point map, which locates each statement as a separate point on the map, with statements placed closer to each other if they were more frequently sorted into the same pile. To accomplish this, nonmetric multi-dimensional scaling of the similarity matrix is conducted to create the point map. This technique takes a proximity matrix and represents it as distances between the original items in the matrix (Trochim, 1989) – most of the time as a two-dimensional solution to make it easier to interpret. The second task is a hierarchical cluster analysis that groups points on the point map into clusters. The X-Y coordinate data from the multidimensional scaling is used to group points into any number of clusters. The difficulty in this task is the decision on how many clusters are optimal to give a viable and meaningful solution because, in general, any number of clusters is possible. The final task is to overlay the clusters with the average rating from the participants to obtain a *cluster rating map* that visualizes all the information, which, in turn, gives a full representation of the conceptual domain to be interpreted.

Step 5: Interpretation of Maps - Several maps that provide different views of the same structure can be created in the fifth step, with different clusters to be analyzed by the participants. The goal is to find a mutually acceptable solution, which makes sense for all participants, with the right number of clusters and proper labeling. Then, cluster ratings can be compared among clusters and the concept domain is fully mapped based on the available information.

Step 6: Utilization of Maps - The final step is to use the maps for evaluation or planning purposes, and other applications, which will be demonstrated in the next sections of the paper.

3. Practical Application and Case Study

3.1. Company Overview

The case study was conducted at the production division of the automotive OEM during the first quarter of 2018. The production system consists of five stations with grouped equipment. Small batches of a broad product mix are produced, and parts are transported between stations in specialized containers, as depicted in figure 1. The press and laser workstations are producing components out of metal discs, which are then assembled at three specialized assembly stations. The aluminum and stainless-steel parts are then cured in a furnace in specialized furnace fixtures to ensure geometry and form of the final product. Finally, products are “finished” to ensure proper surface quality of all external car body parts. Quality checks could potentially be done between all steps of the process but they are costly and time consuming because surface, geometry, and stability of the parts are critical for quality of the final product so they must be closely inspected with specialized equipment. The only full-scale quality inspection is done after the curing furnace since the curing process has a significant impact on the geometry due to heat deformation of the material. The results of the quality inspections are then transferred to the finish department in order to define proper counter measures and potential rework in addition to the standard surface quality improvement activities.

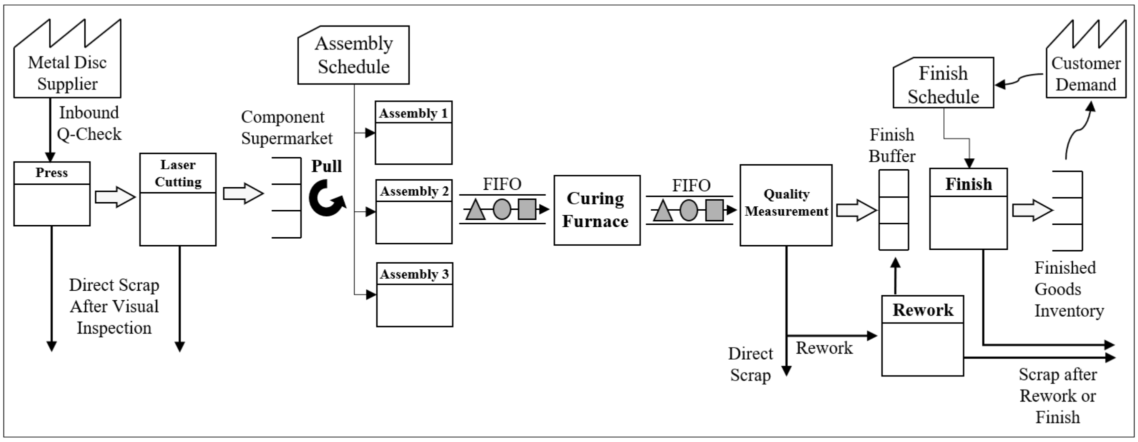


Figure 1. Value stream of the business unit

Contrary to holistically planned large-scale production systems, the production system at hand was created out of different low-cost solutions to reduce initial investment cost for extremely low batch sizes. A typical one or two-week production batch for one of over 25 different products is around 100 to 200 parts for the component production stations (press, laser) and about 50 to 100 parts for the assembly systems before machines are set up for the next batch. It becomes increasingly difficult to achieve stable processes and create reliable quality information with smaller batch sizes compared to large-scale production by about a factor of 30, or more. Most of the equipment is highly flexible so it can produce various different product types. However, there is very little interchangeability between products from one assembly system to the other. Assembly systems usually require extensive ramp-up and quality optimization for dedicated body shop assembly lines, which typically only produce two or three similar product types. For every set-up of each production batch there can be significant variations in process parameters and parts quality which, combined with the curing process, results in inconsistent product quality.

The business unit is an internal supplier of the automotive OEM; finished body shop parts are shipped to various other factories of the OEM in different countries for final assembly of the car body. Feedback on the overall fit of parts into the car body is therefore delayed by one or two weeks and every batch could potentially result in different quality complaints from internal customers. Customers then have to define specific rework required in their manufacturing facilities or send the parts back for rework to the business unit, or, in the worst case, scrap them. The business unit works with internal customers to solve specific and recurring quality issues, but a general collaboration to improve quality management is difficult due to differences in production concepts and processes. Quality optimization measures, typical for large-scale systems, often do not bring the desired results due to high variability and time lag of feedback on quality. It became increasingly difficult for the business unit to react to varying defects and quality problems, which is why the conceptual domain of the problem area should be mapped first to deal with clusters of critical problems with holistic solutions based on causal analyses. Simply adopting existing quality management tools would not yield the same benefits compared to a tailored system based on the aforementioned reasons.

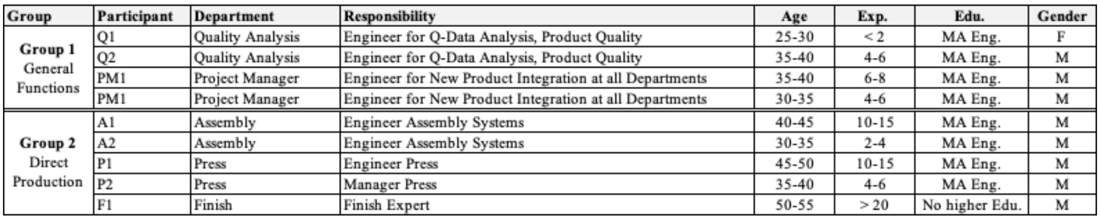
The existing quality system was also not adequate to deal with the high quantity of different quality issues since quality linkages and causal relationships were not very well understood. Generally, the automotive industry is deploying a wide variety of tools and techniques of quality management (Fonseca and Domingues, 2017); however, it is important to select only the most appropriate and useful methods, especially for small-scale production systems. The business unit uses the OEM´s quality management system, which employs tools of lean management (Shah and Ward, 2007) and Kaizen, or continual process improvement (TAhB Academy, 2016). However, no tool was really implemented with significant results because they were not aimed at specific targets and could not solve the underlying quality issues of the production system. Production systems in large-scale production are fine-tuned and holistically planned machines that operate mostly with already proven processes and technologies. For example, several expensive statistical process control (SPC) systems are used at specific points in the process known to be critical for process stability and product quality. The same generalized concept would not be possible, or economical, in small-scale production due to high costs and too many influencing factors unknown to large-scale systems.

The innovative aspects of highly flexible low-cost production equipment and solutions result in several unique challenges faced by the studied small-scale production system. Extensive and holistic restructuring of the quality management system was necessary to improve the business unit in general, and specific quality issues within the production system. Large-scale production systems are usually designed to continually improve specific aspects of product and process quality based on detailed analyses and data from SPC, and rarely implement completely new production concepts on a broad level. These differences require a new and better approach to solve the aforementioned issues because alignment of existing technical and behavioral practices is critical for the success of quality management systems (Asif, 2019).

3.2. Creating the Concept Map

Nine experts, divided into two subgroups for the purposes of pattern matching, participated in several brainstorming sessions to generate statements regarding the sources of quality problems within the business unit. Participants in this study are members of management and operative experts from several departments (production, quality assurance, and engineering), who are responsible for quality performance of the system. With the exception of one expatriate from the headquarters of the company, who is a long-term employee within the business unit, all participants had an MSc degree in engineering. Furthermore, considering the work environment it is not surprising that there was only one female participant.

Table 1. Participant Characteristics



Group	Participant	Department	Responsibility	Age	Exp.	Edu.	Gender
Group 1 General Functions	Q1	Quality Analysis	Engineer for Q-Data Analysis, Product Quality	25-30	< 2	MA Eng.	F
	Q2	Quality Analysis	Engineer for Q-Data Analysis, Product Quality	35-40	4-6	MA Eng.	M
	PM1	Project Manager	Engineer for New Product Integration at all Departments	35-40	6-8	MA Eng.	M
	PM1	Project Manager	Engineer for New Product Integration at all Departments	30-35	4-6	MA Eng.	M
Group 2 Direct Production	A1	Assembly	Engineer Assembly Systems	40-45	10-15	MA Eng.	M
	A2	Assembly	Engineer Assembly Systems	30-35	2-4	MA Eng.	M
	P1	Press	Engineer Press	45-50	10-15	MA Eng.	M
	P2	Press	Manager Press	35-40	4-6	MA Eng.	M
	F1	Finish	Finish Expert	50-55	> 20	No higher Edu.	M

The scope of the analysis was a mapping and analysis of quality linkages between all steps of the process, from metal sheet to finished exterior car body part. All participants were encouraged to contribute as many statements as they could come up with sources of quality issues in the manufacturing unit. Each statement started with the phrase: "O*ne source of quality problems is: …*" and was completed by the participants based on their experiences and opinions on the most important quality issues in the production system. After removing duplicates and cleaning up the list, 41 statements were generated, which are summarized in table 2. The study was conducted in German, then translated by the authors and verified by English-speaking experts in the manufacturing system to ensure translational validity.

Table 2. Brainstormed statements with average participant ratings in parenthesis

Top-three highest-rated statements in bold text

1 Dirty metal discs (3.60)
2 Pressing tools are not clean enough (3.60)
3 Varying surface qualities after assembly (2.90)
4 Finish work not according to defined standards (2.50)
5 Low-cost concepts for containers (3.40)
6 Quality team too small (not enough capacity) (2.90)
7 Manual handling at press (no robotic linkage between pressing operations) (3.20)
8 High quality variability in press due to press tool construction problems (3.50)
9 Employee errors (missing components, wrong sequence of components inserted into fixture) (3.20)
10 Bad positioning in pressing tool and fixture (3.30)
11 Poor metal discs and purchased parts (3.10)
12 **Unstable processes (4.00)**
13 Bad externally sourced products (e.g., external laser cutting) (2.80)
14 Old part numbers (long time in storage and between two production steps, parts become obsolete, FIFO problems) (3.30)
15 Many joining technologies (welding, riveting, press joining, etc.) (2.90)
16 Old and obsolete metal discs end up in production (3.50)
17 Bad fixture settings (e.g., curing fixture) (3.30)
18 Not enough information regarding part changes (missing change management) (3.20)
19 Poor packaging (e.g., wooden pallets for metal discs) (3.00)
20 Missing sample parts or sample parts are not used to check for quality issues (2.80)
21 Containers are in bad condition (missing container TPM) (3.00)
22 Transport damages, bad storage system, too many transports, difficult routes for forklifts (2.70)
23 Many fixture changes and general characteristics of small-scale series production (many products, low quantity, high complexity) (3.00)
24 Dirty fixtures (3.30)
25 **Low-cost concepts for pressing tools, only improved prototype tools in series production (3.90)**
26 Lack of KPIs for production stability (e.g., OEE, OWE and min/max boundaries) (2.50)
27 Lack of influence / participation of manufacturing during concurrent engineering phase (3.33)
28 Missing risk assessments (3.30)
29 Missing quality measurements regarding metal disc quality (breaking stress test, oiling) (3.00)
30 **Weak inspection during production, almost no gauge sampling, not enough visual checks and defective parts are passed on to the next step of the process (4.20)**
31 “Forgotten” parts within production (prototypes, optimization parts, etc.) become obsolete and must be scrapped (no control in SAP) (2.60)
32 Missing TPM (2.80)
33 External storage of pressing tools (temperature and weather conditions not optimal) (2.70)

34 Variable raw material quality causes frequent adjustments of machine parameters ("playing around" with parameters) (3.20)
35 Missing part numbers cause confusion (common parts, e.g., screws, bolts can be mixed up) (2.70)
36 No Poka-Yoke to prevent against forgetting to insert components, bad positioning in fixtures and parts can still be processed until the end (3.20)
37 Bad positioning / movement of parts in fixture (3.11)
38 Missing information / communication with customers regarding quality and performance (3.10)
39 Missing information / communication with planning department in concurrent engineering phase regarding quality and performance characteristics during ramp-up (3.30)
40 No integrated quality information over the whole process chain (from metal disc to final assembly (3.40)
41 Employees do not follow specific quality assurance processes (3.70)

The statements were then sorted by the participants in a different session to create the similarity matrix, showing how many times each statement was grouped together with any other statement. Participants were given a card for each statement which they had to sort into piles in an order that made sense to them. They further had to rate each statement on a 5-point Likert scale based on its influence on quality problems with '1' meaning that it causes only a few light problems, and '5' meaning that it causes many severe quality problems. All results were then entered in a similarity matrix to summarize how many times each statement was grouped together with any other statement for all participants. The average rating of each statement was calculated to give an overview of the importance of each statement based on the judgments of the experts.

Monotonic two-dimensional scaling was used to create the point map (Kruskal and Wish, 1978). The stress value was 0.138 and is a relatively low value compared to other concept mapping applications, which indicates a good fit (Kane and Trochim, 2007). An R^2 of 0.898 further supported the fit of the point map. For clustering, hierarchical cluster analysis using Ward's algorithm was utilized. Generally, it is difficult or impossible to decide in advance which is the "best" clustering method and the number of clusters to be chosen. Regarding the choice of the clustering algorithms we relied on previous empirical studies. Based on a large number of empirical studies, Trochim (1989) found Ward's algorithm to be the most useful. Ward's algorithm, minimizing the within-cluster sum of squares to the between-cluster sum of squares at each level of joining, generally gave more sensible and interpretable solutions than other approaches (e.g., single linkage or centroid method). All statistical calculations were carried out in SYSTAT 13.2.01.

The number of clusters was determined by group consensus. The solution with eight clusters seemed most representative (compared to solutions with four, six, and ten clusters) for the researchers and the experts with a clear relationship of points within each cluster. Each cluster was then appropriately labeled, and the average ratings were added to complete the cluster rating map, as seen in figure 2. In this paper the map is used to create a causal loop diagram based on the clusters of the concept map and to ultimately develop an action plan for the selection of future quality improvement projects within a continual improvement process.

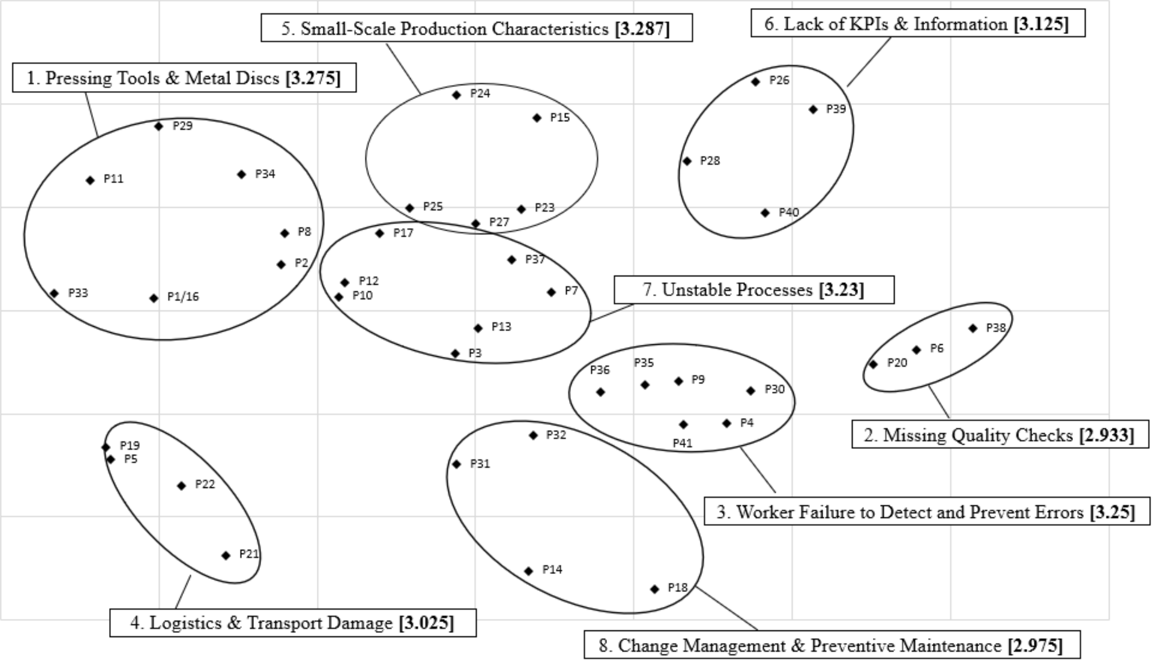


Figure 2. Cluster Rating Map with eight clusters and average ratings

3.3. Using the Concept Map as an Input for Causal Loop Diagrams

A causal loop diagram (CLD) is an intuitive tool of system dynamics (Maani and Cavana, 2007) to visualize and analyze causal relationships within complex systems. They are also used in group model building (Rodney, 2018), and therefore an excellent complement for concept mapping. Like Zeng et al. (2017), we found that the result of an analysis based on soft QM has a significant positive impact on "harder" QM when using the concept map as the foundation to create the CLD. Statements of one cluster could be placed close to each other to facilitate the analysis of causal relationships within the CLD. Only "positive" causal relationships and reinforcing loops exist in the diagram, since only quality issues are mapped in the concept map. "Positive" relationships mean, in the sense of a pure analysis of quality issues, that factors are increasing the negative impact of related factors and reinforcing loops cause even more quality problems. The goal of the causal loop analysis was to get a clearer picture of the relationships between each cluster and each point within the clusters. No balancing factors and loops are considered in this phase. Almost all 41 statements generated in the concept mapping study were included in the CLD, with only a few redundant ones eliminated for the sake of readability and clarity. Also, cluster titles were included as an anchor point in the diagram.

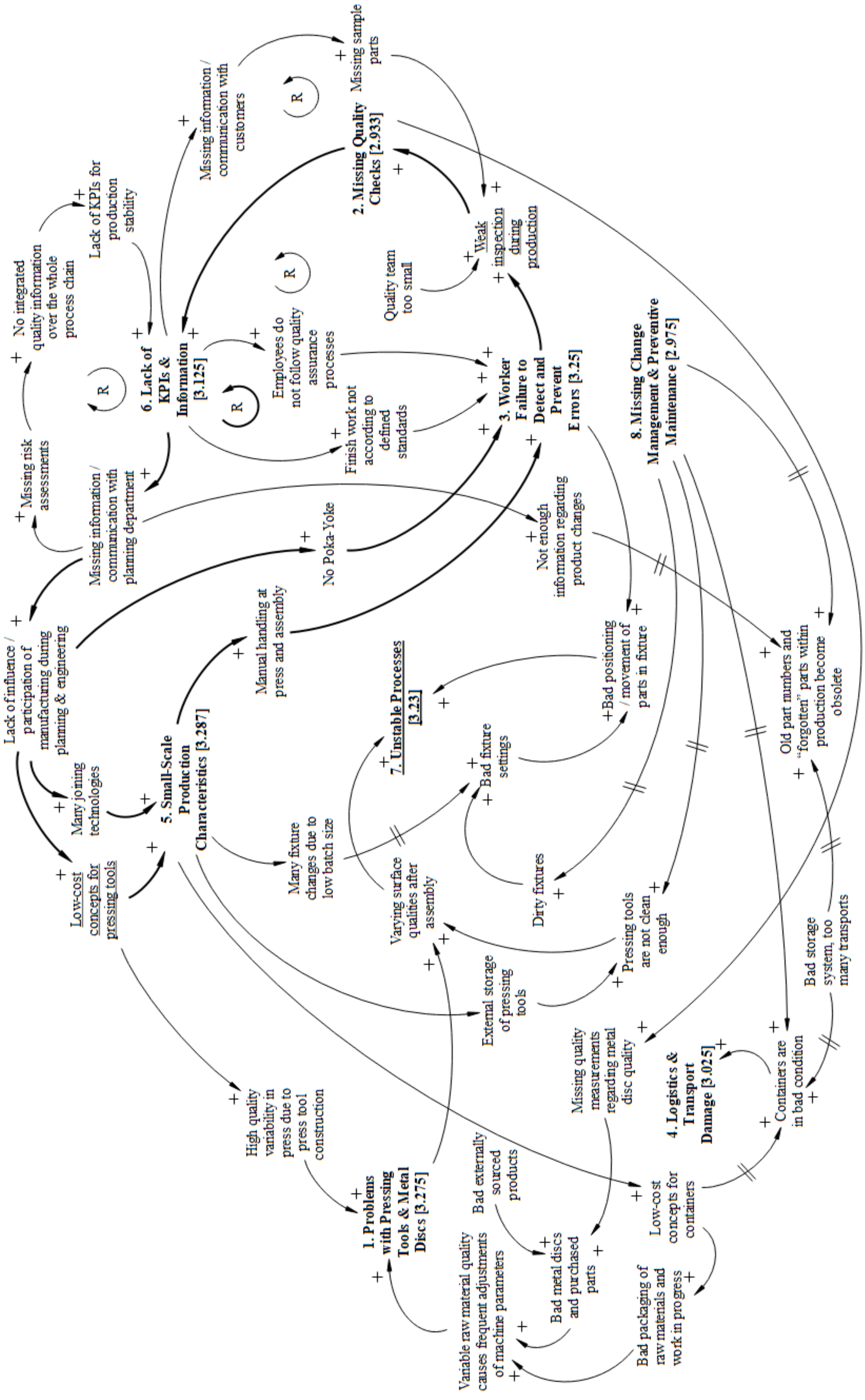


Figure 3. Casual Loop Diagram based on Concept Map

4. Result

4.1. Results of Concept Mapping

The concept map combines similar problems into clusters of statements (ranked by their perceived importance) and shows connections and importance ratings simultaneously. This visualization method is based on expert knowledge and aims to reduce causal ambiguity in decision-making regarding QM, especially quality improvement. The first cluster contains quality issues regarding the pressing department and raw materials (especially metal discs). It has the second-highest rating of 3.275 (see figure 2) and is a critical factor of quality. This is understandable because it is responsible for all components used in the assembly system and can negatively affect all following steps of the process. A critical aspect of this cluster is to ensure that the raw materials and tools coming into the production system have the right quality and are prepared (cleaned) to function at the highest level.

The second and sixth clusters can potentially be grouped together because both deal with missing information due to a lack of quality checks (cluster two) and general lack of KPIs and information (cluster 6). They are relatively less important (3.125 and 2.933, respectively) and contain all points associated with work and capacity of the quality department, including risk assessment, communication with customers regarding quality and the like. This culminates in a general lack of integrated quality information over the whole value stream and related KPIs.

Another critical cluster (three) deals with failures to detect and prevent quality errors by workers in time with an average rating of 3.25 for all points in that cluster. Lack of proper training and finish work falls into this cluster along with weak quality controls by the workers and handling of errors. Its location at the center of clusters two, six, eight and seven means that points in cluster three were also relatively frequently sorted into the same piles as points in those other clusters. One explanation for this could be the failure of workers to follow standardized processes to report quality data properly, which prevents them from analyzing causes and defining measures to prevent quality issues in the first place. The high rating showcases the strong links and implications this cluster has on many other issues when it comes to holistic QM.

The fourth cluster deals with logistics and transportation damages but is not very important (3.025) based on the ratings of the experts for all statements in this cluster. The fifth and seventh clusters, however, are highly important for quality within the system. They deal with the general characteristics of small-scale series production and unstable processes with a rating of 3.287 and 3.23, respectively. It is questionable if factors like "low-cost concepts of pressing tools" and a "multitude of assembly technologies" can be improved but they certainly have an influence on quality due to poor equipment and increased complexity. The position of the cluster for unstable processes is understandably at the center of the point map because it influences many other inputs and was generally grouped together with various other statements by the participants. Clusters five and seven could also potentially be consolidated into one single cluster due to the many relationships between statements and proximity on the point map. We decided against it to ensure that very specific solutions could be generated in the following steps and not to over-generalize the results. It was uncertain that potential solutions to specific clusters would be applicable to other clusters as well; therefore we kept them separated.

The last cluster (eight) contains points regarding change management and making sure that machines and materials are ready for production with the correct part numbers and machine settings. It is relatively less important with an average rating of 2.975 with only four statements falling into this cluster. For example, old and obsolete material entering production because it was not properly tracked throughout the value stream, and FIFO-rules were not kept according to defined standards.

In order to highlight subgroup differences potentially masked by group averages, we also compared the evaluation patterns of two subgroups. Group 1 included general functions responsible for all processes and Group 2 the direct functions for specific production-related processes. Group 1 was mostly comprised of younger people with less experience and Group 2 included highly experienced people, experts in their specific production area, the "old guard." If the two groups had mostly similar importance ratings across the eight clusters then the results would be visualized as a ladder graph with mostly parallel and horizontal rungs. Disagreements between the groups would be indicated by intersecting rungs. In figure 4 below (produced by JMP® Pro 14.3.0) the clusters are listed by their group importance ratings and the identical clusters are linked by the "rung" of the ladder.

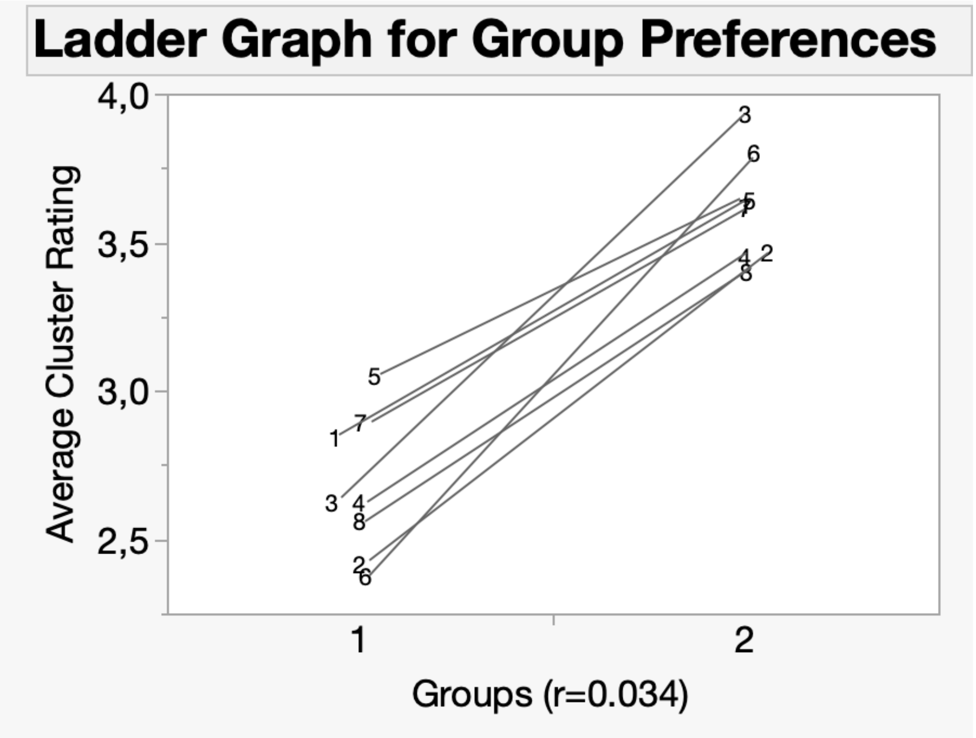


Figure 4. Cluster importance ratings for the two groups

There are two take-away messages from the graph: (i) the two groups are very much different, their importance ratings are not really correlated, (ii) members of Group 2 – the "old guard" – rate, on average, all statements higher than members of Group 1. Even the lowest rated cluster in Group 2 (cluster 8) was rated higher than the highest rated cluster of Group 1 (cluster 5). Group 2 perceives the statements to be much more important, perhaps because they deal with the phenomena described in a much more direct fashion on the shop floor; they are much closer to the problems than members of Group 1.

4.2. Findings from the Causal Loop Diagram

Several root causes have been identified that do not have a direct input from other factors identified by the team of experts. A bad storage system and too many transports were a root-cause of the logistics and transportation cluster, which causes scrap due to transportation damages. The quality team was too small, according to the team of experts, which was one cause of weak inspection during production and, subsequently, missing quality checks and quality information. Poor externally sourced products (metal discs) caused high variability of surface quality and process instability, and in combination with low-cost press tool construction, this affected the press department. The lack of TPM was another cause of problems, specifically dirty and badly set up fixtures in the assembly systems and pressing tools as well.

The CLD identifies three main outcomes based on defined quality issues by the team of experts. Logistics and transportation damage were one of the main factors of quality problems and increased quality cost due to inadequate work in progress- and finished goods containers, albeit not the most critical one. Another end result with no direct outwards-facing connection to other factors in the CLD was the scrapping of old part numbers and “forgotten” parts within production that eventually became obsolete. This resulted in additional quality costs due to a poor storage system with too many transports and missing information on changing and obsolete components parts as a result of a lack of communication between engineering and planning departments. The third, and most important, outcome of the CLD was process instability due to varying surface quality that came from the press and laser departments on one hand, and varying geometry of parts due to badly adjusted fixtures in the assembly department on the other hand. “Unstable processes” was also the second highest-rated statement generated in the concept mapping analysis and supposedly caused the highest amount of problems and quality costs.

Analyzing the causal relationships and reinforcing loops within the CLD, one can identify several loops on the top-right side of the diagram. Several smaller loops reinforce a larger one, which spans across most of the top-weighted clusters, increasing the number of issues due to small-scale production factors and problems resulting from workers on the shop-floor. Additionally, missing quality checks and a lack of KPIs are factors in this loop. This can be explained by the fact that there are many manual processes but no aid for workers to ensure that they perform their work correctly (missing Poka-Yoke). There is also a lack of information for workers regarding KPIs and critical quality issues they should inspect based on defined quality assurance processes. This results in weak inspections during production and a high probability of errors that go undetected. Cluster 3 (worker failure) received the highest score of all clusters for the front-line employees of group two (see figure 4) because they are missing critical inputs and methods to perform their work correctly. Several loops reinforce these effects when considering missing quality checks and, as a result, lack of information and KPIs in the first place. Important information from the shop floor is also missing during planning and engineering, and for the creation of an integrated quality information system to better track KPIs and generate information efficiently. Nothing is being done to prevent detrimental small-scale series production characteristics, which is causing workers to fail due to a lack of aid for more complex manual processes compared to large-scale production systems. This can be confirmed by the authors after analyzing process standards of the assembly systems, which show an approximately seven times longer cycle time (time to produce a unit of output) compared to large-scale systems. Furthermore, they show a three to five times higher number of individual tasks for a single worker in each cycle. This causal loop ultimately results in high process instability because workers cannot cope with the increased requirements of small-scale production due to complex processes and a lack of support.

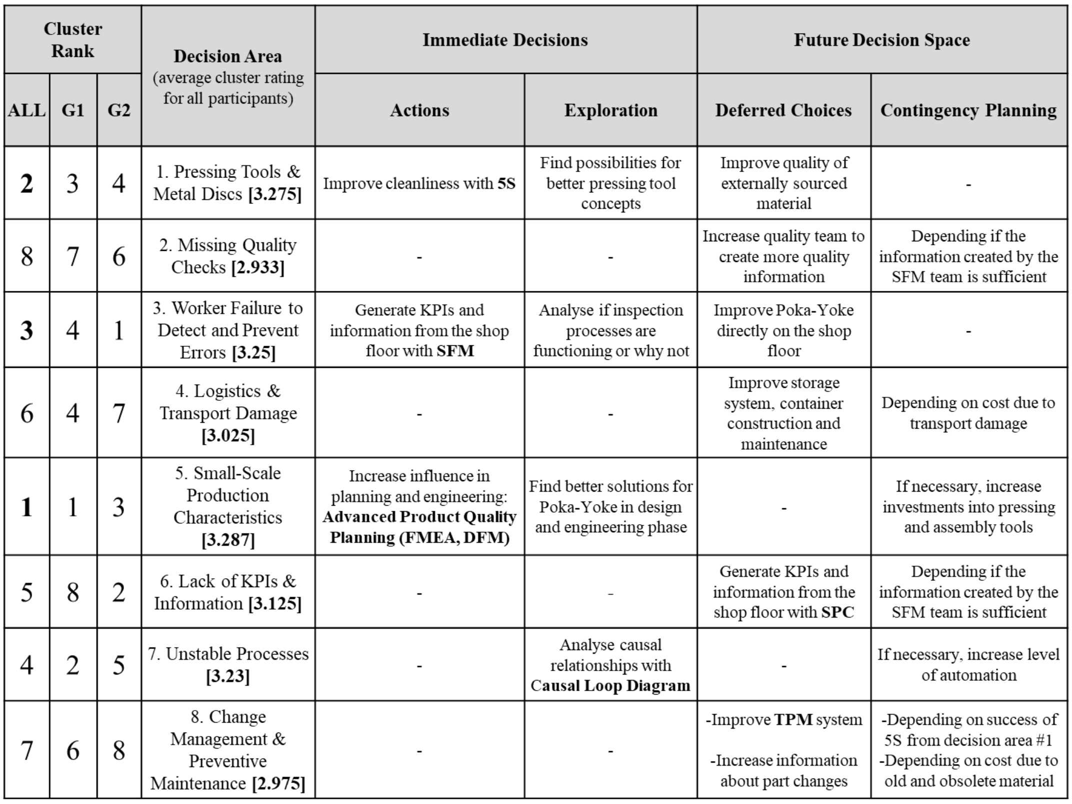
4.3. Integrating the Results to Create an Action Proposal

The results of the analysis can be used to plan and allocate resources to improvement projects with the highest returns in terms of quality performance as perceived by the management team and team of experts. It can also help to define quality measurement strategies to ensure that the most susceptible steps of the process are secured using the highest rate of measurements. The maps are comprised of the collective experience and knowledge of the team of experts to map the conceptual domain of the problem area. The most important clusters lie mostly at the center of the map, emphasizing the linkages and influences towards other clusters. In combination with the relative ratings and the CLD, it gives a clear picture of the overall situation within the system, which helps decision makers define better policies and allocate resources towards the most important improvement initiatives.

Visualizing tacit knowledge can significantly increase common understanding of the whole team regarding a matter of interest; thus, reducing causal ambiguity. An action proposal was developed based on the created information to make results of the analysis even more usable for the management team. The methodology was adopted from Friend and Hickling (2005) and it has been mentioned in the literature that this approach is always useful to increase the applicability of OM/OR interventions (White, 2016). This method defines immediate decisions and future decision space for all relevant decision areas based on the current level of information and uncertainty related to different options. Immediate actions should be taken if the current level of information is sufficient to justify these decisions. However, if there is not enough information regarding a decision area, and there is still time to reduce the risk and uncertainty, resources should be invested into further explorations. A future decision space ensures that other decision areas do not fall off the radar and can still be considered for decisions made in the future. Considering the high number of deferred choices and factors for contingency planning it becomes apparent that extensive analyses based on soft QM and hard QM would be beneficial to support decision makers. Complex and causally ambiguous production areas can especially benefit from structured approaches and detailed cause-and-effect analyses.

Table 3. Action Proposal

5S – Sort, Set/Straighten, Sweep/Shine, Standardize, Sustain (method of Lean Manufacturing to improve workspace conditions and cleanliness); SFM – Shop Floor Management; SPC – Statistical Process Control; TPM – Total Productive Maintenance; DFM – Design for Manufacturing; FMEA - Failure Mode & Effects Analysis.



Cluster Rank			**Decision Area** (average cluster rating for all participants)	**Immediate Decisions**		**Future Decision Space**	
ALL	**G1**	**G2**		**Actions**	**Exploration**	**Deferred Choices**	**Contingency Planning**
2	3	4	1. Pressing Tools & Metal Discs **[3.275]**	Improve cleanliness with **5S**	Find possibilities for better pressing tool concepts	Improve quality of externally sourced material	-
8	7	6	2. Missing Quality Checks **[2.933]**	-	-	Increase quality team to create more quality information	Depending if the information created by the SFM team is sufficient
3	4	1	3. Worker Failure to Detect and Prevent Errors **[3.25]**	Generate KPIs and information from the shop floor with **SFM**	Analyse if inspection processes are functioning or why not	Improve Poka-Yoke directly on the shop floor	-
6	4	7	4. Logistics & Transport Damage **[3.025]**	-	-	Improve storage system, container construction and maintenance	Depending on cost due to transport damage
1	1	3	5. Small-Scale Production Characteristics **[3.287]**	Increase influence in planning and engineering: **Advanced Product Quality Planning (FMEA, DFM)**	Find better solutions for Poka-Yoke in design and engineering phase	-	If necessary, increase investments into pressing and assembly tools
5	8	2	6. Lack of KPIs & Information **[3.125]**	-	-	Generate KPIs and information from the shop floor with **SPC**	Depending if the information created by the SFM team is sufficient
4	2	5	7. Unstable Processes **[3.23]**	-	Analyse causal relationships with **Causal Loop Diagram**	-	If necessary, increase level of automation
7	6	8	8. Change Management & Preventive Maintenance **[2.975]**	-	-	-Improve **TPM** system -Increase information about part changes	-Depending on success of 5S from decision area #1 -Depending on cost due to old and obsolete material

The action proposal was created based on the cluster ratings, the average rating of each point within the clusters, and the findings from the CLD. Immediate actions were defined for the most important clusters, and more specifically, for points within each cluster. This gives an extremely specific set of decisions based on the concept mapping analysis and can be used by the experts for improved resource allocation and QM. Some of the more important statements require further analysis and exploration to create better information on which further decision should be made. Other, less important, points are not completely dismissed and forgotten, but rather pooled in a future decision space to be re-evaluated in the future. This depends on the future state of the system and the outcome of immediate decisions and explorations. The goal is to continuously manage a relatively complete list of actions based on tacit knowledge of the team of experts and allocate resources to the most important points in an efficient and effective way.

Quality problems that arise as a result of small-scale series production characteristics was the highest-rated cluster of the concept mapping analysis and also the most important factor for Group 1. Group 1 considered the inherent issues of small-scale production as the most important factors in general. Therefore, they should focus on the implementation of Advanced Product Quality Planning (APQP) to increase the influence of the business unit during planning and engineering in order to create a holistic production system. Most drawbacks of small-scale series production could potentially be solved with a higher focus on producibility and error prevention in the engineering phase to increase quality performance. Design for Manufacturing/Assembly (DFM/DFA) should be considered when planning and designing products specifically for small-scale series production. An important concept to be considered as well is Failure Mode and Effects Analysis (FMEA) to analyze potential sources of errors before products are introduced to the business unit. The optimal solution would be to find foolproof (Poka-Yoke) product designs and manufacturing concepts to increase process stability and make it easier for workers on the shop floor.

The production-centered Group 2 is more focused on people and missing information – both factors that prevent them from performing a better job on the shop floor. They should focus on the creation of information from the shop floor with improved shop floor management (SFM), which will allow them to report day-to-day problems back to the engineering group so they can be considered in the APQP. SFM includes all people in the workplace into production-related management- and control processes (Suzaki, 1993). It is another method of lean manufacturing and enables continual improvement based on suitable KPIs directly from the shop floor. With this method, workers could immediately improve their own situation and generate the necessary information before investing heavily into statistical process control (SPC) systems at a later stage. To further increase employee awareness, and improve workspace conditions and cleanliness, it is also recommended to apply the 5S (Sort, Set/Straighten, Sweep/Shine, Standardize, Sustain) methodology as a general starting point for improvement of the production system. With only these three specific concepts, which are defined as immediate action in the action proposal, the production system could break the large reinforcing causal loop to prevent the system from spiraling further down into “production hell”.

5. Theoretical and Practical Insights

King and Zeithaml (2001) found that intra-firm causal ambiguity (the lack of a common understanding of cause and effect relationships between people within the organization) could severely reduce the performance of a business. Our study aims to improve quality efficiently and effectively in the production system of an automotive OEM by reducing this form of causal ambiguity. On the theoretical front, following the suggestions of Diamantopoulos and Winklhofer (2001), we propose a formative model for describing a multidimensional latent construct, i.e., the quality problems of an automotive OEM. In simple terms, causal priority differentiates between a formative and a reflective model: in the case of the former, causality flows from the indicator(s) to the latent construct, in the case of the latter, the other way around. We posit that in most organizational settings, manifest (directly measurable) variables are not only preferred to latent constructs but, often, they are the only options. Consequently, manipulating the user-defined measures of our formative model will lead to the improvement of the quality construct.

Based on this analysis and the understanding of the team of experts, most quality issues were caused by poor raw materials and tools right at the beginning of the value stream (clusters 1 and 5). This resulted in defective products, which were handed over to the following steps of the process due to the lack of inspection and not being able to detect those defective products (cluster 3). At the business unit, however, the main quality inspection was located right after the curing furnaces and before the finish department (see figure 5). Explicit information (coming from the monitoring and analysis of scrap and rework rates) showed that most quality costs arose between the curing furnace and the finish department because most of the defective parts were detected there. Therefore, all resources were allocated towards the end of the value stream while mostly disregarding quality linkages in earlier production stages and the engineering phase. Causal ambiguity and the dynamics of the system further aggravated decision-making and efficient resource allocation. However, no tool was available to analyze the conceptual domain in its entirety to facilitate knowledge creation and dissemination of tacit knowledge.

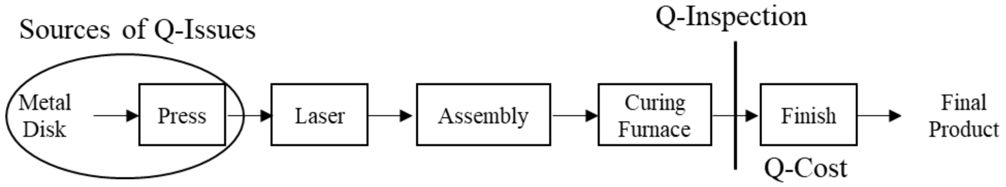


Figure 5. Differences between sources of quality issues and resource allocation

This was the first attempt to fully conceptualize the quality domain of the production system and the aim was to support decision-making regarding quality improvement and measurement efforts within steps of the process chain. Although the experts had knowledge, no effort was made to make it available and use it to improve decision making with the goal of increasing the firm’s performance in terms of reduced quality costs. Knowledge was tacit and dispersed, and not easily accessible without the help of an applicable method that would allow for the visualization of the conceptual domain and quality linkages over the whole value stream in order to reduce ambiguity. As mentioned in the beginning, behavioral QM is needed to facilitate decision making by changing attention paid to measured variables, assessing the specific impact of factors on process variability and quality, and to enhance leadership and trust to boost tacit knowledge creation. This increases the metacognitive understanding of management to adapt to changing situations and make innovative decisions based on the information presented by the concept map.

Using the results of the analysis to create action proposals is a key principle of concept mapping (Trochim, 1989) and was mentioned by White (2016) to increase the relevance of OM interventions. Using the concept map as a starting point for causal loop diagrams generates a large quantity of integrated information for decision makers. This aid that enables the detection of causal relationships, as described by the experts of the business unit, can facilitate an improvement process because the conceptual domain is analyzed by the problem owners in their native language. It provides a basis for discussion and decision-making based on tacit knowledge of the team of experts. It also increases workforce motivation by improving factors that are considered critical by workers on the shop floor and in engineering departments.

Consequently, this kind of analysis has a very high internal validity. Many small-volume batch production systems with high quality requirements (like premium sports car manufacturers) are facing similar problems with causal ambiguity and dynamics. Campbell (1986) suggested a different name for external validity or generalizability: the proximal similarity model. Within the proximal similarity model, researchers can think of contexts that are more or less similar to the one in the study. A gradient of similarity for times, people, settings, and contexts can be developed from the most closely similar to least similar and findings can be transferred to those people, settings, socio-political contexts, and times that are most like those (i.e., most proximally similar to) in the focal study. We believe that our findings can easily be generalized to many of these settings; thus, our analysis and the proposed methodology offer some degree of external validity as well.

The method offers a more holistic approach to learn about the conceptual domain of quality issues, compared to, for example, only a causal loop diagram, or a fishbone diagram. Fishbone diagrams are aimed at a specific problem based on an analysis of predetermined categories (e.g., machine, material, method, etc.). The clusters generated by this study are relatively similar to those generic categories, however, concept maps could potentially offer more tailored solutions, specific to certain production systems, and facilitate more innovative and creative problem solving. Asif (2019) mentions the benefits of fishbone diagrams, among other tools, to generate basic solutions, but acknowledges the much greater potential to provide deeper understanding if individuals, or teams, provide better inputs and analyses based on improved behavioral practices. Also, causal loop diagrams can benefit from the results of concept mapping as a starting point to create the CLD. As mentioned in section 2: “One of the most difficult and important steps in planning is the initial conceptualization”. Zeng et al. (2017) also found a positive influence of soft QM on hard QM to improve quality information and process management within an organization. In the future, we hope to use a combination of hard- and soft methods to integrate more tools into the decision-making process; for example, by substituting the original categories of a fishbone diagram with clusters from the concept maps to create more tailored tools to solve specific problems for various production systems (concept maps define the domain in which specific problems should be solved). By adding more sources of information from members of the production system we hope to increase the applicability of such methods and their focus and accuracy to solve specific problems.

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