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**Service request categorization framework for customer support in a
global manufacturing company**

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ABSTRACT

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<p>Customer experience has become a top strategic priority for manufacturing companies worldwide. More focus should be directed towards customer support case handling practices due to their visibility and impact on overall customer experience. This thesis is conducted for a global multi-level customer support unit aiming to improve and streamline their customer support case handling processes. The goal is to find alternative ways to categorize customer service requests and to set clear case resolution level guidelines.</p> <p>An operational concept for customer support case categorization for manufacturing companies is combined from existing literature. Based on the utilization of the conceptual framework in the customer support unit, up-to 46% of the customer support service requests could potentially be solved on a lower organization level. With the implementation of the conceptual framework, customer support case flow and response time can be improved.</p> <p>The concept developed in this thesis can be utilized in similar customer support units. Further research is recommended to assess the effects of regional and cultural differences that could not be included in the scope of this study. Structured customer support data provides a base for future implementation of machine learning or artificial intelligence applications.</p>	

TIIVISTELMÄ

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<p>Asiakaskokemuksesta on muodostunut yksi tärkeimmistä tuotantoyritysten strategisista painopisteistä maailmanlaajuisesti. Asiakastuen prosesseihin ja asiakaskyselyiden käsittelyyn tulee kiinnittää enemmän huomiota, sillä niillä on suuri näkyvyys ja vaikutus kokonaisasiakaskokemukseen. Tämä työ käsittelee globaalin monitasoisen asiakastuen yksikköä, jonka asiakastuen käsittelyprosessia pyritään parantamaan ja selkeyttämään. Tavoitteena on löytää vaihtoehtoisia tapoja luokitella asiakaspalvelupyynnöitä ja asettaa selkeät viitekehukset palvelutasolle.</p> <p>Työssä muodostetaan käsitteellinen viitekehys asiakastukipalvelupyynnöiden luokitteluun aikaisempaan kirjallisuuteen ja tutkimukseen perustuen. Konseptin implementoinnin perusteella jopa 46% kohdeyksikön palvelupyynnöistä olisi mahdollista ratkaista organisaation alemmilla tasoilla. Viitekehysten hyödyntäminen mahdollistaa resurssien tasaisemman jakautumisen ja tehostuneen vasteajan.</p> <p>Tässä työssä kehitettyä konseptia voidaan hyödyntää vastaavanlaisissa asiakastuen yksiköissä. Lisätutkimuksia suositellaan alueellisten ja kulttuuristen erojen vaikutusten arvioimiseksi, jotka ovat tämän työn rajauksen ulkopuolella. Asiakastuen datan selkeä jäsentely tarjoaa vahvan pohjan koneoppimisen ja tekoälyn hyödyntämiseen tulevaisuudessa.</p>	

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ABBREVIATIONS

AHP	Analytical hierarchy process
DSS	Decision support system
MCABC	Multi criteria ABC analysis
MCDA	Multi criteria decision analysis

1 INTRODUCTION

The research project was conducted in the after-sales service department of a global manufacturing company. Their long-term strategy for the coming years focuses on developing customer experience, high quality in products and service, agility and efficiency as well as new service product innovations. To support the success of these strategies they wanted to start by pinpointing development needs within their key functions. Pre-analysis revealed a need for updated customer service request handling guidelines that take into account the future organizational structure of the global customer support organization. The aim is to create clear summarized guidelines on which organizational level different types of customer service requests should be resolved at. For this a case specific framework for finding alternative ways of customer support service request classification had to be developed. And based on the new classification a categorization model was drafted. The goal is to support decision making at all customer touch points and to strive for superior customer experience by providing fast and accurate customer support. This is achieved by providing the knowledge closer to the customer, streamlining global support processes and defining common guidelines on which organization level is primarily responsible for which type of service requests.

This introduction aims to clarify the background and motivation of this research; how and why the research was conducted. It will portray the scope and delimitations and describe the research methodology and the analysis process. The last section will present the overall structure of the report and open the objectives behind each chapter.

1.1 Research motivation

Manufacturing companies are striving for added value through better service functions. At the same time core expertise is being centralized into tools for better

control of domain knowledge. The rapid development of IT-support systems enables flexible customer support independent of location. Digitalized systems gather domain knowledge into one database to be shared and accessed more widely. In order to not get lost in the growing amount of data and to maximize the benefit of centralized domain knowledge assets, clear guidelines are needed. Customer relationship management tools with integrated case management modules are developing at a fast speed and integrating intelligent algorithms to support decision making. (Kastalli, 2013; Rothenberger, 2007)

Guidelines and categorization methods for organizations with global customer support can be very case specific and hard to generalize. Previous research fitting this specific context was limited. Current research has not yet offered a general base framework that could be implemented directly to this specific setting. Most categorization methods for manufacturing companies are still focused on physical inventory management. Reference can however be found for example from data science and from insurance related studies.

1.2 Objective and delimitations

This study is conducted for a global customer support unit that is looking for ways to improve and streamline their customer support case handling processes. A new perspective on case classification aims to identify the most effective target service levels for certain types of customer support cases. The common patterns and categories recognized in this study will act as a base to set guidelines for future machine learning implementation possibilities and to better understand where to target and gain the most value with the help of automation.

Previous analysis by the case company indicates that customer support cases take too long finding their way to the right unit and person that has the needed knowledge to solve it. In order to solve this issue, the company wants to streamline the customer support case handling and needs a unified system with

clear process guidelines. This research aims to support the change by clarifying service level guidelines at each organization level. An earlier conducted current state analysis and a pre-defined to-be model act as the background of this research. The study is conducted in a globally operating manufacturing company. Furthermore, it is limited to one business unit's customer support functions. This limitation was set in order to get more detailed and case specific results. The data set that was utilized was provided by the target company. For further research the study aims to provide a framework for analysis that could be replicated within other units as well. General categorization could help streamline customer support processes and help improve response speed by defining clear service levels and competence needs for each organizational level.

To achieve this, the following research question was formulated to reflect the main objective of this study:

- How can customer support service requests be managed?

Additional supporting research questions were formulated:

- How can categorization methods support the decision-making process?
- On what organization level should cases be solved at?

The main research question is formulated to present the overall goal of this study. The company needs guidelines on how to maximise the efficiency of their customer service request handling process. During the preliminary research a need for new case categorization methods was discovered and thus two additional research questions were formulated. The first aims to find new ways to categorize and classify the cases by analysing existing customer support data and identifying common patterns. The chosen categories are then used to build common easy to interpret guidelines for the customer support organization. Based on the guidelines, all organization levels should be able to easily check on which level each case should be targeted and solved.

Customer support functions, containing technical support and warranty, have been identified to have a big impact on customer experience and thus this study will focus on those functions. The results will be aligned with the case company's common guidelines and global strategy.

1.3 Research methodology and process

This study was conducted within the case company unit in an iterative manner (figure 1). It relies on local case specific knowledge and combines universal frameworks to find case specific solutions. First introducing the topic and methodology, then a data test set was used to define the data field needs and to give a general idea about possible additional literature review needs. Then the literature review was conducted to find functional models from theory for the selected data set. Data was collected and analysed based on the literature review and experts' input. Lastly the functionality of the modified categorization model was verified together with the customer support's experts. Quantitative and qualitative research methods were combined by complementing statistical data analysis results with quantitative case data and expert input. (Saunders, 2009 p.138)

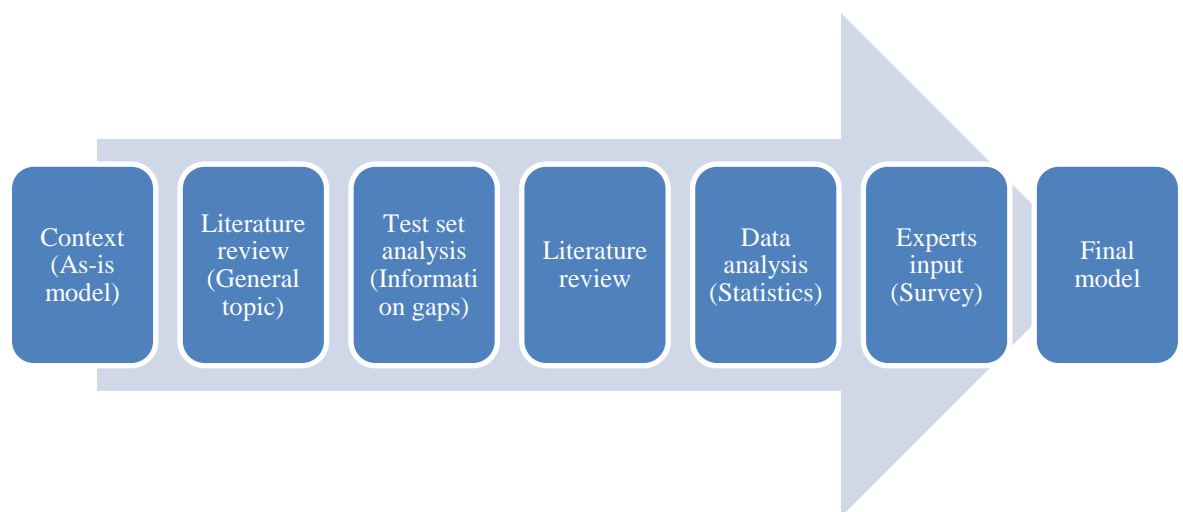


Figure 1. Research process

The main source of data for this study was secondary data, which is data that was originally collected for another purpose. This study is based on first analyzing secondary data in the form of customer support case data. As it is internal company data, it is to be handled anonymously and discreetly. The case database in question consists of over twenty years of customer support cases. From this a compiled data set of recent cases was chosen to represent an up to date sample. Part of the documented secondary data was in text form and had to be collected manually. Content analysis is used to generate a categorization model from statistical frequencies together with frameworks and methods found in the literature review. (Saunders, 2009 p. 316-320)

Secondary data was chosen due to the short time frame of the project and because a large amount of higher-quality data was needed for this certain research project. The case company perceives this data as a trustworthy representation of their customer support case data. Possible challenges regarding this was to define the sample size and quality, as well as avoid getting lost in irrelevant sections of the data. The data is confidential and should at all steps of the research be handled and documented in an anonymous matter according to the confidentiality agreement and personal information protection laws. Risks include measurement validity, as in needed measures for the research to not be included, and to find the correct sample size, big enough to gain quality data without outweighing the benefits. (Saunders, 2009 p.330-336)

To complement and verify the findings from the customer support case data with primary data, additional interviews with the unit's experts were conducted. Strengthening the research findings with multiple sources and types of data is called triangulation. Triangulation is important to gain insight on the topic from multiple perspectives and to better argue on the finding's relevance to research knowledge. Combining related domain knowledge helps verify the main findings as well as notice and uncover possible inconsistencies within the secondary data analysis. (Farguhar, 2012 p.7)

1.4 Structure of the report

This thesis consists of four main chapters, starting with this introduction of the research objectives and process. The second chapter introduces previous research and concludes a conceptual framework for service request categorization. The framework utilizes a decision support system development process together with selected categorization methods.

Chapter three consists of four main sections following the steps of the conceptual categorization framework. The first section introduces the research setting and internally gathered current state analysis of the customer support unit. By first understanding the current processes and challenges, the need for an alternative service requests classification was identified. Then with the help of clustering and data analysis, common service request categories were identified from the data gathered. The third section verifies and complements the data analysis results by adding expert input. The ultimate purpose is to present how the theoretical analysis in the previous chapters is utilized in the actual research setting of this study. The fourth chapter concludes the whole study and the results. It also addresses the reliability of the research and assesses future research need. The last part is a general summary.

2 CATEGORIZATION AND MANAGEMENT OF CUSTOMER SUPPORT SERVICE REQUESTS

According to a survey conducted by Forrester, 86% of decision -makers in organizations rank customer experience as one of their top strategic priorities. Over half are targeting to become customer service leaders in their industry. Organizations are looking for ways to differentiate in this sector and one of the most visible factors is how customer contacts are handled. Service reliability is a key value for achieving this goal and can be defined as ‘the firm’s ability to provide the service correctly the first time’ (Hensley, 2011; Galetzka, 2006). Contact channels have expanded to contain a variety of case management tools and contact methods over the past years. (LogMeIn A, 2012; Rothenberger, 2007)

2.1 From customer data into useful knowledge

Knowledge management is an important success factor in customer support processes. Service engineers spend a big part of their time either recording and classifying incoming service requests or searching existing databases for known solutions and fixes. One of the most common challenges in customer support knowledge management is documenting and classifying service requests. Also missing knowledge base articles and the lack of documented procedures for urgent incidents are known challenges in customer support functions. With most of the customer data getting centralized around one or few databases, it is important to understand how the collected data can be changed into useful knowledge. For this one should start by understanding the definitions of data, information and knowledge and how those three are related to each other. (Jantti, 2009)

According to the Cambridge dictionary data can be defined as facts or numbers collected to be examined, considered and used to help decision-making. So, it is something that is stored but has not been processed yet. Data then becomes information when it is given a meaning and is evaluated through a context. Oxford dictionary defines information as facts learned about something in particular. Information contains facts about a certain situation, person or event. Information then becomes knowledge when theoretical and practical understanding of the subject is gained through experience or study. Knowledge is awareness related to a certain fact or situation gained through experience or association. It can be attained through reasoning, learning and perception. (Singh, 2010; Oxford dictionary, Merriam-Webster dictionary, Cambridge dictionary)

Gathered data can have little or no use before it is organized, processed and analyzed. Data-information-knowledge hierarchy is visualized in figure 2. The effort put into processing data into information and knowledge increases its usefulness. Knowledge can then be transformed further to wisdom that can be the base for decision making. At the same time, the more data is processed the more its availability decreases. (Singh, 2017)

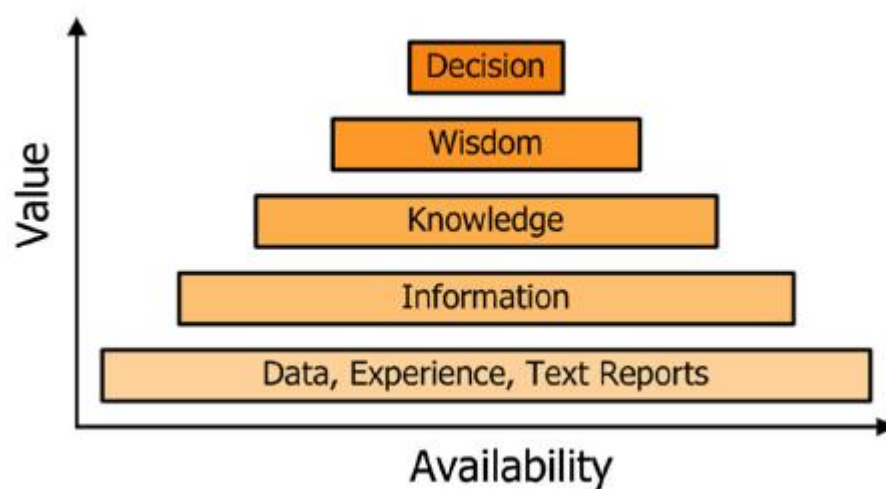


Figure 2. Knowledge hierarchy

As a growing amount of data is being collected throughout all processes, it is essential to be able to make proper use of it. To make use of the stored data an organization must make the decision to organize, process, analyse and represent the collected data in a form that can be understood by the users and be useful in decision making. Usually most companies already have one or multiple in-house systems, such as SAP, where they store the data. Many of the common customer support challenges are related to knowledge management. One major recommendation is to identify knowledge gaps (what kind of needed knowledge has not been available) and to have a dedicated person responsible for knowledge management related topics. (Jantti, 2009; Singh, 2017; Singh, 2010)

Singh et al. 2010 listed the following benefits to be expected from making use of the stored data in a proper way. Relevant data is acquired, and suitable models can be used to support a systematic interpretation of data. It will most likely help the exchange and build-up of knowledge. Other expected improvements related to decision making are the support of formalized records, consistency and accuracy of decisions. (Singh, 2010)

2.1.1 Best practices and challenges in service request management

A well-functioning support desk can help use resources more efficiently and is linked directly to better service quality and end-user satisfaction. Clear responsibilities, process guidelines and supporting tools (such as model answers) help increase incident resolution efficiency and at the same time create better customer care quality. All needed information should be gathered in one place in order to avoid having to switch between multiple different tools. Leading customer support solutions integrate related functions, such as ticketing systems, customer relationship management and for example site visitations, into one system. An incident resolution process should give a united front view to the end-customer, no matter where and through what channel the customer initially first contacted the company. To achieve this, clear easily follow able processes should

be in place. Forwarding a customer case to the right person within the company should be made easy and all previous contact information should be logged into one system. (LogMeIn B, 2012)

Service desk solutions can easily become a hindrance when not properly managed. They might even have the opposite effect regards the expectations and consume more time and slow down processes with too much complexity. This then leads to customer and user frustration. The before mentioned knowledge management challenges should be considered when identifying and developing customer support processes. To ensure that enough information is collected and received from service requests, it is important to identify what knowledge is available in the organization and what is still needed. Proper training in service request documentation, classification and escalation processes could support quicker resolution times. (Jantti, 2009; Rothenberger, 2007)

Customer experience has been emphasized in recent and future strategic aligning of the target company as one of the top development priorities. Satisfactory incident resolution was identified as one of the case companies' biggest factors related to customer satisfaction. According to earlier findings from previous research, resolution time, first response and accurate one-time solutions were generally highly appreciated by the customer. To achieve this, the case company wants to develop ways to streamline their incident resolution process and to be able to more efficiently find the correct person to solve the incident. (LogMeIn B, 2012)

2.2 Decision support system development process

A decision support system is meant to help make fast and accurate decision making easier. Among other things it should provide its' users relevant data at the needed moment to derive the best solution available. The data provided needs to

first go through a series of processing to limit it to only the essentials. This can be done by filtering out non-related data, processing and combining useful information together and adding analysis steps before providing it to the support system user. By helping the user make better and faster decisions and by making use of both, the strength of computers (capacity and speed) and the strength of humans (intuition and creativity), the overall quality and effectiveness rises. (Singh, 2017)

Singh et al. 2017 present a framework on how a decision support system could be build. The process has four main phases that are presented in figure 3. The major steps are collecting and then processing data, reasoning on the results and then supporting the decision making. The first step of the risk management procedure ‘establishing the context’ is in relation to the first step of collecting data. In this step it is also important to check the cohesiveness of the data, by highlighting or removing imperfections in within the data, identifying conflicting or missing attributes and to organize and understand which parts of the data are relevant to for the certain case in question. (Singh, 2017; Singh, 2010)

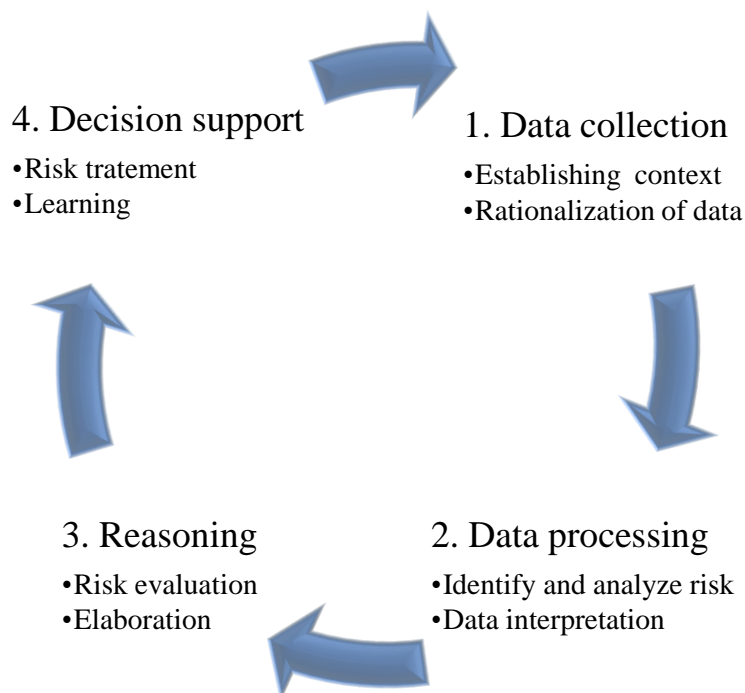


Figure 3. Process for building a decision support system

The second step is processing the data by identifying risk and analysing them. Then the data collected in the previous step is used to extract useful information. Degradation and failure analysis tools should be used in this stage. It corresponds to the risk identification and analysis sections. The third step is reasoning, and it should be noted that processing uses algorithms whereas reasoning uses soft-computing techniques such as models, hypotheses, rules, past experiences, arguments, new explanations and suggestions. It corresponds to the risk evaluation stage. Due to the subjective nature of this stage and being based on past experience, the outcome can differ quite a lot depending on the persons involved. It uses two types of reasoning processes, rule-based reasoning (representing collected knowledge as decision trees, fuzzy logic, etc.) and case-based reasoning (using similar past cases to solve new ones). After reasoning the fourth step relates to decision support and presentation (risk treatment). Making decisions and taking actions to reduce, remove the risk or consequences. (Singh, 2017; Singh, 2010)

2.3 Categorization methods

Classification is a basic activity that children learn very early when they start to group objects in their environment. These groups are then associated with nouns to describe them. In science classification is needed to define concepts that are necessary for the development of new theories. (Aldenderfer, 1984)

Clustering methods and procedures are used to create classification. A cluster is a group of similar entities and clustering attempts to divide information within a data set into relatively homogenous groups. In other words, clustering attempts to find patterns in the data by first raising similarities and then grouping them based on the target features. The term ‘cluster analysis’ refers to a variety of methods and procedures that aim to classify data. The amount of literature and research on

clustering methods has grown along with the development of computers able to process large amounts of data. The principal goal of clustering is to develop terminology or classification and to explore data to generate and test hypotheses. (Alderfelder, 1984; Altman, 2017)

Content analysis technique is a data analysis procedure where qualitative and textual data can be converted into quantitative data. It was first formulated by Berelson in 1952 and has been mainly used in social sciences, but in recent years it has appeared in a growing number of other science fields as well. Before the actual analysis, categories and rules are established based on the purpose of the analysis and the targeted end results. These categories and rules are chosen based on attributes from which needed, not yet existing, knowledge can later be statistically analysed. Then the wanted information is extracted from the data and systematically classified into the pre-established categories. (Benedettini, 2014)

2.3.1 ABC analysis and Multiple criteria ABC analysis

ABC-analysis is widely used in the management and classification of large inventories and in many cases only considers one or two criteria which are often of quantitative kind. Models that take into account multiple criteria (MCIC, Multi Criteria Inventory Classification) affecting the decision have been developed, but they heavily depend on quantitative data. Traditionally the main idea is to pre-establish specific criteria for three different categories and then divide, for example inventory items, into the fitting category based on those criteria. These categories are A, B and C, and commonly category A contains items that are critical but few in numbers, category C contains volume items that are less important and category B is something in between. (Torabi, 2012)

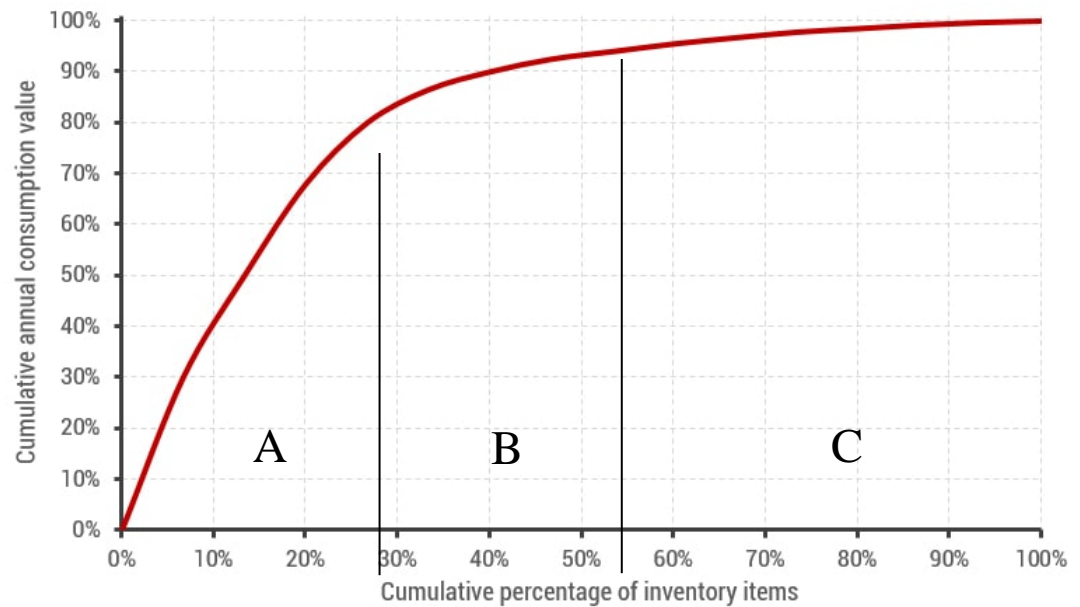


Figure 4. ABC analysis categories (adapted from Smirnov, 2019)

In classical ABC analysis A-category items are the critical ones and should be managed more closely, so they need the most effort and attention. Whereas a single item in category C has less impact and minimal needed effort should be applied in the management of these items. Classical ABC analysis mostly focuses on annual income from a certain item. The base rule is that volume wise most items should fall into category C and items fewer in volume, but bringing the biggest share of income should be managed more closely in category A. The so called “80-20” rule portrays the idea that 80% of annual income comes from only 20% of the total number of items. (Chen, 2008)

Multiple criteria ABC analysis (MCABC) is another term used for ABC analysis considering multiple criteria. Various MCABC methods have been developed to complement traditional ABC analysis. Those methods are based on processes such as Analytical hierarchy process (AHP), artificial neural networks, data development analysis and statistical analysis, some of which help combine traditional quantitative criteria with qualitative ones. One framework specifically developed for service organizations on manufacturing companies applies traditional ABC analysis principles with one selected critical factor in addition to

the annual dollar usage. This criterion should be chosen based on development focuses of the unit and industry. (Chen, 2008; Flores, 1987; Peng, 2010)

2.3.2 Analytical hierarchy process (AHP)

The analytical hierarchy process (AHP) was developed by Thomas L. Saaty in 1996 as a basic approach to decision making. AHP is a powerful tool for situations that involve multiple objectives. It is a scale prioritization method that allows to categorize and prioritize between a set of chosen criteria. By doing pairwise comparisons on a set of chosen alternatives, it can be used to develop priority ranking among the alternatives. (Saaty, 2012)

Analytical hierarchy process can be categorized under the variety of Multiple criteria decision analysis (MCDA) methods. MCDA methods aim to assist decision making by helping sort, rank and choose the best alternative combination when two or more criteria are involved. The basic process of MCDA is to first define the objectives, then arrange criteria based on the objectives, to identify all alternatives and to measure possible consequences of all different criteria-alternative combinations. The challenge is to acquire the decision makers' preferences and to change them into a measurable form, such as weights and values. It can also be argued that each decision maker relies on their own expert opinion and thus the decision makers involved in the ranking may only give a subjective result. (Chen, 2008)

The factors included in the AHP-model should represent the goals of the analysis. They should be relevant and detailed enough to contribute to the problem addressed. They should form a homogenous comparison level and provide an overall view on the relations between the different criteria. AHP uses pairwise comparisons and evaluated all the alternative combinations of the pre-defined criteria. A fundamental scale (figure 5.) is used to capture the intensity of the comparison value. It enables to evaluate how many times more important one

compared criterion is over the other and also makes it possible to evaluate two almost equally important alternatives by permitting fractural values. (Saaty, 2012)

Intensity of importance	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
2	Weak	
3	Moderate importance	Experience and judgment slightly favor one activity over another
4	Moderate plus	
5	Strong importance	Experience and judgment strongly favor one activity over another
6	Strong plus	
7	Very strong or demonstrated importance	An activity is favored very strongly over another; its dominance demonstrated in practice
8	Very, very strong	
9	Extreme importance	The evidence favoring one activity over another is of the highest possible order of affirmation

Figure 5. AHP Fundamental scale (Saaty, 2012)

In the fundamental scale value 1 indicates that the compared criteria are equally important and non-should be prioritized over the other. As the scale value grows, the intensity of evaluated criterions compared to its pair grows. The highest value on the scale is 9, which indicates that the evaluated criterion is of extreme importance compared to its pairwise comparison and should clearly be prioritized over the other. Each alternative combination has two opposite sites in the comparison matrix. In example if it is evaluated that A is twice as important compared to B, there will also be the mirroring comparison of B being 1/2 of the importance compared to A. This also leads to comparisons valued 1 on the scale, for each criterion as it is also once compared with itself. An example matrix valued with the help of the fundamental scale is shown below in figure 6. (Saaty, 2012)

Matrix	Criterion 1	Criterion 2	Criterion 3	0	0	0	0	0	0	0	normalized principal Eigenvector
	1	2	3	4	5	6	7	8	9	10	
Criterion 1	1	5	1/3	-	-	-	-	-	-	-	27,9%
Criterion 2	1/5	1	1/7	-	-	-	-	-	-	-	7,2%
Criterion 3	3	7	1	-	-	-	-	-	-	-	64,9%
0	4	-	-	1	-	-	-	-	-	-	0,0%
0	5	-	-	-	1	-	-	-	-	-	0,0%
0	6	-	-	-	-	1	-	-	-	-	0,0%
0	7	-	-	-	-	-	1	-	-	-	0,0%
0	8	-	-	-	-	-	-	1	-	-	0,0%
0	9	-	-	-	-	-	-	-	1	-	0,0%
0	10	-	-	-	-	-	-	-	-	1	0,0%

Figure 6. AHP comparison matrix (Goepel, 2018)

Based on the intensity given to the alternative comparisons, a consistency ratio and index are calculated. The target being that the hierarchy set for the alternatives has less than 10% inconsistency between the intensity of the compared alternatives. If the inconsistency is higher than that, then the problem should be studied, and the judgment revised and changed to fit the minimum consistency expectancy. Tolerance for inconsistency allows for slight variation of judgement. AHP analysis should support people in organizing their thoughts to be able to make better decisions. To reach such an outcome, AHP focuses on solving the set problem and it is important to gather enough information on the context and topic first. The outcome allows slight differences in opinion and concludes the best available compromise. (Saaty, 2012)

AHP-based models are hard to employ. They need extensive expert judgement, which is time consuming and has no quantitative data to back it up, misjudgements affect the results. AHP combines quantitative and qualitative data based on expert opinions. It uses pairwise comparisons of pre-defined criteria, giving them weights and values based on experts' judgement. The number of

pairwise comparisons needed for the analysis grow significantly with every criterion added. Having too many alternative comparisons may lead to computational difficulties. The accuracy and consistency of the values given by the decision maker involved will most likely degrade the more time it takes to complete the comparisons. Since the method relies on the subjective opinion of the decision makers involved, it may not generate reliable results. (Torabi, 2012)

2.4 Service request categorization model

Based on the knowledge gained from the literature review a service requests categorization process is proposed. The process steps and aims of the data analysis are concluded in figure 7. The conceptual framework loosely follows the previously introduced decision support system (DSS) development process (Singh, 2017). The four steps of the DSS process are shown on the right side and the six steps of the proposed framework on the left side.

The proposed framework is combination utilizing the process steps of the DSS development framework (Singh, 2017) with basic principles found from service request management literature. Unlike the DSS framework the target is not to build a system that actively gives input, but rather combine methods that help identify important factors affecting decision making. The basic idea of filtering, processing, combining and analysing data is in this setting used to set-up customer support case classification guidelines. This then helps recognize information gaps (Jantti, 2009) and improves the consistency and accuracy of decisions (Singh, 2010). Chosen categorization methods are used to process and extract relevant knowledge from historical service requests data and to include qualitative knowledge from domain experts.

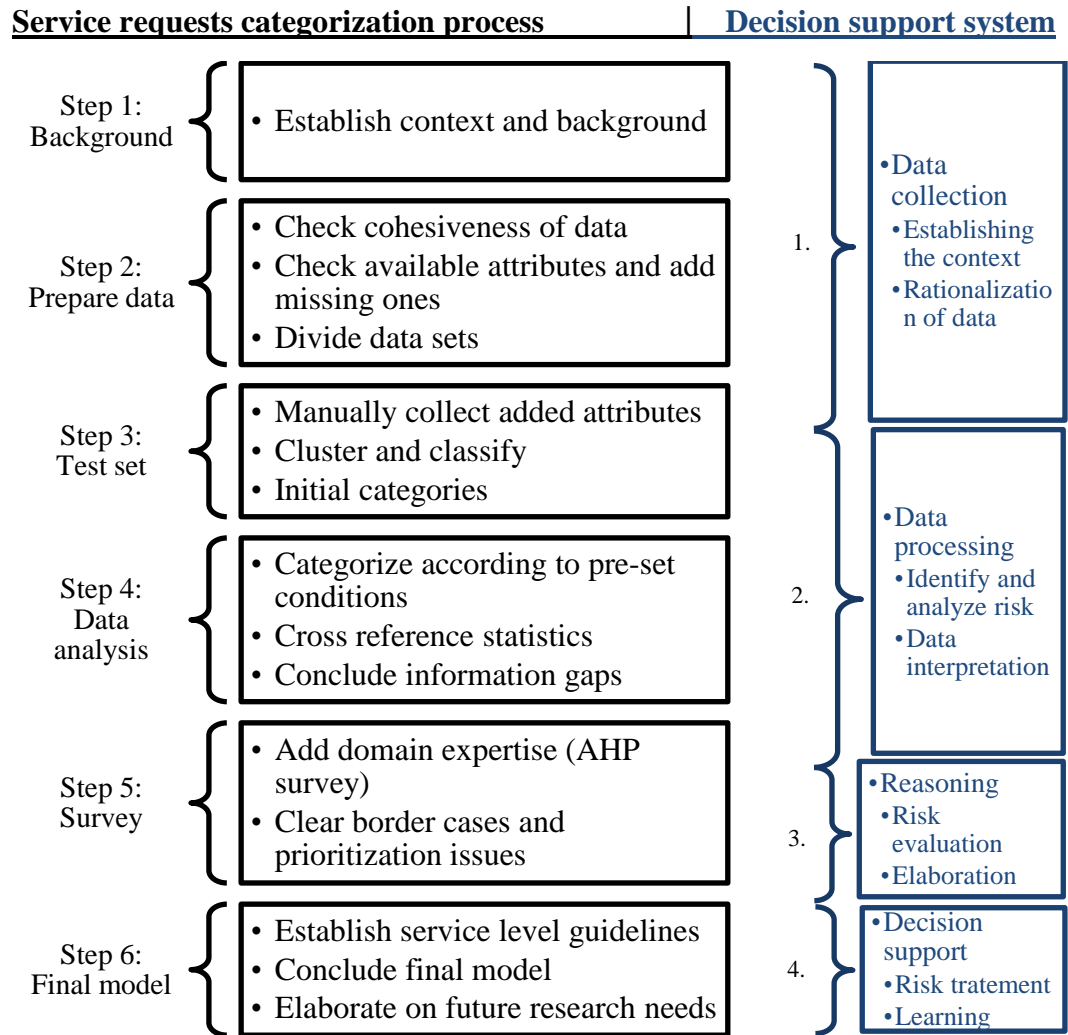


Figure 7. Data analysis steps and targets

The process starts with data collection, where existing data is gathered, and the case context is established. This should give insight on the delimitations and goals of the project (step 1.) and prepare the chosen data (step 2.). Rationalization is important to gain enriched data that is relevant, cohesive and structured. In the suggested model this also includes gathering existing data attributes to help find information gaps and to distribute the data into needed exclusive sets (step 3.) to ensure validity. To ensure quality and consistency during data handling and collection, data should be handled taking notice of the main reasons for measurement bias according to Hair (2011). The data used for analysis should be divided into explicit samples each for one of the analysis phases, piloting and the

actual case analysis. Both phases need to be conducted with exclusive case sample sets to avoid overlapping data and to ensure the validity of the results.

In this model a test set and main data analysis set are separated. The purpose of the test set is to raise modification needs at an early stage into the process. Random sample cases can be studied to gain a general overview of the quality of the available data. Needed corrections and data enrichment needs can then be implemented in time for the main data analysis. Clustering is done based on the target outcome and pre-set categories and rules are chosen based on attributes from which needed, not yet existing, knowledge can later be statistically analysed (Benedettini, 2014).

Data processing helps interpret the prepared data and should contain additional focus on risk identification and analysis. This can be achieved by clustering and classifying data with the help of categorization methods such as content analysis and ABC-categorization to gain information on common patterns and initial category options (step 3.). Processing a larger data set (step 4.) helps conclude statistics, that can be cross-referenced with pre-set conditions established during the background analysis. By analysing the larger data set more trustworthy statistics can be gained on the categories identified during the test set analysis. It will also help research how different data attributes correlate with the indicators used when defining the initial categories. The initial categories should be re-evaluated and possibly combined under more general definitions, until all necessary informative needs are fulfilled with the smallest possible category count. Data processing can also raise additional information gaps that need to be addressed.

After collecting and processing the set data, reasoning should be applied (step 5.) to elaborate on the results. With the help of domain knowledge, a more specific prioritization line-up of the categories can be conducted. With the help of an additional survey the goal is to understand how the remaining border cases, that do not have a clear categorization group, should be categorized. The goal of the

survey was to add experts' opinion to verify the results of the data analysis and to complement them by adding prioritization guidelines. Expert input can be used to prioritize the earlier established categories by utilising analytical hierarchy process based cross-comparisons (Saaty, 2012). Additionally, the risk identified during the data processing phase should be further evaluated.

Finally, all the information and knowledge gained during the process is concluded into one model. A compact and simplified categorization model will support fast decision making and easy to recognize general categories give clear guidelines to support decision-making in service teams.

3 BUILDING THE SERVICE REQUEST CATEGORIZATION MODEL FOR THE COMPANY

Customer support functions, containing technical support and warranty, have been identified to have a big impact on customer experience. In customer support speed and accuracy are appreciated and it is important to provide the users with easy to understand alternatives, when they are working on a limited time frame and facing pressure from the customer (Peng, 2010). This study aims to support the target company's global customer support to streamline their customer support case handling process with the help of case categorization. The goal is to follow the steps of the proposed categorization model development process, introduced in figure 4, to define clear guidelines for the unit in question.

To better understand the research environment and starting point, the first section will introduce internal findings and present the current and future support organization structure and current processes. Data collected from the customer support case database is processed and analysed according to the categorization model. The analysis findings are then complemented and verified with the help of domain experts and lastly the concluded case categorization guideline model is presented.

3.1 Global customer support organization

The development project was conducted for a market leading global B2B-company in the industrial section. The study concentrated on a selected business division's customer support functions in their global service unit (figure 8). The department in question has customers all over the world. The current organization is built on three levels; local sales units, back-end customer support and expert services. The local sales units usually each cover one country's business and have direct contact with the end customer. If additional support is needed, they contact

the global customer support. The global customer support then handles the cases based on whether they are warranty related or technical support. If a case needs additional analysis or supplier domain knowledge, the global customer support can request support from expert services.

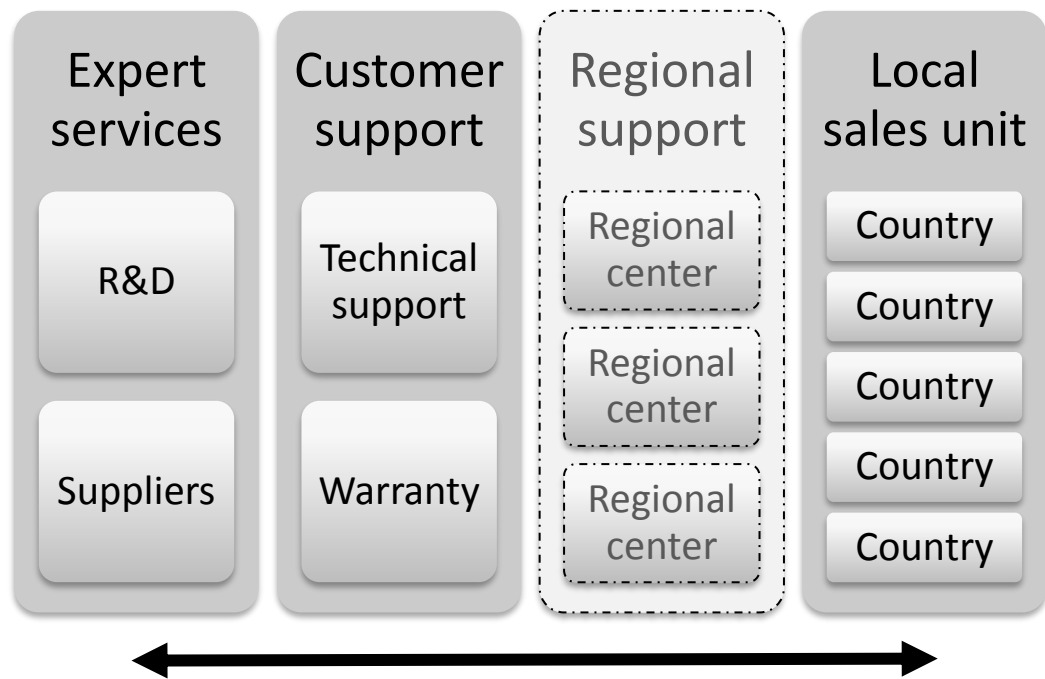


Figure 8. Organization structure of the customer support unit

The company is planning to add a fourth organization level between the local sales units and the global customer support unit. Regional support centers would each be responsible for cases coming from local sales units within their area. They would utilize documented domain knowledge provided by the back-end support to solve cases. The goal is to share workload and guide cases to be solved at the level with the needed capabilities closest to the end customer.

Each organization unit has different levels of technical capabilities. In the front, in the local sales unit, the case owner is usually from a sales background. The customer support unit, in back-end operations, has specialized technical support and warranty handling teams that can also request support from expert services. Whereas, the planned regional support users would be trained to be specialized service advisors with additional knowledge on product lifecycle services. The

technical capabilities of each organization level need to be considered when defining guidelines of target case resolution levels. By defining clear guidelines each unit can make use of their strengths and knowledge without spending time on cases that could be better solved on another level.

3.1.1 Customer support cases

The back-end unit handles approximately 1800 customer support cases per year. The cases can be divided to warranty and technical support cases, each of which have their own team and team leader. Annually around 800 cases are estimated to be warranty cases and the remaining 1000 technical support cases. A more detailed division of the case types currently recognized is presented in table 1. The division is based on the level of escalation and it directly correlates to the resolution time of the case.

Table 1. Customer support case statistics

CUSTOMER SUPPORT		
Warranty (800/year)	Duration	%
Failed parts	2h	80
Internally handled	1d-1m	13
Application engineering	1w-1m	5
R&D	1w-6m	2
Technical support (1000/year)	Duration	%
Internally handled	1-5d	80
Application engineering	1w-1m	15
R&D	1w-3m	5

The case distribution shows that in both warranty and technical support the internally handled cases (also includes failed parts) build up to be over 80% of the cases. Cost of different cases, taking into account time, amount and number of people involved, has not been followed with the current system. However, field service is known to be the biggest visible cost. The unit is using a common case management tool that is also used by the local sales units. Currently the categorization of the cases is based on agreed fault codes, indicating in what part of the product the reported problem has occurred. The only key performance indicator currently followed in the customer support unit is first response, with a target of one working day. No other key performance indicators are currently in use.

In addition to the division based on the level of workload and escalation within the back-end unit, another division was drafted to indicate what type of capabilities or additional support services are needed to solve a case (figure 9).

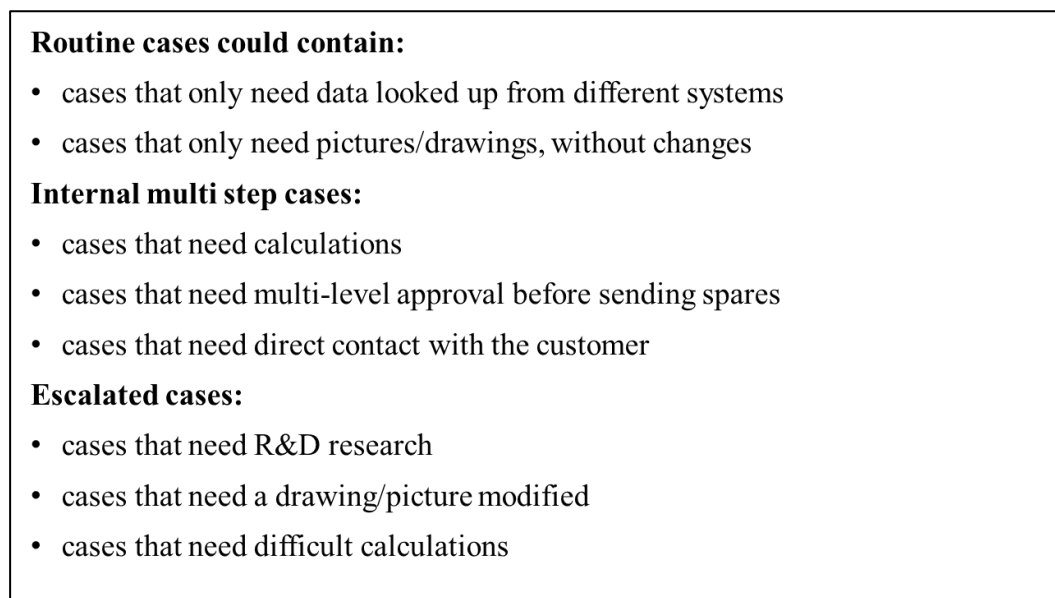


Figure 9. Service request divided based on capabilities and escalation needed

In this service-based division there are three main categories; routine cases, internal multi-step cases and escalated cases. Routine cases include cases that can be solved directly by retrieving data from existing databases. Internal multi-step

cases refer to cases that can be solved by the back-end unit but need approvals or reference to previous similar cases. Escalated cases are cases that must be further escalated to expert services for additional calculations, modifications or analysis. These initial categorization drafts are later used as the base of reasoning for the to-be categorization model design.

3.1.2 Identified challenges

Some clear future development needs surfaced during the initial current state analysis. These findings were supported by research material gathered through additional internal meetings and monthly reportings. Four central themes revolved around the identified improvement possibilities; communication processes, IT-systems, knowledge management and cross-culture management.

Communication towards entities that some cases need to be escalated to, were perceived as a clear bottleneck. The aftersales cases in question do not have any means to be marked with criticality when escalated. High priority warranty and technical support cases sometimes stay stuck in general work order queues of for example the R&D department. Currently this issue has been avoided by calling after the cases to let the other departments know which cases need to be prioritized. After calling the process works as designed, but the teams wish to remove this unnecessary step and find a permanent solution.

Multiple internal applications and systems were referred to as time consuming and somewhat confusing. A lot of cases needed data from several of these systems in order to be solved. Some of the systems had overlapping data and one needs to request user rights to separately access them. Combined to the fact that the main case management tool had recently been changed to a globally common tool had caused some change resistance and critique towards the IT-systems in general. A remarkable portion of the current cases include a possibility to make better use of

automating some of the current processes or developing self-help tools and utilising machine learning based solutions.

As information needed to solve the case is sometimes hard to find, the importance of tacit knowledge is high. Responders in the interview felt that it is often easiest to quickly ask whether others remember similar cases. A lot has been documented and a document management system is in use. The customer support case database has a search function and most answers can be found somewhere within old cases or in the management system but finding the right information might still be faster acquired through colleagues.

Many cases could have been solved by country based local sales units that serve the end customer. Common policies to help solve the cases closer to the front are hard to integrate due to areal and cultural differences. This has led to the situation where the cost of the work put into the case can be over the value of the warranty claim or replacement part that it is related to. Especially in the case of more expensive product lines, the front line is very hesitant to solve cases on their own even if they have the required permissions to do so.

3.2 Data analysis

To gain insight into the recent situation and statistics of the case unit, a case data analysis on recent customer support cases was conducted. This provided the possibility to recognize common patterns and relations between the support cases. To ensure quality and consistency during data handling and collection, the data was handled taking notice of the main reasons for measurement bias according to Hair (2011). All analysis phases were conducted with exclusive case sample sets to avoid overlapping data and to ensure the validity of the results.

The data set was gathered from the back-end customer support case databases. It can only give limited perspective of the complete situation, focusing on the cases

currently solved by the back-end. As ABC-analysis principles are used to categorize the cases, it is important to notice that in this case study the volume of the categories is not directly applicable to theory. This is due to only analysing cases on one organization level. Many of the easier cases that need to be handled closer to the end customer are already solved by local sales units and are not visible in the scope of this research. That's why the ABC categorization 80-20 rule can't be directly implemented in this analysis (Chen, 2008). The data analysis will give insight on which organization level the cases currently solved by the back-end support could be handled. The decisions are based on comparing the capabilities of the service levels with the technical knowledge required to solve a certain case types.

3.2.1 Processing case data

The customer support cases were directly exported from the case handling system into Excel for further processing. This formed the base for the Excel tool and provided numerical and textual data for the analysis. The gathered data was directly in line with the attributes documented during case handling, such as details about the product and customer, originating country and relevant dates.

The initial data set for this study was built with customer support cases from a relatively recent four-month time frame. This ensured large enough sample sizes during piloting and the actual case data analysis, as each individual case could only be used once. The whole process started with preparing the Excel tool for data collection and analysis. For this purpose, filtering options were added, and random sample cases were studied to first get a general overview of the quality of the data available. Based on the findings in the test phase the cohesiveness of the remaining data was checked according to the first step of building a decision support process as described by Singh (2017).

To ensure data validity the following actions were taken:

1. Duplicate cases were deleted
2. Cases with multiple case numbers were deleted
3. Key account customer cases were highlighted
4. Still ongoing cases were excluded
5. Cases handled in other than English were excluded
6. Cases lacking necessary attributes or real content were excluded

One major notice was that many cases were still under process or lacked necessary data, and thus, had to be systematically excluded from the final case batch. The existing case data attributes gained directly from the system were focused around customer, product and general fault type information. Based on the previously conducted current state analysis and the sample batch findings, some additional data needs were recognized in order to complement the existing ones. The added data fields and the reasoning for adding them are shown in the table (Table 2.) below.

Table 2. Added attributes

Attribute	Reasoning
Case age (days)	Indicated case age did not match real case age
Emails received & sent	Indicator for work load
People involved	Indicator for work load
Stakeholders involved	Indicator for work load, clarify effect on case age
Main theme	Indication for service level (includes justification)
Bottleneck	Development needs (analyzing contradictions)
Documents	Statistics on requests related to certain documents

Even though case age was one of the attributes already gained directly from the system, it was noticed that due to varying use ways of case statuses and multiple exceptions, it did not properly represent the actual case age. Other added indicators to represent work load were the amount of emails sent and received, the number of people involved in the solving of the case and whether the case needed

input from expert services, such as suppliers. Work load indicators can help recognize routine cases that could potentially be solved on a lower organization level.

The remaining attributes added were intended to further support the work load findings by giving insight on the main theme of the case, the challenges faced while solving it and documents needed to solve it. The main theme or service need of the case brings a different approach on side with the existing fault code system that is based on the product fault occurred. The initial findings are loosely based on the classification presented earlier in the report.

In addition, an attribute describing bottlenecks was added to gather common development needs, by documenting and clustering reasons for delay of case resolution. It can also help provide explanations for possible contradictions in the end results and give indication how much certain factors affect the other case attributes such as resolution time. The last attribute to be added indicated which documents were used and needed for the case resolution. This was added to help recognize cases that could be solved on a lower organization level, by finding the biggest needs related to document availability.

Most of the added fields required manual data collection from the case database. In order to ensure that all of the relevant data needs were recognized and could be retrieved at the first try, a small pilot sample was first used to catch any remarkable additional needs before starting with the actual analysis batch. During the process some additional cases were excluded from the research. The most common reasons for this were previously missed duplicate cases and still ongoing cases that were already marked as closed. After making some slight changes to the data collection plan, manual data collection was carried out.

3.2.2 Identifying common categories

The next step was to cluster common patterns and to draft the initial case categories. This was done to limit and pre-define the established categories for the larger main data set. The previously defined additional attributes were manually collected from the test case data set. As the attributes describing the main theme, possible challenges and used document did not have any clear pre-set classification options, they were first documented in a free text form into the Excel tool. Then the main themes were clustered under common topics based on the service provided to solve the case. The clusters helped define the categories to be used during the main data analysis.

After all added attributes had been filled out, the ones in free text form were grouped under common themes and topics until the number of categories was limited enough. The target was to have a maximum of 10 main categories. During the pilot phase this goal was not yet reached and to be able to better distinguish between certain types of cases they were divided into 14 categories. Based on the findings of the pilot phase and the current organization structure the identified case categories were divided as shown in table 3. The as-is model does not include the local sales unit perspective, as the provided case data only contained cases solved by the back-end. The as-is model is a representation of the current situation with the new customer support case categories that are based on the type of service needed to solve the service request.

Table 3. Categories and service levels in the as-is model

Service level	Categorization
L3: Global customer support	<ul style="list-style-type: none"> - Small warranty - Documents and warranty dates - Incomplete delivery - Medium to large warranty - Retrievable data & documents - IT-system related - Old documentation - Field service involved - Key account customer - Complex technical inquiry - Serious product failure
L4: Expert services	<ul style="list-style-type: none"> - Serial quality issue - Internal support; calculations, drawing updates etc. - Root cause analysis

Common cases currently solved by the back-end (including expert services) contained in example deliveries missing something, bigger warranty cases, data and documents available only in factory systems, issues related to IT-systems used between the organization levels, documents related to older products (only available in paper copy) and complex technical inquiries. In addition, all field service related cases are handled by the global support, as the field service team is located in the back-end unit. Serious product failure cases are always promptly escalated directly to the back-end, as co-operation with the expert services are always required and further damage needs to be minimized. Some end customers have special service agreements and are in direct contact with the global support. These cases were categorized as key account customer cases and need to be considered as a whole during the case analysis. Other end customers should always initiate contact through the local sales unit of their region/country.

If serial quality issues are detected, they are always handled together with expert services to minimize further damage and to ensure that the root cause is fixed, and improvement actions are implemented into production. The expert services also

support cases that need additional calculations, drawing updates or root cause analyses.

This first version categorization model represents the current back-end organization with the newly identified case categories. It functions as an as-is model of the current situation. Later this model is further processed and developed into the target to-be model that will also include the future regional support center and local sales unit support levels.

3.2.3 Data analysis results

The goal of analysing a larger data set was to gain more reliable statistics on the initial categories identified during the test set analysis. This section will attempt to find answers on how the cases in each category correlate with the case age and other work load indicators. The missing two organization levels (regional support center and local sales unit) were added to the model. Based on the findings and before stated limitations the categories were assigned to the most fitting organization level that has the needed knowledge to solve the case type. The target being that a case is always solved as close to the end customer as possible to ensure accurate and fast customer experience. A compact categorization model will support fast decision making and easy to recognize general categories give clear guidelines on which organization level the case should be handled at. For this the categories identified in the pilot data analysis were previously narrowed down to 14. These categories are divided according to the general principals of traditional ABC-analysis and case-based reasoning.

The main data set consisted of 100 cases from the back-end's case database. Originally the whole case set consisted of 400 cases, from a four-month time frame, of which 100 were set aside for the pilot set and 300 for the main data analysis. To ensure data quality and validity almost 200 cases were excluded from the final set and thus the data analysis set formed to be smaller than originally

planned. The case categories defined in the pilot set analysis were used in the main analysis and the distribution of these categories can be seen in figure 10. The most common case type building up to a fifth of all cases were cases with complex technical inquiries. In second came cases sent by key account customers but it should be noted that those included cases from multiple different categories.

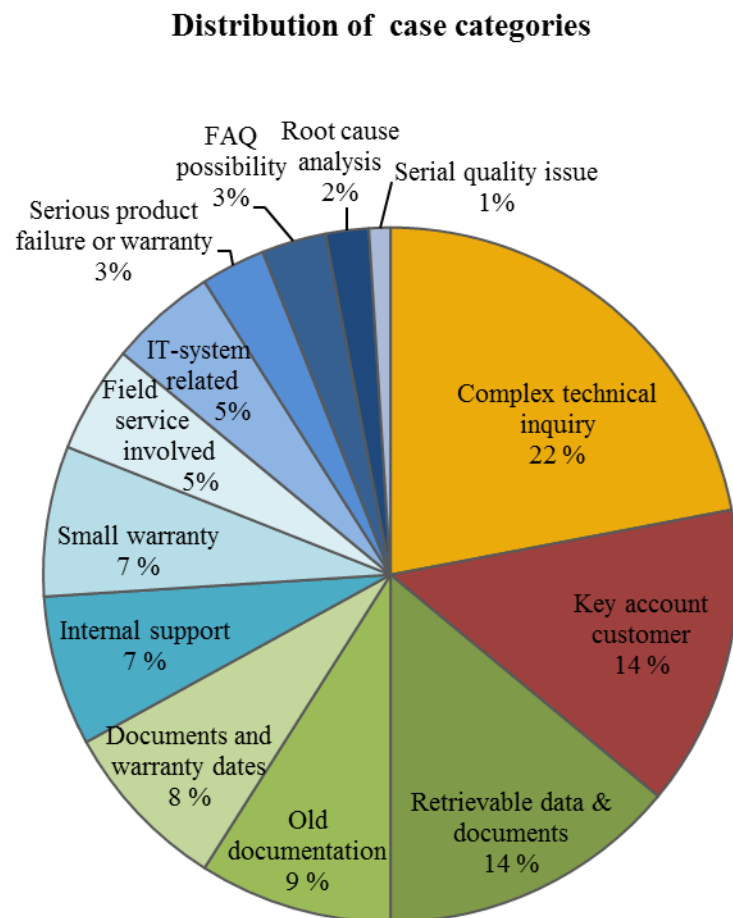


Figure 10. Distribution of case categories (sample set of 100 cases)

The third, fourth and fifth biggest case categories were all related to documented information. Together those categories build up to 30% of all cases. Retrievable data & documents refers to cases that needed available information and documents from one of the systems used in the back-end. Old documentation also refers to cases that requested information from documents but the documents in

this category have not been digitalized. Many older product documents are still only available in paper copy tied to a single location. The fifth biggest category was product documents and warranty dates and those cases needed information available in a specific information system. The system in question is also accessible to local sales units. The remaining categories together also build up to about a third of cases.

Based on the chosen categories and gathered work load indicators a rough draft of the categorization model was mapped out (table 4). This first draft shows how the recognized categories could be divided solely based on the duration of the cases in regards with ABC-analysis principles. The other workload indicators also correlate to this, with lower average values in C-cases and growing averages towards the A-cases.

Table 4. Initial categorization based on work load indicators

Averages	Real case age (days)	Emails to (pcs)	Emails from (pcs)	People involved
C-cases	(1-3)			
FAQ possibility	1	1.0	1.3	1.0
Documents and warranty dates	1	1.3	1.4	1.0
IT-system related	2	1.6	2.0	1.4
B-cases	(4-9)			
Old documentation	4	2.2	1.3	1.0
Small warranty	4	2.7	2.3	1.5
Retrievable data & documents	6	1.9	1.9	1.1
A-cases	(10+)			
Complex technical inquiry	12	3.1	2.2	1.5
Key account customer	27	5.5	5.7	1.8
Serious product failure or warranty	28	10.3	9.3	3.0
Internal support	29	8.3	5.6	1.6
Field service involved	30	12.2	11.8	4.0
Serial quality issue	120	19	20	7
Root cause analysis	144	29.5	17.0	4.0

Next the categories should be aligned with organization levels and target resolution levels need to be added to the model. Cases that do not line up with similar ones in the category, that need more time or differ in work load (emails, people involved etc.) should be analysed closer to identify exceptions. It was identified that the case data analysis was not enough to make definitive decisions on the resolution levels. It was also recognized that a single case may be related to multiple of the identified categories, this poses the question on which of the categories should then be dominant.

Information gaps that could not be answered without additional research were the evaluation of the possibilities to utilize self-help tools, such as FAQ articles, and how the case types recognized should be prioritized within organization levels. To verify the data analysis results and to specify the prioritization line-up of categories a survey was conducted. The survey will give insight on how to prioritize cases with multiple categories and how unsure border cases should be situated. In addition to the categories and workload indicators attributes slowing down case resolution process were gathered from the case data. Factors slowing down the case resolution process were similarly first freely textualized and grouped together based on common themes. The most common factors and their frequencies are presented in the table 5 below. Overall 35% of cases in the data set had some challenge prolonging the resolution.

Table 5. Challenging factors prolonging case resolution (100 cases)

Challenge	Frequency
Discontinuity	18%
IT-processes	9%
Pending response	8%

It was discovered that the most common factors to slow down case resolution was discontinuity in the case ownership. A case could either get stuck while being transferred or escalated to another team or user. For example, the case owner left

for holiday and did not transfer the case to someone else. Another clear factor was the age of the product related to the case. Older products tended to not have digitalized documentation, or the needed information was partly incomplete or not available. In addition to these two, some cases were pending for a response from the customer or supplier for a long time. There were also clear indicators of some IT-system processes causing confusion. The systems were either not up to date or the local sales unit did not have enough training in the use of those systems and this resulted in routine cases coming through to the back-end.

3.3 Verification survey

The objective of the survey was to add experts' opinion to verify the results of the data analysis and to complement them by adding prioritization guidelines. Four experts from the back-end customer support team participated in this survey. With the help of an additional survey the goal was to understand how the cases without a clear ABC-category group should be situated and how the ABC line-up should be positioned with regards to the organization levels.

The first part of the survey consisted of a list of the identified case categories. The idea was to choose on what organization level each claim should be handled at. The answers were concluded and compared with the results of the data analysis. This first part of the survey helped verify a suitable organization level for each category and the reasoning behind the survey decisions gave insight to some exceptions that must be considered in the final model. In the second part of the survey a excel tool (Goepel, 2018) was used to gain insight on how experts would prioritize cases that should be solved in the global customer support and expert services. The tool is based on analytical hierarchy process principles and gives weighted results on the preferences based on comparing given alternatives. With the help of the second part of the survey the case categories could be listed in order of prioritization.

3.3.1 AHP based comparison tool

The four participants were first presented with basic principles of the analytical hierarchy process and the functionalities of the Excel-tool used. The different criteria and scales were explained to make sure that all participants have a common understanding on the options. Based on the first part of the survey, seven categories were chosen for the AHP comparison matrix to represent back-end cases. There were two clear reasons for choosing those categories for the survey. The first was that most back-end case categories were A-category cases and have the highest single impact of all case categories. Secondly it is recommended to narrow down the number of criteria in an AHP style survey due the rapidly growing number of needed comparisons. By keeping the number of criteria lower, the number of needed comparisons is manageable, and the participants are more likely to be able to focus until the end of the comparisons, resulting in higher quality input. List of the chosen criteria are presented in figure 11. (Saaty, 2012)

n	Criteria	Comment	RGMM	+/-
1	Field service		32.5%	13.6%
2	Serial quality issue		21.4%	10.9%
3	Serious product failure		32.5%	13.6%
4	Technical inquiry		2.6%	1.1%
5	Key account customer		4.6%	2.0%
6	Internal support needed		4.6%	2.0%
7	Paper documentation		1.8%	1.0%

Figure 11. Prioritization survey comparison options

The excel tool had separate questionnaire sheets for each participant and a summary sheet that concluded all the processed answers and presented the weighted results based on the input of the four participants. It also indicated the percentage of inconsistency of each participant's answers and the consensus between the participants. The set consistency ratio for an individual participant was set to 10% so for the comparisons to be in acceptable with each other the consistency ratio of each participant's answers had to be under 10%.

To be able to compare the different criteria and their relations with each other, a value comparison had to be made. With seven criteria to be compared the number of cross comparisons to be made is twenty-one. In order to minimize the comparison count, the excel toll is structured with a scale that compares the relative importance between two criteria with a two-step input. The first step is to choose which of the compared two criteria in question should be prioritized against each other and the second input asks for intensity on how much the chosen criteria should be prioritized over the other. The two-step input Excel sheet and the scale of intensity with definitions are presented in figures 12 and 13.

Participant 6			1		α : 0.1	CR: 0%	
Name	Weight	Date	Criteria		more important ?	Consistency Ratio	
i	j	A		B	A or B	Scale (1-9)	
1	2	Field service	}	Serial quality issue			
1	3			Serious product failure			
1	4			Technical inquiry			
1	5			Key account customer			
1	6				Internal support		
1	7				Paper documentation		
1	8						
2	3	Serial quality issue	}	Serious product failure			
2	4			Technical inquiry			
2	5			Key account customer			
2	6				Internal support		
2	7				Paper documentation		
2	8						
3	4	Serious product failure	}	Technical inquiry			
3	5			Key account customer			
3	6			Internal support			
3	7			Paper documentation			
3	8						
4	5	Technical inquiry	}	Key account customer			
4	6			Internal support			
4	7			Paper documentation			
4	8						
5	6	Key account customer	}	Internal support			
5	7			Paper documentation			
5	8						
6	7	Internal support needed	}	Paper documentation			
6	8						
7	8						

Figure 12. AHP survey comparison template

Intensity	Definition	Explanation
1	Equal importance	Two elements contribute equally to the objective
3	Moderate importance	Experience and judgment slightly favor one element over another
5	Strong Importance	Experience and judgment strongly favor one element over another
7	Very strong importance	One element is favored very strongly over another, it dominance is demonstrated in practice
9	Extreme importance	The evidence favoring one element over another is of the highest possible order of affirmation

Figure 13. AHP survey scale intensity definitions

A lower value on the intensity scale indicates that the compared criteria in question are closer to equal importance. The larger the scale value is the more one criterion should be prioritized over the other. Towards either end of the scale, the larger values, the relative importance of the chosen side will grow and thus the other criteria's importance relative to the chosen one will diminish. The tool also analysed the reliability of the results by comparing consistency of the answers. Each participant was first evaluated separately and then the results were concluded together. With a score of $0.09 < 0.10$ the results are below the 10% inconsistency limit and can be used as guidelines for the chosen prioritization problem.

3.3.2 Survey results

The first part of the survey shows on which organization level the participating experts would target to solve cases from certain categories (table 6.). Each expert would choose the most fitting organization level for each of the given service request categories. The results were combined and compared to the data analysis results. A full black circle indicates the answers that gained full consensus between participants and the white circle shows the second most popular answer with categories where some participants had multiple answer options. Full consensus was reached on twelve out of the fifteen presented customer support case types.

Table 6. Expert opinion on resolution level

	L1	L2	L3&4
Small warranty case	●	○	
Large warranty			●
Complex technical inquiry			●
Paper documentation			●
Retrievable data & documents		●	
Field service involved			●
IT-system related		●	○
Serious product failure			●
Root cause analysis			●
FAQ-possibility	●	○	
Basic product support		●	
Product documents and warranty dates	●	●	
Internal support (i.e. calculations)			●
Serial quality issue			●
Key account customer			●

According to the answers cases to be solved in level 1 support in the local sales units are small warranty cases, cases with FAQ-possibility and cases needing product documents and warranty dates. All these three categories also had straying answers. Experts reasoned that due to greatly varying capabilities in different local sales units, even the most straightforward routine cases might need to be supported by the regional support center. This raised discussion on a possibility of mapping the capabilities of the local sales units.

According to the survey answers cases in the categories; retrievable data & documents, IT-system related, basic product support and product documents and warranty dates, could be solved in level 2 support in the regional support centers. Out of these the last mentioned had full consensus on two answer options, level 1 and level 2 support. The other straying answer was the 'IT-system related' category, which some participants chose for both level 2 support as well as level 3&4 support (back-end). The reasoning was based on unclear definition of this

category. If an IT-system related case was about checking order tracking or about giving general instructions on how to use a related system, then regional support centers should be capable to solve the case. In cases where IT-system development managers' input is needed, the target resolution level would be the global customer support.

The answers also suggested that cases involving large warranties, complex technical inquiries, paper documentation, field service, serious product failure, root cause analysis, internal support, serial quality issues and key account customers, should be handled by the back end. Based on the category division in the case data analysis phase most of these were A-category cases, implicating that on average they had the highest workload indicator values. However, there was one exception, the cases requesting old documentation. In the data analysis such cases were B-category cases based on their workload indicators, but in the survey the experts highlighted that all old documents are only available in one location in the back-end office.

In the second part of the survey the categories mapped to be solved on level 3&4 support were used as criterion in the AHP comparison-based Excel-tool. The summary of the concluded average results is presented in matrix form (figure 14.) that shows how much each criterion is prioritized over the other after all the comparisons and calculations had been finished. The same results are presented in the bar chart (figure 15.) that shows the prioritization order of the case categories.

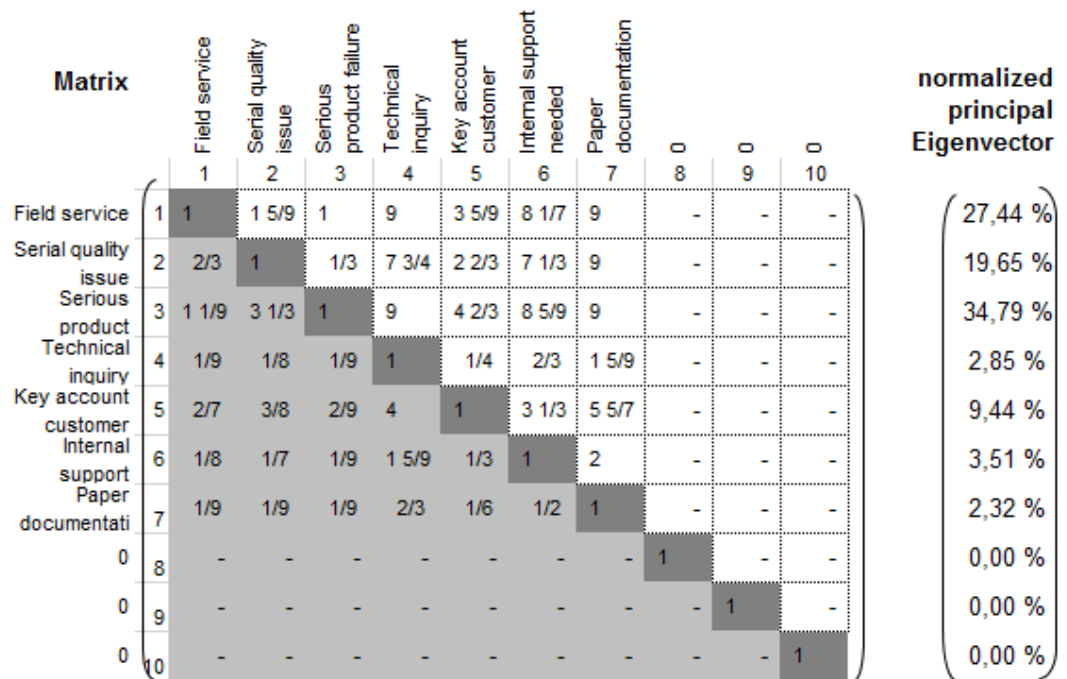


Figure 14. AHP result matrix

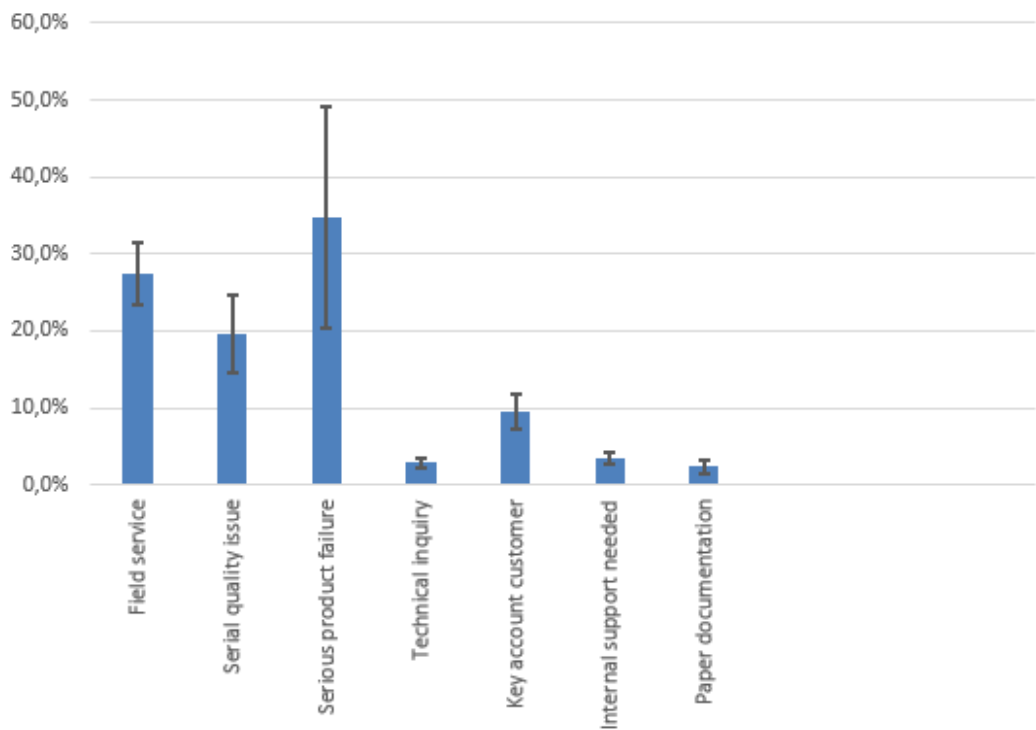


Figure 15. AHP prioritization order

Based on the survey the chosen cases had three clear case types to be prioritized, with the first one being cases related to serious product failure. These cases were commented to have high cost, high immediate risk and serious effect on customer relationships and company image. The other two case types to prioritize next were cases with field service being involved and cases related to serial quality issues. Reasoning for field service related prioritization was that cases with field service on site have high cost and tight schedules of field service agents need immediate actions to prevent further issues. Third are cases related to serial quality issues, as these cases tend to have major impact and lead to corrective actions throughout the manufacturing processes.

The fourth to be prioritized were key account customer cases, though this was a conflicting criterion and had the most inconsistency within the answers. This was due to the fact that key account customer cases can include any of the other case types and they have dedicated persons responsible for solving any cases related to certain key accounts. Thus, it can be said that key account customer cases are always prioritized by having dedicated experts handling them and those cases should be further prioritized according to the same principals as other cases.

After these, cases that need internal support from expert services should be directed to the needed parties for further handling. At last technical inquiries and old documentation issues should be handled. It was agreed on, that this prioritization needs additional guidelines on when to raise the importance of a certain older case over other new ones.

3.4 Suggested categorization model

The next step is to conclude a guideline model that includes all the organization levels and shows on which level cases from a certain category should be resolved at in the new target to-be model. The target model will add the regional support

centers that will be the link between local sales units and the back-end. Based on the literature review, data analysis and the clarifications gained through the survey a case categorization and prioritization model was concluded. The goal of this model is to support decision making by giving clear guidelines and service level targets for customer support case handling.

The model (table 7) shows which of the identified case types each organization level is mainly responsible for. To simplify the model, the ABC analysis categories were set to line up with the organization levels and named according to the expertise needed to solve them. The company refers to the local sales unit as the organizational level 1. Regional support center is referred to as level 2 support, global customer support is level 3 and R&D in expert services in level 4.

Following the basic principles of ABC-analysis the cases to be solved by level 1 (local sales unit) apply the logic of C-cases that are generally routine cases. They are high on volume, but one individual case usually has low overall impact and the target is to not put too much effort and time in the resolution process. Cases fitting the description of B-cases are targeted to be solved at the future level 2 support (regional support centers). These cases require more effort or knowledge than C-cases but should still be relatively straightforward.

These cases would be supported with resources and technical knowledge transferred from the back-end. A-cases are usually fewer in numbers and generally have high impact on the customer and higher average costs related to them. These types of cases need domain knowledge and expert support and represent the cases to be solved by level 3 and 4 support (global support center and expert services).

Table 7. Final categorization model

Service level	Categorization
L1: Local Sales Unit	Routine-cases - FAQ possibility - Small warranty - Product documents and warranty dates
L2: Regional support center	Documented-cases - Small warranty - Retrievable data & documents - IT-system related
L3: Global customer support	Technical service-cases - Old documentation (exception) - Field service involved - Key account customer - Complex technical inquiry - Serious product failure or warranty
L4: Expert services	Escalated-cases - Serial quality issue - Internal support; calculations, drawing updates etc. - Root cause analysis

From the pre-conducted current state analysis, it was established that due to approval policies cases with high individual costs can only be resolved at the back-end. From the case types identified in the pilot analysis, such cases are field service related cases, serial quality issues and serious product failure and larger warranty cases. All cases that need expert services, such as drawing modifications, root cause analyses or calculations can only be directed to the back-end and further to the corresponding expert service team with the needed know-how. Cases requesting documentation are clear C-cases to be routinized and target resolution level would be the local sales unit. However, documents regarding some older products could only be solved in the back-end as access to the older paper copies is restricted by location and many have not been digitalized yet. Those cases are exceptions and do not correspond in terms of cost and work load parameters as indicators of ABC-categorization, but until all old documents

have been digitalized this is the only physically possible solution. Another pre-defined case type to be solved by the back-end are cases from key account customers. They have separate service agreements and unlike other end customers they are in direct contact with the back-end customer support.

The capabilities of the organization levels were pre-given, and this determined the possible knowledge and expertise needed to be able to solve the case. The cases suggested to be solved by the local sales units could not require too much technical expertise. This narrowed it down to three categories; cases to be solved with the help of existing knowledge articles, small warranty cases and cases requesting documents or warranty status information available on internal systems. Currently no up to date knowledge articles exist. Small warranty cases should be handled directly through the first contact point, as otherwise the cost of labour put into the case can easily pass the cost of the small warranty. Case categories to be solved by the back-end (global support and expert services) were noticed to be somewhat intertwining with each other and the border is not so set, as compared to towards the local sales unit. The reason is that these units cooperate closely, and the global customer support unit may be able to solve a variety of cases as long as there are similar references to be found in past cases.

The second part of the survey gave insight to the participating experts' opinion on case prioritization. According to the results the first to be prioritized are cases that need to follow emergency response plan (i.e. fire or other events that endanger human capital). Then cases that have a field service agent currently on site should be handled next, as it is not only the single biggest direct cost but also on a very tight schedule. Then other field service involving cases should also be prioritized due to availability challenges of field service agents. The third most important case criterion to be prioritized are serial quality issues. These cases pose a very high capital and customer relationship risk.

After these top priorities, cases that will need internal support should be forwarded accordingly in order to expedite the resolution, as internal support

request need to follow through additional work queues. Then complex technical inquiries should be handled according to expert experience. Cases escalated from lower support levels, need a separate prioritization method depending on how long the response has already been pending. Also, old paper documents need time-based prioritization guidelines, not to be left unanswered due to them being significantly lower in priority than other A-level cases. Customer satisfaction and expectation for response time varies between customer requests that are perceived as easy versus those perceived to be more complex.

4 DISCUSSION AND CONCLUSIONS

The final categorization model was concluded in table 7 in which knowledge attained from previous literature, limitations stated by the case company, data analysis and survey results were combined.

During the data analysis some information gaps and development needs were discovered. One challenge was that the available data was not cohesive and needed to be processed quite a bit to exclude duplicates and cases with incomplete content. The cases contained domain specific knowledge and vocabulary, which through possible misinterpretations posed a risk to affect the validity of the results. There were also multiple affecting factors, some of which were not in the scope of this study. As there were many overlapping processes and systems involved, not all perspectives could be covered.

The most common challenge prolonging cases was the insufficient use of the new case handling tool and discontinuity of case management in abnormal situations. Already in the pilot phase of the data analysis it was evident that the users need more training related to the new case management system. A common understanding of the usage and case handling processes on all organizational levels would give a better baseline for all. One clear bottleneck was the tracking of cases, especially in special conditions such as holiday fill-ins. Another improvement need was the efficient usage of existing code systems, for example fault occurrence had been filled out in only 45% of cases and failure reason in 32% of cases.

Another IT-system related bottleneck was the upload process of product specific documents. In multiple cases the needed documents were either missing from the database or the local sales unit did not have enough training to access them by themselves. Document handling also came up with cases related to older products which did not have digitalized documents in the database. Such cases had to be sent to the back end with access to the paper document archive. An additional

evaluation on where the benefits and costs of document digitalization would cross should be conducted. To reach a functioning result these challenges should be addressed, as they have been identified to have a major impact on the case resolution process. The to-be model, including the future regional support centers, is designed as a target state without these bottlenecks. Cases that come past the targeted resolution level towards the back end should be checked on to identify possible shortages in training or support materials.

According to the suggested categorization model there is potential to move part of the current back-end cases to be solved closer to the end customer. The cases analysed in this study have all been solved by the back-end and the percentage of cases that could be solved on other organization levels are shown in figure 16 below.

Percentage of cases per organization level

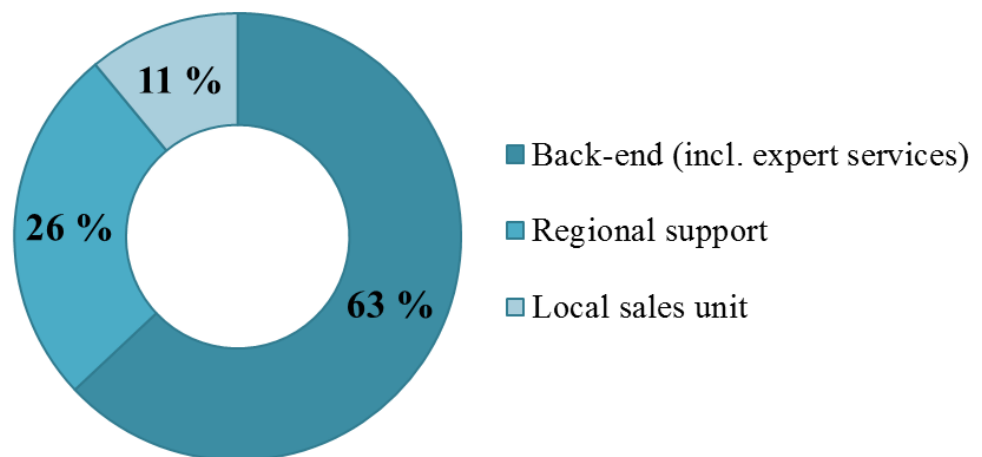


Figure 16. Percentage of potential cases that could be moved to other organization levels

The percentages are calculated by comparing amount of cases within categories assigned to each organization level as shown in the suggested categorization model. If the suggested categorization model would be used, 37% of cases

currently solved by the back-end could be moved to the regional support centers and local sales units. This does not directly mean a third of the workload could be transferred but certainly the back-end could better focus their resources towards cases with higher impact. One noticeable factor are cases related to paper documents that must be handled in the back-end because they have not been digitalized. If also those cases could be handled from elsewhere, the percentage of cases to be handled by the back-end would drop down to 54%.

4.1 Reliability of the results and future research

This study attempts to positively affect the reliability of the results by triangulation, meaning it uses multiple data sources to minimize bias. However, in order to improve the accuracy and reliability of the results, a larger test set should be analyzed over a longer time period. (Farguhar, 2012 p. 101)

The data analysis poses a risk for measurement bias as there might have been multiple different data collection ways with the secondary data used. Part of the data set had not been documented correctly or had to be excluded from the analysis set for other reasons such as duplicate cases. (Hair, 2011) The actual analyzed data set was much smaller than originally planned and this needs to be considered when drawing direct assumptions from the results of the data analysis. However, the analysis workload turned out to be much bigger than initially planned as the needed attributes had to be manually collected case by case. To gain more reliable results a longer time frame could be analyzed but it should be considered whether this proves to add enough beneficial value considering the resources needed to carry out the manual data collection.

This study uses analytical hierarchy process-based results to verify data analysis findings and it should be noted that the survey answers rely on experts' subjective opinions. There is always also a risk for differing interpretation of the same question and this might affect the end results. Regional and cultural differences

were not in the scope of this study. This is something that should be considered during the future implementation, to make needed alterations to the end model based on these differences. To be able to encourage responsibility to solve service requests on lower organization levels, knowledge sharing practises need to be developed. To utilize the tacit knowledge, build up in the back-end unit tacit to explicit knowledge exchange and knowledge sharing practises should be further researched.

5 SUMMARY

Customer experience has become a top strategic priority of manufacturing companies worldwide. With customer contacts being the most visible factor involved, more focus should be directed towards customer support case handling practices. This study was conducted for a global multi-level customer support organization that is looking for ways to improve and streamline their customer support case handling processes. The aim is to find alternative ways to categorize customer service requests and to set service requests resolution level guidelines for the units.

Aiding methods from literature were combined and the outcome was an operational concept for customer support service requests categorization in a manufacturing company. Based on analysis of old service requests an alternative way to classify customer support cases was introduced. The new classification categories were verified by customer support specialists. With the help of attribute comparison, the experts' input was utilized to add prioritization rules among the new case categories.

If implemented in the target units, up-to 46% of the customer support service requests currently handled through the back-end unit could potentially be solved on a lower organization level. This would streamline customer support case flow and improve response time by removing uncertainty and minimizing escalation time.

Further research is recommended to assess the effects of regional and cultural differences that could not be included in the scope of this study. Structured customer support data gives a base for future implementation of machine learning or artificial intelligence applications.

REFERENCES

Aldenderfer, M., Blashfield, R. (1984) *Quantitative Applications in the social Sciences: Cluster analysis*. Thousand Oaks, CA: SAGE Publications, Inc.

Altman, N., Krzywinski, M. (2017) Clustering. *Nature Methods*, 14(6), pp.545-546.

Benedettini, O., Neely, A., Swink, M. (2015) "Why do servitized firms fail? A risk-based explanation", *International Journal of Operations & Production Management*, Vol. 35 Issue: 6, pp.946-979

Chen, Y., Li, K., Marc. K, Hipel, K. (2008) A case-based distance model for multiple criteria ABC analysis. *Computers and Operations Research*, 35(3), pp. 776-796.

Data (2019) In Cambridge dictionary [www document] [Accessed 10 April 2019]. Available <https://dictionary.cambridge.org/dictionary/english/data>

Farquhar, J. D. (2012), What is case study research?. *Case study research for business* (pp. 3-14). London: SAGE Publications Ltd

Flores BE, Whybark DC. (1987) Implementing multiple criteria ABC analysis. *Journal of Operations Management* 1987;7(1):79–84.

Galetzka, M., Verhoeven, J.W.M. and Pruyn, A.T.H. (2006), "Service validity and service reliability of search experience and credence services: a scenario study", *International Journal of Service Industry Management*, Vol. 17 No. 3, pp. 271-83.

Goepel, K. (2013). *Implementing the Analytic Hierarchy Process as a Standard Method for Multi-Criteria Decision Making In Corporate Enterprises – A New*

AHP Excel Template with Multiple Inputs, Proceedings of the International Symposium on the Analytic Hierarchy Process

Goepel, K. (2018) New AHP Excel template with multiple inputs. [www document]. [Accessed 13 March 2019] Available <https://bpmsg.com/new-ahp-excel-template-with-multiple-inputs/>

Hair, J.F., Celsi, J.W., Money, A.H., Samouel, P. and Page, M.J. (2011) Essentials of Business Research Methods (2nd edn). Armonk, NY: M.E. Sharpe.

Hensley, R., Utley, J. (2011) "Using reliability tools in service operations", International Journal of Quality & Reliability Management, Vol. 28 Issue: 5, pp.587-598

Information (2019) In Oxford dictionaries [www document] [Accessed 10 April 2019]. Available <https://en.oxforddictionaries.com/definition/information>

Jantti, M. (2009) Knowledge Management Challenges in Customer Support: A case study. International Conference on information, Process, and Knowledge Management.

Kastalli, I., Looy, B., Neely, A. (2013) Steering Manufacturing Firms Towards Service Business Model Innovation. California Management Review, 56(1), pp. 100-123.

Knowledge (2019) In Merriam-Webster.com [www document] [Accessed 10 April 2019]. Available <https://www.merriam-webster.com/dictionary/knowledge>

LogMeIn A (2012) "The State Of Customer Experience," February 17, 2011, Forrester Research, Inc.

LogMeIn B (2012) Five Steps to Improving the Customer Service Experience: Metrics, Tips, and Tools for Utilizing Customer Feedback,” January, 2012, Ovum

Peng, Y., Zhang, Y., Tang, Y., Li, S. (2011) An incident information management framework based on data integration, data mining, and multi-criteria decision making. *Decision Support Systems*, 51(2), pp. 316-327.

Rothenberger, S., (2007) Strategic and operational issues in implementing a CRM tool. *International Journal of Business Environment*, 1(4), pp. 462-475.

Saaty, T. L. & Vargas, L. G. (2012) *Models, Methods, Concepts & Applications of the Analytic Hierarchy Process*. 2nd ed.

Saunders, M., Lewis, P. and Thornhill, A. (2009), *Research methods for business students*, 5th ed., Pearson Education Ltd, England.

Singh M., Fosselie T., Wiggen F. (2010) Data, information, knowledge and decision-making in condition monitoring. In: *Proceedings of the 23rd international congress & exhibition on condition monitoring and diagnostic engineering management COMADEM*

Singh, M., Hetlevik, S. (2017) Data–information–knowledge hierarchy based decision support system for risk based inspection analysis. *International Journal of System Assurance Engineering and Management*, 8(Supplement 2), pp. 1588-1595.

Smirnov, Y. (2019) ABC Analysis of inventory. [www document] [Accessed 23 April 2019]. Available <http://financialmanagementpro.com/abc-analysis/>

Torabi, S., Hatefi, S., Saleck Pay, B. (2012) ABC inventory classification in the presence of both quantitative and qualitative criteria. *Computers & Industrial Engineering*, 63(2), pp. 530-537.

Yin, R. (2009) *Case Study Research: Design and Methods*, fourth edition, Thousand Oaks, CA: Sage Publications.

APPENDIX I: Current and suggested categorization model

