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A study for the automotive industry

FAU UNIVERSITY PRESS

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Translating the determination of subjective customer perceptions from the health care sector to the automotive industry

Übertragung der Determination der subjektiven Kundenwahrnehmung aus dem klinischen Bereich auf die Automobilindustrie

Der Medizinischen Fakultät
der Friedrich-Alexander-Universität
Erlangen-Nürnberg

zur

Erlangung des Doktorgrades
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vorgelegt von

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Abstract

Background and aims

Customer satisfaction is a major goal to secure and increase competitive leads in every service industry, such as the health care sector or the automotive industry. The first main contribution of this work will provide an approach for an effective determination of perceived satisfaction based on a cross-industrial knowledge transfer from the health care sector to the service industry, using the automotive as a representative example.

Today, perceived customer satisfaction in the automotive industry is determined a posteriori to the customer service contact via customer surveys. However, vast amount of data are produced and collected daily, due to the rising amount of connected cars for example. The benefits of these collected sensor and service process data will be presented by the second main contribution of this work. Machine learning techniques are applied with the goal to predict perceived customer dissatisfaction.

Service industries are forced to follow the trend of digitalization to remain competitive. The product itself tends to play a downstreamed role, while services will be the main differentiator. Therefore, new data driven business models need to be developed to fulfill these changing customer expectations. Concrete implications to enhance todays business models within the service industry need to be identified. This need is addressed by this work.

Methods

To identify the most important determinants to capture perceived customer satisfaction, a detailed literature review for perceived satisfaction determination is conducted. The contribution is an industrial comparison of the healthcare sector and the automotive industry to examine the common concepts of satisfaction determination. Using the identified similarities, the concrete potentials of a cross-industrial knowledge transfer are developed.

To predict customer dissatisfaction based on the subjective customer feedback and objective service process data, these isolated data sources need to be combined. Therefore, a new data consolidation method to map subjective customer perceptions, conducted via questionnaires, with objective data, extracted from the service processes, is developed.

Using the overall satisfaction as the class label, the performance of various machine learning techniques is evaluated with the goal to classify dissatisfied customers before the customer-service interactions ends.

Results and observations

The identification of the main concepts to determine perceived satisfaction in every service business is the first main result. These are service encounter, situational factors and sociodemographics. They result from the comparative literature review for the health care sector and the automotive industry. These concepts are relevant to determine perceived satisfaction in every service interaction and thus the basis for the cross-industrial knowledge transfer that is conducted. The similarities between the two businesses are presented.

Based on the consolidation of perceived customer satisfaction determinants and objective service process data from the automotive industry, dissatisfied customers can be classified in real time. The best result for customer dissatisfaction classification is 88.8%. Considering the whole history of customers' service experiences to predict the satisfaction of the current service interaction resulted the best classification rate. The most relevant determinants for customer dissatisfaction could be identified from the applied feature selection.

Practical conclusions

Based on this research it is shown how the automotive industry can adapt findings and methods from the health care sector in order to improve customer understanding and thus improve service processes sustainably. The health care sector is following the service model of patient centricity. This requires a thorough understanding of patients' needs. The models to capture these needs are transferred to the automotive industry and can be used there in a likewise manner. The resulting implications,the potentials and the requirements coming with this cross-industrial knowledge transfer are illustrated in this work.

This work presents a methodology to use the available subjective and objective data more efficiently. An application was developed that allows the service industries a more individualized customer treatment. Special emphasis is put on data privacy. The individual regulations are addressed and solutions to cope with these are given. The requirements

that need to be fulfilled to make most effective use of customer data are provided. The outlook shows how this methodology can be transferred to other service industries.

Future possibilities for new customer services arising from trend of digitalization are presented in an outlook. Special attention is put on the use of data received from connected cars. Future research capabilities are shown for the health care sector, the automotive industry and the service industries in general.

Zusammenfassung

Hintergrund und Ziele

Die Kundenzufriedenheit ist ein Kernelement zur Sicherstellung und Steigerung von Wettbewerbsvorteilen in der Service-Industrie, sei es im klinischen Bereich oder der Automobilindustrie. Im ersten Teil dieser Arbeit wird ein industrieübergreifender Ansatz zur Ermittlung der subjektiv wahrgenommenen Zufriedenheit erarbeitet. Hierzu wird am Beispiel der Automobilindustrie die Möglichkeit sowie der resultierende Mehrwert eines industrieübergreifenden Wissenstransfers aus der Medizin aufgezeigt.

Heute wird in der Automobilindustrie die wahrgenommene Kundenzufriedenheit stets nach Beendigung der Serviceinteraktion mit dem Kunden, meist durch Befragungen, erfasst. Während der Serviceinteraktion selbst werden große Datenmengen generiert und gespeichert. Mit der steigenden Anzahl an vernetzten Fahrzeugen wird dieser Datenbestand stetig weiter steigen. Den größtmöglichen Nutzen aus diesen Daten für den Kunden, und die Automobilindustrie im Allgemeinen zu generieren, ist Bestandteil des zweiten Teils dieser Ausarbeitung. Ziel ist es, subjektiv unzufriedene Kunden durch Anwendung von Methoden des maschinellen Lernens zu prognostizieren.

Die Serviceindustrie befindet sich in einem Wandel, der durch die Digitalisierung geprägt ist. Um wettbewerbsfähig zu bleiben, gerät das materielle Produkt zusehendst in den Hintergrund, während die angebotenen Services zum maßgeblichen Differenzierungsmerkmal aus Sicht des Kunden werden. Um diesem disruptiven Wandel zu begegnen und zu bestehen, sind datengetriebene Geschäftsmodelle unabdingbar. Konkrete Handlungsempfehlungen sind nötig, um die heute etablierten Geschäftsmodelle der Serviceindustrie entsprechend zu erweitern und anzupassen. Ziel dieser Arbeit ist es, diese am Beispiel der Automobilindustrie aufzuzeigen.

Methoden

Zur Erfassung der wesentlichen Determinanten, die die wahrgenommene Kundenzufriedenheit abbilden, wurde eine umfassende Literaturanalyse durchgeführt. Die Ableitung gemeinsamer Konzepte und Determinanten aus der Medizin und der Automobilindustrie zur Erfassung

der subjektiv wahrgenommenen Zufriedenheit ist das Kernelement dieses Literaturvergleichs. Die identifizierten Gemeinsamkeiten sind die Basis für den Wissenstransfer von der Medizin auf die Automobilindustrie.

Um unzufriedene Kunden individuell, und noch vor der Beendigung der Serice-Interaktion, prognostizieren zu können, müssen deren subjektive Rückmeldungen sowie die vorhandenen, objektiv generierten Daten aus den Serviceprozessen kombiniert werden. Eine Konsolidierungslogik wurde entwickelt, welche die heute isolierten Daten der Kundenzufriedenheitsbefragungen mit den objektiven Daten aus den Serviceprozessen verknüpft. Verschiedene Methoden des maschinellen Lernens wurden mit dem Ziel der Klassifikation von unzufriedenen Kunden verglichen und bewertet.

Ergebnisse und Beobachtungen

Die Ermittlung der relevanten Konzepte zur Erfassung der wahrgenommenen Kundenzufriedenheit in der Serviceindustrie sind das Kernergebnis des ersten Teils dieser Arbeit. Die 3 relevanten Konzepte, die aus dem vergleichenden Literaturvergleich von Medizin und Automobilindustrie abgeleitet werden sind: Interaktionskomponenten ('Service Encounter'), situationsbedingte Faktoren und Soziodemografika. Diese wurden als Hauptbestandteil jeder Service-Interaktion in der Medizin und Automobilindustrie identifiziert und bilden somit die Grundlage für den industrieübergreifenden Wissenstransfer. Die Gemeinsamkeiten der Konzepte in der Medizin und der Automobilindustrie werden präsentiert.

Eine Methodik zur Konsolidierung von Determinanten der subjektiven Kundenzufriedenheit und der objektiven Daten der Serviceinteraktionen wurde für die Automobilindustrie entwickelt. Basierend auf den Daten einer etablierten Befragung und den zugehörigen Daten der Serviceprozesse wurde eine Datenbasis zur Klassifikation unzufriedener Kunden generiert. Diese Kunden konnten mit einer Klassifikationsrate von bis zu 88,8% identifiziert werden. Dabei zeigte sich, dass die beste Klassifikationsrate unter Berücksichtigung aller historischen Serviceprozesse und der zugehörigen subjektiven Wahrnehmungen erzielt wird. Die relevantesten Indikatoren für die Kundenunzufriedenheit wurden ermittelt.

Praktische Schlussfolgerungen

Die Ergebnisse dieser Arbeit zeigen die Möglichkeiten und den Mehrwert eines industrieübergreifenden Wissenstransfers aus der Medizin für die Automobilindustrie auf. Es werden Implikationen abgeleitet, die das Verständnis über die Kunden verbessern und damit einen signifikanten Beitrag zur Verbesserung der Serviceprozesse liefern. Der klinische Bereich verfolgt das Servicemodell der Patientenzentrierung. Dies setzt ein fundiertes Verständnis über die Erwartungshaltung der Patienten voraus. Die Methoden, um diese Bedürfnisse zu erfassen, wurden auf die Automobilindustrie in einer generischen Weise übertragen. Die resultierenden Implikationen, der Mehrwert und die Voraussetzungen für diesen industrieübergreifenden Wissenstransfer werden dargelegt.

Diese Arbeit zeigt Verfahren für die Service-Industrie auf, um die vorhandenen subjektiven und objektiven Daten effizienter zu nutzen, beispielsweise für eine individualisiertere Kundenbetreuung. Neben dem praktischen Nutzen wird der Fokus auf Datenschutz und Datensicherheit gelegt. Die Anforderungen im Umgang mit Kundendaten werden aufgezeigt und Lösungsvorschläge erarbeitet, um diesen gerecht zu werden. Im Ausblick werden die Transfermöglichkeiten der entwickelten Methodiken auf weitere Bereiche der Service-Industrie dargelegt.

Der Ausblick zeigt zukünftige Möglichkeiten für neue datengetriebene Kundendienste aus verschiedenen Bereichen, die aus dem Trend der Digitalisierung resultieren, auf. Der Schwerpunkt liegt hierbei auf der Nutzung der Daten aus vernetzten Fahrzeugen und den resultierenden Möglichkeiten für die Kunden. Die Arbeit endet mit der Ausarbeitung des weiteren Forschungsbedarfs in der Medizin, der Automobilindustrie und der Service-Industrie im Allgemeinen.

Dedicated to Prof. Dr. Hellmut Erzigkeit.
†29.06.2010

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Stefan Meinzer

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1 Introduction

Buzz-words like Big Data, Artificial Intelligence, machine and deep learning, disruptiveness, Data Lakes and many more built the picture in todays industrial environment, especially with respect to the digitalization of the service industries. However, the general purpose remains the same: Make use of the vast amount of data to increase performance and competitiveness Einav and Levin (2014).

This work addresses this need based on data that is produced every second within the service industry. Being more precise, it is about improving the customer understanding and consequently the customer service by applying machine learning techniques in the automotive industry. This work has a high practical and managerial relevance as it demonstrates how organizations can benefit from sensor-, process- and service data combined with perceived customer feedback.

The scope of this thesis is to develop an approach that addresses the strategic target of the service industry, the increase of customer satisfaction. Therefore, the first part of the introduction provides a conclusive definition of the perceived satisfaction concept. Second, the relevance of customer satisfaction for the service industry is examined. This section is divided into three paragraphs that present the general importance, the strategic impact and the role of customer satisfaction for the automotive industry. Third, the importance of perceived customer satisfaction for the health care sector is presented. The health care sector is used as a benchmark for the cross-industrial knowledge transfer of perceived satisfaction determination. The fourth section illustrates the contribution of this thesis to the pattern recognition research. The introduction closes with the structure of this work.

1.1 Definition of customer satisfaction in the service industry

The customer satisfaction concept is well researched since decades Mittal and Frennea (2010). However, in industrial markets, especially the perceptive part of customer satisfaction is an under-researched area so far Gebauer et al. (2008); Homburg and Rudolph (2001). From a managerial perspective, it is a high level targeted goal within companies. It represents the ability to satisfy its customers with their services and products Mittal and Frennea (2010).

However, a gap exists between the academic and practical definition of customer satisfaction Parker and Mathews (2001). The most frequent definition is customer satisfaction as an expression of the discrepancy between expected and received values Anderson and Sullivan (1993); Oliver (1980, 1977, 1993). The main focus is put on the antecedents of satisfaction. One concept that is highly connected to customer satisfaction and often identified as the most important antecedent is service quality Cronin Jr and Taylor (1992); Grönroos (2001); Vesel and Zabkar (2009). This perspective of considering service quality as an antecedent of customer satisfaction is also taken in this work. An encompassing overview on service quality and its measurement can be found in the work of Seth et al. (2005). As service quality is seen as one of the most significant indicators of satisfaction and also profitability Seth et al. (2005); Zeithaml (2000), a brief definition is necessary in this context. The concept of service quality can be differentiated into functional and technical quality Grönroos (1984). Functional quality is defined as the perception of the outcome of a service, the customer receives. Friendliness of the providers or the way of communication are examples of functional quality, also interpreted as the "How" of service quality. Technical quality expresses the "What" and thus defines the result of a customer-provider interaction within the service industry. The service treatment a customer receives at a dealer once he shows up with his car is an example for the technical quality component Grönroos (1984). Summarizing, service quality plays a significant role in the concept of customer satisfaction for the service industry in general and is defined as an important antecedence for this work.

Determination of satisfaction can be assigned to the psychological construct assimilation - contrast theory Anderson (1973). It is strongly related to the known confirmation - disconfirmation paradigm defined

by the work of Oliver Oliver (1977): If the received value is higher than expected (confirmation), satisfaction increases. Once the received value is lower than expected (disconfirmation), satisfaction will decrease. This theory is still valid today. However, research proved that the validity depends on the goods that are consumed Churchill Jr and Surprenant (1982). For durable goods, the effects could not be replicated in the same way as for non-durable goods Churchill Jr and Surprenant (1982). A differentiation between these two is recommended. Therefore, the focus of this work is on intangible goods in order to make a comparison between different industrial sectors meaningful. Consequently, the scope of this work is not on the products of service industries but on the perceived services of the customers. While the products, their values and costs for the consumers differ a lot within various businesses, the evaluation of services can be compared cross-industrial Corbin et al. (2001); Meinzer et al. (2012b, 2016). Intangible goods, such as services Shostack (1977), gain high business attention as they play a significant role in competitive diversification Stryja et al. (2015). They can be easier adapted and improved than sold products. Thus, it is an efficient way to increase competitive advantage by increasing the service performance. Comparable service constructs can be identified in different business sectors of the service industries. Certainly, the kind of services has to be differentiated and the in-depth comparison is limited. Especially, critical and non-critical consumer services have to be separated, such as treatments within the health care and industrial sector. Nevertheless, comparable relationships are present on a meta-level, such as the degree a consumer is participating in the service interaction Bettencourt (1997). On a meta-level a cross-industrial comparison of customer satisfaction determination for intangible goods is possible. Comparable constructs like service failures (i.e. waiting times), service encounter (i.e. communication), situational factors (i.e. location of the service station) or sociodemographics are present and in general equally relevant for the service industries Chuang et al. (2012); Corbin et al. (2001); Meinzer et al. (2012b, 2016); Sivakumar et al. (2014). Most important for customer satisfaction or dissatisfaction is the individual perception as shown by Spreng and Mackoy (1996); Westbrook and Reilly (1983). In order to create maximum strategic benefit for the service industries, the definition of customer satisfaction in this work is as follows: Customer satisfaction is an evaluation of the perceived customer experience represented by the services, interactions and product that are received as intangible

goods. Consequently, the scope of this work is on the antecedents such as service quality, service performance or service failures.

1.2 The relevance of customer satisfaction for the service industry

1.2.1 The general importance of the customer satisfaction concept

Today, it is not anymore the product of a service industry itself that defines the companies success, it is the customers' perception of the received services. Companies define the value of their products through customer satisfaction Meinzer et al. (2016); Sivakumar et al. (2014); Yarris et al. (2012). Especially for the service industry, the customer switching barrier is lower than compared to other business sectors due to the variety of similar offers Mittal and Lassar (1998). As services are intangible, they can not be completely standardized. An individualized approach is needed based on the customers' expectations. Consequently, the subjective customer value needs to be understood in order to create individualized processes to secure maximum customer satisfaction Keaveney (1995); Mittal and Lassar (1998). Satisfied customers have a high probability to repurchase and to deliver good reputation Homburg and Rudolph (2001); Jones and Suh (2000); Mittal and Frennea (2010). From a cost perspective it is important to keep existing customers loyal. Costs for acquiring new customers are up to 5-6 times higher than keeping existing ones Bhattacharya (1998); Xia and Jin (2008). As the relationship between customer satisfaction and loyalty is controversially discussed in literature, satisfaction is defined as a predictor for customer loyalty in this work.

The two constructs, loyalty and satisfaction, are not linearly related, therefore it is necessary to separate them as different concepts as literature is also recommending Kumar et al. (2013); Meinzer et al. (2016); Vesel and Zabkar (2009), whereby the focus of this work will be the satisfaction concept.

Generally, the concept of customer satisfaction plays a fundamental role for business success in every service industry Rigdon et al. (2011). There is no doubt about the importance to fulfill customers' expectations in order to increase revenue. Individualized, customer-focused processes are necessary to survive in the highly competitive environment

and is identified as one of the most important managerial goals in the service industry Blocker et al. (2011); Sun et al. (2000). Understanding the indicators of customer satisfaction or even more important dissatisfaction, helps to achieve this intended goal. Especially for the competitive automotive sector, this understanding is essential to survive as shown in the next section.

1.2.2 The financial aspects of the customer satisfaction concept

The managerial importance of the customer satisfaction concept is not only related to a better company reputation or higher customer loyalty, it can be strongly tied to the sustainable financial success. Based on the American Customer Satisfaction Index (ACSI), several financial outcomes can be derived. An increase of 1 unit of customer satisfaction measured by ACSI Fornell et al. (1996) generates an 11.4% average increase in Return on Invest (ROI) over the next five years Anderson et al. (1994). Annually, 2.4% inrease in ROI can be achieved Anderson and Mittal (2000). Beside the ROI, a significant impact on the cash flow can be found in literature Gruca and Rego (2005); Morgan and Rego (2006). Furthermore, a 1-unit increase within ACSI yields to a 2-unit increase in stock returns Luo and Bhattacharya (2006). This fact is also based on the higher stock recommendations from the analysts for such companies Luo et al. (2010).

From a long-term perspective, customer satisfaction helps to increase the company value and its assets, measured by the index for the company value Tobin's q Tobin (1969). A 1-unit increase in the ACSI measurement can yield up to 0.36 unit increase in Tobin's q Luo and Homburg (2007). Important for customers is the risk that is assigned to companies. Up to 1.8-unit decrease in systematic risk can be achieved by increasing customer satisfaction Mittal and Frennea (2010); Tuli and Bharadwaj (2009). Beside these financial benefits, commercials may be more efficient for satisfied customers. Based on the positive correlation between job satisfaction of employees and customer satisfaction, the performance of human capital will increase Luo and Homburg (2008); Mittal and Frennea (2010). Summarizing, performance indicators that define the company success positively correlate with the customer satisfaction rate that is achieved. Consequently, beside the importance of the

satisfaction concept from a customers' perspective, it is of fundamental relevance for a sustainable company success.

1.2.3 The role of customer satisfaction for the automotive industry

The automotive sector is in the middle of a changing process Gao et al. (2014). The product *car* itself is playing more and more a background role, customer service is the biggest future value. Cars as well as dealers and especially the related services around these two are getting digitalized. Vast amount of data is produced every day and the question arises: How can the automotive industry benefit from the growing amount of data sustainably? The sector that achieves the highest margin and generates the most customer interactions is the after-sales environment. In the next years, the competition around services will increase and consequently the switching barriers for customers get lower. Platforms that sell spare parts or offer independent repair services due to new data transfer solutions (for example using Dongles Bell (2016)) are just two examples that represent the change in the after-sales sector. In earlier times, the biggest profit was gained by selling new cars. Nowadays, at least 50% of the profit is realized within the after-sales business Blanchet and Rade (2006); Sarstedt et al. (2010). In the US, after-sales business create 6-8 billion dollars revenue annually Gaiardelli et al. (2007). Generally, after-sales meanwhile create more margin than sales profit ADL (2015). In 2016, profit from after-sales from German car manufacturers is estimated up to 80% Kleimann et al. (2013). Consequently, the automotive sector is striking for concepts to meet the huge variety of customer expectations, especially in the service processes. The most successful market players will be those that best address the demands of their various customers as shown by Kleimann et al. (2013). This fact yields to company strategies to push especially customer satisfaction, like the *Strategy Number ONE* of the German car manufacturer BMW Pries and Seeliger (2014). Today, *Big Data* is more than a buzz-word in the automotive industry. Latest studies estimate that data driven services will generate potentials up to $800 per car Reportlinker (2015). Estimations state that the automotive industry is the second largest data generator in 2015 IBM (2013). Latest car models generate up to 25 Gigabyte of data every hour Hansen (2015). Even 1 TB of data is realistic to be generated by self-driving cars within an hour Mearian (2013). This data

also includes various states of the cars and their components Rodgers et al. (2014). Useful data is not only generated by the cars themselves, but also by the dealers. Each dealer visit of a customer represents a service interaction that produces information. At least 5 GB of compressed data are generated every day by the dealers within various service processes Kohl et al. (2011). This work will demonstrate the potential arising from after-sales data and its value due to enhanced customer understanding. Therefore, the focus of this work is to contribute to the existing research regarding the determination of customer satisfaction in the service industry, taking the automotive industry as an example. Furthermore, the value of the increasing amount of data is presented in a novel approach to classify dissatisfied customers before the service interaction ends.

1.3 The importance of perceived patient satisfaction for the health care sector

In the clinical environment, perceived patient satisfaction is a main concept of long-term success. Knowing patients' needs is the key requirement for a successful treatment. The health care sector strives towards a transparent measurement of the perceived quality of clinical services and patient satisfaction. For instance, the Centers of Medicare and Medicaid Services established the Hospital Consumer Assessment of Healthcare Providers and Systems as a satisfaction measurement approach Giordano et al. (2009); Makarem and Al-Amin (2014). There are various standardized measurement approaches for perceived satisfaction that help patients to rate and compare clinical departments according to their specific needs. These kind of hospital ratings are public Darby et al. (2005). Consequently, perceived and transparent patient satisfaction is a key element to create competitive advantage.

Furthermore, specific questionnaires exist to review the individual competencies of specialized clinical department Boudreaux et al. (2000); Raposo et al. (2009). Using the output of these surveys, service processes can be improved so that they incorporate patients' needs.

A fundamental role regarding perceived satisfaction is the patient-physician interaction. Therefore, health care sector is following the principle of patient centricity Steel (2015). The closer the interaction is, the higher is the chance for patients to be correctly understood. The basis for this interaction is the expression of the patients themselves and their individual needs. Consequently, patients need to be actively

involved into the service process by the physicians. This active role of patients within the service process allows an individualized treatment that results in an increase of the perceived quality of medical outcome Brody et al. (1989). Beside service quality, several other factors have influence on the perceived patient outcome, such as the communication concepts Andaleeb (2001); Saad Andaleeb (1998) or the sociodemographical factors that help to gain a thorough understanding of patients Venn and Fone (2005); Walker et al. (2003). The broad field of influencing determinants is already well researched in health care, compared to other service industries and thus the starting point of this work. In the health care sector, the degree of the medical concern plays a significant role regarding the perceived satisfaction. The flexibility of patients decreases with the urgency of patients' needs or the perceived criticality of the disease. Thus, the importance of perceived service failures, such as waiting times, varies significantly with the degree of illness Mack et al. (1995). Therefore, it is essential to consider the severity of the medical concern as a separate influencing factor in reviewing literature and analyzing the significant determinants of perceived patient satisfaction. Consequently, this work is focusing on the determination of perceived patient satisfaction on a meta-level, independent of the severity of illness. This allows the cross-industrial knowledge transfer. The health care sector is a tough and competitive environment within the service industries. In order to increase market share, pure service quality is no longer sufficient. Clinical departments need to define themselves additionally via patient perceptions Yarris et al. (2012). Thus, a solid knowledge of patients' expectations is a key factor to create satisfaction, particularly for those with less flexibility due to a high degree of illness for instance Makarem and Al-Amin (2014). The health care sector always strives to create an encompassing knowledge about patients' needs in order to allow a highly individualized service treatment. The personalized service interaction is a key component to create competitive leads for the health care sector Blocker et al. (2011). Patients of a clinical department can be seen as customers of a service interaction Hudak et al. (2003). Adapting this generalization allows the cross-industrial comparison of perceived customer satisfaction on a meta-level. Transferring existing knowledge from health care allows the service industry, in particular the automotive, to increase the service performance by improving their customer understanding.

1.4 State of the art of machine learning applications in the service industry

Practical applications based on machine learning techniques are of increasing importance for the service industry Jordan and Mitchell (2015); Wuest et al. (2016). The following section provides an overview about current industrial applications.

1.4.1 State of the art in the service industry

The potential of customer data in order to apply machine learning has been shown by various studies in literature Jordan and Mitchell (2015); Liao et al. (2012); Ngai et al. (2009). Retaining existing customers based on the customer value is a significant factor to increase profitability. Even more, it is the basis for an effective customer relationship. The prediction of customer lifetime value (CLV) in order to improve the customer relationship model (CRM) is one example for an application of machine learning based on customer data.

Traditionally, these methods were found within companies focusing on customer data in their daily business. Internet or telecommunication providers are identified as representative examples Hwang et al. (2004); Prasasti et al. (2014). Closely related to CLV prediction is the application of machine learning to identify customers with high probability to churn. Predicting churning customers as a consequence of dissatisfaction is identified as a significantly relevant field of practical applications Datta et al. (2000); Gopal and Meher (2008); Hung et al. (2006); Vafeiadis et al. (2015); Xia and Jin (2008). Again telecommunication providers are the most present business areas in literature, followed by insurances Hur and Lim (2005) and the retail business Vafeiadis et al. (2015).

Applying machine learning techniques is an established method in literature to identify customers with an increased likelihood of switching to other companies Bauer and Kohavi (1999); Vafeiadis et al. (2015). In the telecommunication sector, machine learning techniques have been examined for their performance in order to determine dissatisfied customers based on customer feedback as an indicator for churn Mozer et al. (2000).

1.4.2 Applications in the health care sector

Within the health care sector, machine learning techniques are applied for various purposes. Classification models have been used to identify patients with insufficient diagnostics that tend to be at-risk patients Yoo et al. (2012). The scope of this application is an improved treatment and increase of revenue. Using data resulting from diagnostics allows the use of machine learning techniques to classify different characteristics and the state of progression of cancer for instance Delen et al. (2005); Harper (2005); Yoo et al. (2012). Further applications are the prediction of types of Alzheimer diseases, classification of Parkinson or Epilepsy patients. Gait analysis using sensor and marker data is one representative field of application Barth et al. (2015); Eskofier et al. (2013); Heldberg et al. (2015); Klucken et al. (2013). Beside these applications using sensor data, patient feedback analysis is in focus of machine learning applications. The prediction of the overall satisfaction and identification of relevant indicators of satisfaction are representative examples Boudreaux et al. (2000); Meinzer et al. (2016); Sun et al. (2000); Yarnold et al. (1998). Results from questionnaires of patients from various clinical departments have been conducted for these analysis. Subjective patient perceptions are highly relevant for the health care sector in order to provide an optimal and patient-centered medical treatment. One representative example is the treatment of Tinnitus patients as the perception of the severity of illness has a major influence Cima et al. (2012); Crummer and Hassan (2004). The better perceptive determinants can be captured and mapped to objective diagnostic results, the better the treatment can be individualized. Machine learning approaches may be an effective instrument to predict the subjective Tinnitus perception using diagnostic results and personalized patient information.

1.4.3 Applications in the automotive industry

Within the automotive industry, the possible application fields for machine learning are huge. Various data is generated by car-, customer- or service- touch points that result in different practical needs Prenninger (2013), as illustrated by fig. 1.1.

In the manufacturing sector, machine learning techniques are applied in order to improve the supply chain of the production or marketing campaigns for the customer. Within the manufacturing process vast

Figure 1.1.: Possible car-, customer- and service- touch points that generate data within the automotive industry Prenninger (2013), p. 5.

amount of data are produced in the various industries. The most common use of this data is focusing on quality monitoring and enhancements. Using sensor data from the production processes, supervised machine learning models could be trained that allow a quality outlier detection Wuest et al. (2013). The prevention of tool breakdowns by a developed early warning system has been shown as one other field of application Cho et al. (2005). For the metal foundry, quality insurance could be optimized as machine learning techniques allow the identification of parts that need special attention Bettin and Osuna (2007). Within the manufacturing process, the variety of potential applications is huge Gehrke et al. (2016); Prenninger (2013). A general overview is provided by fig. 1.2 according to Prenninger (2013). In order to improve the design of produced elements within the automotive industry, customer feedback could be mapped to production data by adapting fuzzy logic methods Chan et al. (2011). Machine learning techniques can be applied to improve the car configuration process with the goal to increase sales performance Mavridou et al. (2013). Recommender systems are generally identified as a huge trend in machine learning Jordan and Mitchell (2015) in the automotive industry. Generally, most of the current machine learning applications within the automotive industry focus on the manufacturing process and the increase of sales performance Salini and Kenett (2009).

Summarizing, the applications of machine learning techniques are most prominent in order to improve CRM models. Identifying potential churning customers based on their feedback is the most frequent area of application. The telecommunication and retailing sectors are the leading service industries that apply these methods to improve competitive leads.

The health care sector already gains a thorough patient understanding based on the well researched field of patient satisfaction determination. Patients' feedback has been used as features for machine learning applications to increase the quality of the medical treatment and thus the perceived outcome. The manufacturing industry, such as automotive, uses features extracted from sensors or production tools for machine learning applications. Most applications focus on quality improvements for the production process and optimization of the supply chain. Furthermore, customer feedback is analyzed to improve the sales performance.

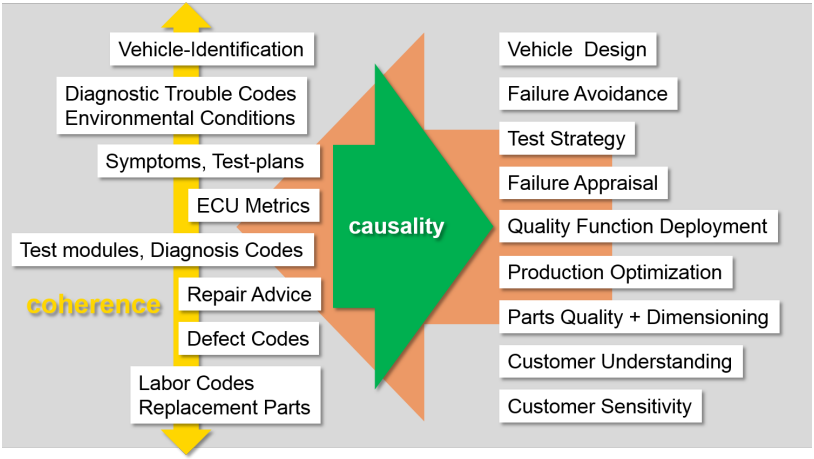

Figure 1.2.: Overview on possible application fields of data driven business models within the automotive industry Prenninger (2013), p. 10.

1.5 Contribution of this work

This work contributes to the existing research of machine learning applications as it presents an approach to map subjective customer responses with objective service and process data from the service industry. Taking the automotive industry as a representative example, various machine learning techniques are evaluated for their performance with the goal to classify dissatisfied customers in real time. Performing feature selection, the most important indicators for dissatisfaction can be identified. This is a novel approach in the field of practical machine learning applications and can be transferred to various sectors within the service industries. Applying machine learning techniques to a combined dataset consisting of subjective customer feedback and objective service, process and sensor data has not been researched in literature before. The health care sector already gains a thorough patient understanding based on the well researched patient satisfaction determination. This benchmark position is used to extract the underlying concepts of perceived satisfaction determination from literature to allow a cross-industrial knowledge transfer. These concepts are service encounter, situational factors and sociodemographics. The most relevant determinants of each concept

have been identified. The similarities across the service industry, in particular health care and automotive, are shown. These similarities of the satisfaction concepts and the related determinants are the basis to enable the automotive industry to transfer knowledge from the health care sector and thus allow an improved customer understanding. Within the automotive industry, the area with the highest margin is examined to be seen in after-sales Ahn and Sohn (2009). Existing research focus mainly on quality improvements and the increase of customer loyalty Ahn and Sohn (2009); Bandaru et al. (2011, 2015); Chougule et al. (2013). Mapping subjective customer feedback with objective data encompassing the full after-sales process to classify overall dissatisfied customers in real-time is a new field of machine learning application in the automotive industry. Furthermore, adapting feature selection methods, the most critical indicators for customer dissatisfaction can be extracted from the established service process. Consequently, the developed approach within this work helps the service industry, the automotive in particular, to increase knowledge about customers' perception of received services. Furthermore, indicators for dissatisfaction with the service process can be identified as well as potentially dissatisfied customers. Using this information, the service quality can sustainably be increased which will yield to an increased overall customer satisfaction. This is a core element of many company strategies and secures the increase of competitive leads within the automotive industry.

1.6 Structure of this work

The present work is performed in (partial) fulfillment of the requirements for obtaining the degree Dr. rer. biol. hum. This thesis comprises contributions to two different research fields, each documented by publications in subject-specific scientific journals. First, the fundamental findings in the area of cross-industrial knowledge transfer of perceived customer satisfaction determination in service industries is examined Meinzer et al. (2016). Second, machine learning techniques were applied to generate practical benefits for the industrial sector Meinzer et al. (2017). Thereby, perceived satisfaction can be increased by classifying dissatisfied customers and identifying the most relevant indicators of dissatisfaction. A general overview about the two main components of this work, the literature review and the machine learning section, is provided by fig. 1.3. The detailed structure of this work is as follows.

- Chapter 2 provides the theoretical background and the conceptual framework of perceived customer satisfaction based on a literature review followed by an empirical study that shows the practical application of satisfaction determination in the automotive industry and the implications for improvements of the determination. The literature review introduces the techniques of measurement, the major constructs and the importance of perceptions with respect to customer satisfaction in the service industries. The three underlying constructs of the satisfaction concept are presented: The service encounter, situational factors and sociodemographics. The most important determinants of these constructs are worked out for the automotive industry and the health care sector. Common determinants are examined that allow the cross-industrial knowledge transfer. The methodological section is based on an existing customer satisfaction survey, that illustrates the lack of research and practical need for this knowledge transfer from the health care sector to the automotive industry. Applying multiple linear regression models, the most important determinants according to the three introduced constructs are analyzed for a premium car manufacturer. At the end of this chapter, results of the analysis are examined that show the practical impact of the findings from the health care sector to the automotive industry. Implications to improve the existing customer satisfaction determination are presented. Chapter 2 closes with the implications and recommendations for further research.

- Chapter 3 illustrates the application of machine learning techniques to the automotive industry in a feasibility study. The work answers the two most important questions in the area of customer satisfaction management in service industries: 1. Can dissatisfied customers be classified in real time based on data that is produced during a service visit? 2. Can indicators of dissatisfaction be derived from service process data? Therefore, the importance of these two research questions to the practical world is examined by a literature review in the first part. Second, an encompassing overview on the various sources of available data in the automotive industry is provided. Third, a data consolidation logic has been developed, that allows the matching of subjective customer feedback with objective service, process, and car data received by the dealers

and cars. Fourth, in an experimental design, 5 different classifiers have been applied and evaluated for their performance. Fifth, the results of the experimental design are provided and show that the two raised questions can be answered. Sixth, the results are critically discussed and practical relevance of the developed approach is worked out. It allows a significant increase of transparency, an improvement of the individualized customer treatment and consequently provides an opportunity to sustainably increase competitive advantage.

- Chapter 4 addresses the practical implications resulting from the approach to classify dissatisfied customers, identify the critical dissatisfaction indicators and the precise determination of perceived satisfaction presented in this work. First, implications resulting from cross-industrial knowledge transfer are presented. The competitive advantages that can be realized and the according requirements are shown. Second, the need for data driven business models that arises from the trend of digitalization is illustrated. Specific attention is spent on the use of customer data as an input for improving service processes to be competitive in the future. Requirements that need to be fulfilled to make most effective use out of customer data are presented. Taking online platforms such as Google as representative examples, methods to handle customer data while considering privacy conditions and other constraints are shown.

- Chapter 5 provides the outlook of this work. The possibilities for the automotive industry arising from the methods developed in this work are presented, such as real-time services, predictive maintenance, predictions of breakdowns or safety increasing features. The work closes with limitations of this work and the presentation of further research needed within the health care sector, the automotive industry and the service industries in general.

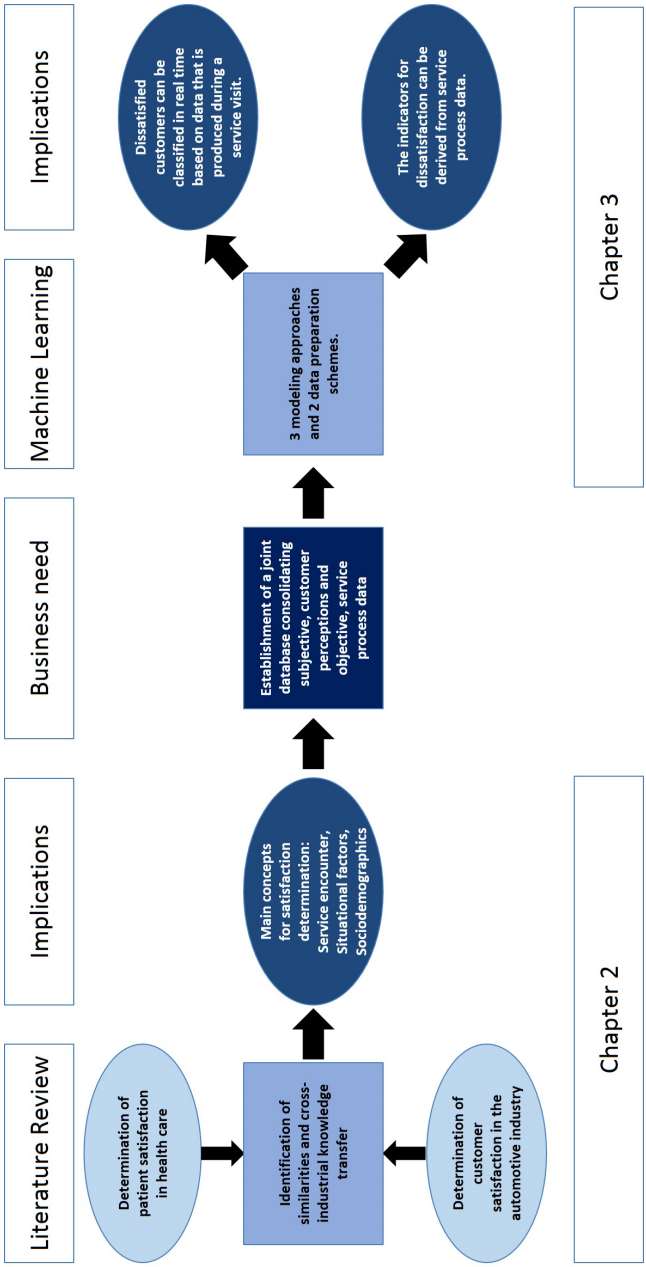

Figure 1.3.: Overview about the structure of this work and the implications resulting from the main chapters 2 and 3.

2 Translating satisfaction determination from health care to the automotive industry

2.1 Overview and structure of the chapter

The following chapter illustrates the cross-industrial knowledge transfer from the health care sector to the service industry. It is the first main contribution of this work. Based on the solid determination of perceived customer satisfaction, a prediction of potentially dissatisfied customers will be possible. This determination is the scope of the following chapter.

The resulting benefit is proven for the automotive industry taking the premium manufacturer BMW as a representative example. A literature analysis of the health care sector and the automotive industry was conducted to identify the common concepts of determining satisfaction. These were the service encounter, situational factors and sociodemographics. An empirical analysis has been performed based on an existing survey. Results of this analysis show the applicability of the cross-industrial knowledge transfer. Furthermore, they show the improvements of the existing methods of perceived customer satisfaction determination that can be derived.

The chapter is structured as follows: First, the need for the knowledge transfer is examined in general and for the automotive industry in particular. Second, the theoretical background that shows the role and measurement of perceived satisfaction in service industries is provided. Third, the conceptual framework is provided by a literature review that examines the most important concepts for the determination of perceived satisfaction in health care and the automotive industry. The

fourth section proves the findings from the literature empirically. Section fifth shows the results of a customer satisfaction survey from BMW. Sixth, the management implications of the new concepts for the automotive industry are explained. The chapter closes with limitations and ideas for further research.

This chapter was successfully published in the journal Service Business Meinzer et al. (2016). Minor changes have been done that the publication properly fits to this work.

2.2 Introduction

The time when success in a service industry was defined only by products and services is already history. Good products and services are no longer sufficient to survive in a tough competitive environment. Companies must now define themselves by consumer expectations Duenzl and Kirylak (1997); Rao et al. (2006); Sivakumar et al. (2014); Yarris et al. (2012). In health care, a solid knowledge of patients' expectations, such as the information they want to receive and how, is the fundamental basis to satisfy patients even in critical situations Leydon et al. (2000); Makarem and Al-Amin (2014). Transferring this phenomenon to service industries, the question arises: Would applying the mechanisms for determining patient satisfaction help to improve customer satisfaction in, for example, the automotive industry? The questions is raised how knowledge transfer could help to satisfy customers who experience service failures such as repeat repairs Meinzer et al. (2010) and in general how the automotive industry can learn from the health care sector by transferring existing knowledge to new instances, problems and domains.

There is a high focus on personalized consumer treatment in health care Blanchard et al. (1990); Laith and Feras (2011); Sun et al. (2000); Yarris et al. (2012) not at least because of the potential consequences that can arise as a result of treatment. The knowledge of patients' expectations arises from well-defined questionnaires that help the health care sector to identify the most important satisfaction indicators and patient expectations. However, individual treatment is identified as a key component to securing competitive advantage in every service-oriented business Blocker et al. (2011); Zeithaml (1988). Using the metaphor of Hudak et al. (2003), treating patients as customers allows the transfer of

insights into the determination of perceived satisfaction from the health care sector to the automotive industry.

Cross-industrial translations of customer satisfaction and service quality models have made valuable contributions to the literature Corbin et al. (2001). For example, transferring best practices from retailers to the health care sector has been done before Blanchard et al. (2008). Corbin et al. (2001) compares service processes from the health care sector with other service industries such as Wal-Mart or McDonald's. They argue that every service process and customer treatment, such as patient-physician or customer-provider relationships, need to follow certain principles to create and secure customer satisfaction. According to Corbin et al. (2001), a cross-industrial knowledge transfer is possible for intangible goods as defined by Shostack (1977), such as service processes.

Services are always related to customer treatment. Independent of the service industry, they can only be evaluated after consumption Bouman and Van der Wiele (1992); Corbin et al. (2001); Parasuraman et al. (1985), for example, using questionnaires. A patient with a health issue needs to be treated in the medical health care environment and consequently becomes a health care service customer Hudak et al. (2003). In the automotive industry, a customer needs a service treatment such as a maintenance or repair visit Bloemer and Lemmink (1992); Mueller (1991); Tukker (2004). To make comparisons of these sectors meaningful, the car-buying process is characterized as a highly tangible good and not the primary focus. The car as a product has to be excluded for a greater focus on the intangible aspects of service processes in terms of car repair or maintenance. Intangible goods are given greater attention from a management perspective to increase the competitive advantage of their business Stryja et al. (2015) and are the focus of this paper. They are used as the common construct for the cross-industrial comparisons. Similar approaches have been performed in the health care and retail sectors as shown above. A lack of research on service enhancement has already been identified in manufacturing, such as the car industry Gebauer et al. (2008). Despite best efforts, the existing research or established approaches for a cross-industrial translation from the health care sector to the automotive industry could not be found in existing literature. This gap will closed by showing how to improve the determination of perceived satisfaction in the automotive industry using a questionnaire to

show knowledge transfer from the health care sector based on the common denominator of intangible goods. It is examined how to improve the determination of service satisfaction based on health care findings. The fundamental role of consumer treatment is well known in the health care sector Hare et al. (2013), but has also been examined as a key concept to strengthen service businesses and secure competitive advantages, especially in the after-sales environment Gebauer et al. (2008).

2.2.1 The role of customer perception in the automotive industry

After-sales services in the US industries generate an estimated revenue of 6-8 billion dollars annually Gaiardelli et al. (2007) and generally after-sales service profit is higher than sales profit ADL (2015). Consequently, the focus on implications for the after-sales services as intangible goods in the automotive industry based on findings from the health care sector in this work is considered as a new contribution to the existing research. Therefore, this chapter follows the definition of treating patients as customers as described by Hudak et al. (2003).

The main differentiation between the two sectors is the customers' independence in service selection. This independency is limited, especially in critical medical health care situations; therefore, the definition of patients as being customers is also limited. However, comparable service relationship constructs are present in this scenario, such as the customers' participation in a service Bettencourt (1997). The better the interaction between service industries and its customers, the better the perceived experience and consequently the perceived satisfaction. This argument does not address situations where patients are no longer able to participate in the service relationship because of their poor medical conditions.

Overall, the cross-industrial comparison of the health care and automotive industries is possible at a meta level for the customer treatment as an intangible good. Comparable constructs such as service encounters or failures (such as waiting time) are equally relevant for all service industries to secure competitive advantages in satisfaction and loyalty Chuang et al. (2012); Corbin et al. (2001); Reichheld and Sasser Jr. (1990); Sivakumar et al. (2014).

2.2.2 Representative practical example from the automotive industry

Taking the premium car manufacturer BMW as a representative example, the J.D. Power Survey results from 2013 J.D.Powers (2013) and 2014 J.D.Powers (2014) showed an increase in the Customer Service Index, but the company remains behind the luxury brand average. BMW, however, is still the most valuable brand in the automotive industry, based on the Forbes ranking from November 2013 Forbes (2013). BMW has a high focus on customer satisfaction, as the chairman of the board, Dr. Reithofer, has made clear BMW (2014).

The goal was to show that the determination of perceived customer satisfaction in health care and the automotive industry are closely related. Currently, the importance of perceptions in the two sectors and the concepts to capture them are separately researched. Examining the similarities between the concepts for perceived satisfaction determination, this study will show the implications for the automotive industry that can be derived from the health care sector. By identifying the most important determinants, based on an empirical analysis, the aim is to improve the understanding of customer expectations of a dealer service and hence to increase their satisfaction with BMW.

2.3 Theoretical background

Customer satisfaction is an important strategic concept especially for the management as it fundamentally influences activities to increase competitive leads. The first section provides a brief overview about the role of satisfaction for service industries. Second, the measurement concepts and the antecedents of customer satisfaction are provided.

2.3.1 The role of satisfaction in general and for management

Customer satisfaction can be seen as one of the most important pieces of information for management decisions. Repeat purchase, brand loyalty, and willingness to pay are significantly affected by customer satisfaction Churchill Jr and Surprenant (1982). It is, therefore, a very important construct, which receives considerable management attention Mittal and Frennea (2010).

Customer satisfaction plays an important role in establishing successful long-term customer relationships Chojnacki (2000); Homburg and Rudolph (2001). Even if there is no common understanding of the exact relationship between satisfaction and loyalty, there is no doubt about its existence Bennett and Rundle-Thiele (2004); Blocker et al. (2011); Dong et al. (2011); Flint et al. (2011); Homburg and Giering (2001).

Jones and Suh (2000) identified overall satisfaction to be the main predictor of loyalty. However, satisfaction does not linearly result in loyalty, which is why it is necessary to differentiate between these constructs Kumar et al. (2013); Mittal and Lassar (1998). Herrmann et al. (2000) found that customer price elasticity could be optimized as a result of customer satisfaction, resulting in a greater willingness to pay for products and services. Customer satisfaction also often leads to positive word-of-mouth recommendations to other consumers as a positive side effect Mangold et al. (1999); Reichheld and Sasser Jr. (1990). Because such recommendations increase revenue, this aspect has high managerial relevance. The general impact of customer satisfaction on profitability and the share of wallet has been proven by several studies, including Anderson et al. (2004) and Cooil et al. (2007). The Return on Invest of a company is described as a function of customer satisfaction, strongly based on previous customer experiences Anderson et al. (1994). To maintain high customer satisfaction and thus create customer value, consumer orientation is identified as the most important management target Blocker et al. (2011); Zeithaml (1988). Highly consumer-oriented processes were shown by Seth et al. (2005) to be main predictors of satisfaction. High customer understanding and knowledge of the key indicators of satisfaction are therefore important. Effective customer satisfaction measurement is vital to reach the desired outcomes. The different measurement concepts and the differentiation of customer satisfaction and service quality will be described in the following section.

2.3.2 The measurement of customer satisfaction and the importance of perceptions

Perceived customer satisfaction expresses how well the services provided by companies meet customer needs Anderson and Sullivan (1993). This definition has broadly been established and the measurement and interpretation of perceived consumer satisfaction has long been an important field of research in the service industries Anderson and Sullivan

(1993); Herrmann et al. (2000); Homburg and Rudolph (2001); Huang and Dubinsky (2013); Mittal and Lassar (1998); Yarris et al. (2012). If services do not fulfill customers' expectation (disconfirmation), consumers may be dissatisfied Anderson (1973). Consequently, expectations need to be fulfilled or exceeded to achieve the customer's confirmation and secure satisfaction Anderson and Sullivan (1993). The relationship between customer satisfaction and expectations is known as the confirmation/disconfirmation paradigm Anderson and Sullivan (1993); Anderson (1973); Churchill Jr and Surprenant (1982); Oliver (1980).

The importance of capturing the perceived performance is consequently highly relevant to measure satisfaction Cheng and Yang (2013); Johnson and Fornell (1991) and is uncontroversial across different services and industries Herrmann et al. (2000); Homburg and Rudolph (2001); Huang and Dubinsky (2013); Mittal et al. (1998); Rao et al. (2006); Rhee and Bird (1996); Trout et al. (2000); Yarris et al. (2012). Companies define a detailed understanding of customer needs as an essential factor in their competitive strategies Anderson and Sullivan (1993); Herrmann et al. (2000).

The consideration of service quality as one of the most important antecedents of customer satisfaction helps service industries to establish a professional understanding of potential customer satisfaction indicators Oh (1999).

Customer satisfaction and service quality are highly connected; therefore, it is helpful to define this connection. Three theoretical conclusions are discussed in the literature Grönroos (2001, 1984); Hennig-Thurau and Klee (1997): First, that service quality and customer satisfaction are one and the same. Second, that customer satisfaction is an antecedent of service quality or third, that service quality is an antecedent of customer satisfaction.

The last approach is perhaps the most popular Caruana (2002); Cronin et al. (2000); Grönroos (2001); Lee et al. (2000a,b); Xu et al. (2007); Zhang et al. (2005) and the perspective taken in this study. However, a detailed understanding of the critical components of service quality is important for organizations to increase customers' perceived satisfaction Seth et al. (2005) and their profitability Zeithaml (2000).

Measuring service quality by using the **SERVQUAL scale** Parasuraman et al. (1988, 1991) and the **SERVPERF scale** Cronin Jr and Taylor (1992) is one of the most popular ways and widely used in recent studies Jemmasi et al. (2011); Lee et al. (2000b). These two measurement

scales can be seen as generic instruments Randheer and Al-Motawa (2011); Rocha et al. (2013) to measure service quality as an antecedent for consumer satisfaction. They are based on a questionnaire consisting of 44 (SERVQUAL), respectively 22 questions (SERVPERF). In a review of various models, Seth et al. (2005) found 19 different approaches, which shows that various industries need to adapt service quality measurements, such as the retail industry Sweeney et al. (1997); Teas (1993), hospitality sector Mattsson (1992); Oh (1999), higher education Spreng and Mackoy (1996), transportation industry Frost and Kumar (2000) or the banking sector Seth et al. (2005); Soteriou and Stavrinides (1997).

Comparable generic measurement batteries can be found for the determination of customer satisfaction. The most popular cross-industrial models are the American and European **Customer Satisfaction Indices (CSI)** Gilbert and Veloutsou (2006), which comprise consumer expectations, perceived quality and perceived value Fornell et al. (1996). The CSI model is generally applicable to various sectors of the service industries and is produced annually to benchmark the considered companies. However, this cross-industrial assessment model is limited because the models need to be specified to continuously monitor processes and identify indicators for improvements in specific industrial sectors Gilbert and Veloutsou (2006).

For example, Deng et al. (2013) applied the **American CSI** to the hospitality sector by integrating consumption emotions, which resulted in the **Hotel CSI**. In addition, Hsu (2008) developed the **e-CSI** model for the online customer satisfaction determination and Kristensen et al. (2000) applied the **European CSI** to the Denmark Post by combining the generic measures with specific determinants from the post sector.

A way to measure service features is the **Customer Satisfaction Survey**, which is related to transactional-specific service satisfaction Gilbert and Veloutsou (2006). Service quality and various technical and functional service satisfaction measures are determined by this approach.

Measuring the perceived quality of the complete consumption process is the scope of the **Customer Satisfaction Barometer (CSB)** based on Fornell (1992) and Hackl et al. (1996). Johnson and Fornell (1991) used the CSB as a standardized measurement battery for the general customer satisfaction, the perceived confirmation of customers' expectations and the distance to the ideal consumption result from the customers' perspective. Generally, cross-industrial customer satisfaction is defined as

a function of prepurchase expectations and postpurchase perceived performance.

Specifically for the health care sector, the most popular and standardized satisfaction and quality measurement approach is related to the **Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS Hospital Survey)**, which was established by the Centers for Medicare and Medicaid Services in 2008 Giordano et al. (2009); Makarem and Al-Amin (2014); Rothman et al. (2008). A survey consisting of 16 questions assessing specific perceived aspects of care was established Darby et al. (2005). These hospital ratings are public and accessible by the patients. However, the causes for satisfaction in the health care sector need to be analyzed in detail and specific cultural and demographical conditions need to be determined Raposo et al. (2009). Therefore, specific questionnaires were developed to capture the relevant process information perceived by the patients. Exemplary surveys to measure perceived satisfaction in the health care sector can be found in the literature Boudreaux et al. (2000); Jackson et al. (2001); Oliver (1980); Raposo et al. (2009); Sun et al. (2000); Westbrook et al. (1983).

2.4 Conceptual framework

To generate a thorough understanding of the effective determination of perceived consumer satisfaction, the most important concepts and corresponding determinants in the automotive industry and the health care sector were examined.

2.4.1 Concepts of customer satisfaction in service industries

Service encounter

Historically, service encounters were considered as a dyadic process of customer interactions Solomon et al. (1985); Surprenant and Solomon (1987). The construct was defined as the way the service provider interacted with the customer, for example, in a face-to-face communication. The service encounter is considered the basis for building customer satisfaction Gil et al. (2008), because this concept is one of the most important antecedents in customer evaluation of service performance Brown and Swartz (1989); Parasuraman et al. (1985). Perceived personal interaction is most often studied in service encounters Gil et al. (2008);

Meuter et al. (2000) and especially as an antecedent of customer satisfaction Bitner (1990); Gil et al. (2008). Customized communication often helps to enhance the customers' relationship with service providers Boulding et al. (2005). It is important to understand customers' expectations to optimize personalized information transfer Ford (2001). From the customers' perspective, the basic event is the moment when they interact with a service provider Bitner et al. (1994). Relational benefits result from customer-provider interactions, such as time savings due to the communication of waiting times Gwinner et al. (1998); Reynolds and Beatty (1999). To capture personal interaction during service encounters, it is important that both directions of communication between staff and consumers are recorded.

Beside personal interactions, service encounters also involve perceived processes and service characteristics Bitner et al. (1997); Shostack (1985). It is the total workflow that defines customers' perception about the quality of service encounters and thus their satisfaction Wynstra et al. (2006). A well-established customer-interaction strategy has been identified as fundamentally important Lindgreen et al. (2006). Personal customer interactions not only refers to service providers' interactions, but also to their delivery of services and goods Brown and Gulycz (2006); Lindgreen et al. (2006). Therefore, for service encounters, the focus was set on personal interactions and perceived service characteristics. These two are the most relevant factors according to service encounters based on the literature review and the practical relevance

Situational factors

Beside the service encounter itself, external factors may also influence perceived consumer satisfaction Bagozzi (1978); Dabholkar and Bagozzi (2002); Lau and Ng (2001). These determinants may be defined by external influences, process-related circumstances in a service organization, or environmental conditions, and are described as "situational factors".

"Waiting time" or "perceived crowding" (for example, busy receptions in hospitals) are examples of these factors Dong et al. (2008); Hui and Tse (1996); Nie (2000); Pruyn and Smidts (1998), which are described as being frustrating, stressful, and expensive when related to costs van Dun et al. (2011). Underlying situations, such as "time pressure", significantly influence the individual perception Blackwell et al. (1999); Hennig-Thurau and Klee (1997); Ravald and Grönroos (1996). In contrast, services that

are perceived as convenient are likely to result in a higher degree of consumer loyalty and satisfaction Blackwell et al. (1999).

For specific consumer goods, situational factors also affect brand selection and impact. Some facility-specific determinants are also related to situational factors like the "location of a store" Hennig-Thurau (2004). Lau and Ng (2001) examined the importance of the "proximity of others" as a significant factor that should be considered by service industries because consumers are more likely to talk about negative experiences, which may therefore affect reputation and satisfaction Lau and Ng (2001); Mangold et al. (1999). There is a common understanding that inconvenient factors such as crowding or social anxiety decrease perceived service quality and thus consumer satisfaction Dabholkar and Bagozzi (2002); Hui and Bateson (1991); Keaveney and Parthasarathy (2001); Maher et al. (1997). The internal climate (measured by the job satisfaction of the employees for instance) of the organization may also affect consumers' perception Yagil (2002), as can the "availability of goods" (like the availability of spare parts for car repairs without additional waiting) Bloemer and Pauwels (1998).

Sociodemographics

In most studies, sociodemographic information was captured as a relevant indicator Darley et al. (2008); Walker et al. (2003), with determinants such as age, sex, domicile, race, education level, and level of income. The determination of sociodemographics is considered particularly important for customer relationship models Verhoef et al. (2003).

However, the understanding about the relationship between the sociodemographic data and satisfaction vary in literature. Some authors have shown that there is no significant correlation between sociodemographics and satisfaction Boudreaux et al. (2000); Bursch et al. (1993); Hall and Press (1996). Others observed clear dependencies Baker and Cameron (1996); Jha et al. (2008); Sun et al. (2000).

A moderating effect of income on satisfaction and on the share of wallet was identified by Cooil et al. (2007). Homburg and Giering (2001) examined personal characteristics and found income, age, and variety seeking to be strongly influential factors of the satisfaction-loyalty construct. They observed these factors in detail in oder to analyze its impact on individualized actions to increase perceived satisfaction, such as the impact of age. Customers have to be individually treated according to their age because satisfaction in younger people is highly influenced by

service encounters, whereas older people's satisfaction is also based on previous experience.

The role of education is important, because better-educated consumers ask for more information to make their decisions. Studies show that this is reflected in perceived satisfaction Cooil et al. (2007); Keaveney and Parthasarathy (2001). Furthermore, the relationship between income and product satisfaction was identified as being weaker for people with high incomes than for those with low incomes Homburg and Giering (2001).

2.4.2 Literature review of the customer satisfaction determinants in the automotive industry

The following literature review aims to identify the most important determinants of perceived customer satisfaction in the automotive industry. Therefore, literate is reviewed according to the three main concepts: Service encounter, situational factors and sociodemographics. After a brief examination, the full overview of the relevant determinants is given in Table 2.1.

Service encounter

For the automotive industry, two dimension of service encounters are identified as significantly important: personal interactions and perceived service characteristics Keaveney (1995). The most prominent determinants for personal interactions within service encounters were information about administrative issues such as waiting time or forthcoming steps Bloemer and Lemmink (1992); Yieh et al. (2007) and the explanation of results and charges Bei and Chiao (2001); Brito et al. (2007). Brito et al. (2007) and Yieh et al. (2007) defined personal interaction as information transfer to the customer, while the reverse direction of information transfer was examined by Bloemer and Lemmink (1992).

With respect to the personal interaction between customers and service personnel, honesty and integrity were prominent in the literature review Devaraj et al. (2001); Hünecke and Gunkel (2012); Yieh et al. (2007). Customer satisfaction with staff skills was the most significant determinant in perceived service characteristics Brito et al. (2007).

Situational factors

Situational factors were examined as the second fundamental concept of perceived consumer satisfaction. The most important determinants are time-related factors, such as perceived waiting time or the length of stay Devaraj et al. (2001); Mueller (1991). Related factors include whether the car is ready at the promised time Devaraj et al. (2001) and the ease of getting an appointment. Furthermore, the time to first contact has also been identified as a relevant factor Yieh et al. (2007). The total time for servicing a car or for a repair was identified as being significant by Biehal (1983) and Mueller (1991). The ability to do the repair correctly at the first service encounter is identified as being an important predictor of consumer satisfaction in the literature Hünecke and Gunkel (2012). A defect that is not fixed during the first attempt is a service failure that may require a repeat attempt to be repaired. Samuels et al. (1986) were among the first to show the high rate of dissatisfaction with repeat auto repairs and their importance in this industry. Especially in the automotive sector, facility- or car-related situational factors were frequently captured by surveys, such as the appearance of the service area or cleanliness of the car Jones and Sasser (1995); Yieh et al. (2007). Whether or not service use was voluntary (for example, car breakdown) has been identified as an additional important situational factor Meinzer et al. (2010); Ravald and Grönroos (1996); Samuels et al. (1986).

Sociodemographics

In the automotive sector, sociodemographics such as sex have been identified as having a significant influence on satisfaction Darley et al. (2008). Darley et al. (2008) found that women who perceived contact with salespeople as being positive were satisfied with different aspects of their service encounter. The distinction between private or business use was examined as a relevant determinant because value for money is closely related to the purpose of car use Bloemer and Lemmink (1992). Cultural differences based on the country of origin were identified by Hünecke and Gunkel (2012). Devaraj et al. (2001) found that they needed to capture sociodemographics such as age and income to measure perceived satisfaction accurately. They found that older people were more satisfied with the service encounters than younger people were. It is useful

for the automotive industry to examine these sociodemographics Homburg and Giering (2001); Verhoef et al. (2003) because they show an impact on perceived satisfaction.

The most important determinants for perceived customer satisfaction in the automotive industry are summarized in Table 2.1.

Table 2.1.: The most important concepts and corresponding determinants for perceived consumer satisfaction in the automotive sector, ordered by ascending date.

Reference	Determinants	Concept	Empirical method	Comments
Mueller (1991)	• Customer treatment • Time for repair • Perceived repair quality	Service encounters	Survey analysis from 660,000 VW customers in Germany within 2 years.	No detailed analysis of more determinants or empirical proof.
Bloemer and Lemmink (1992)	• Contact personnel • Communication from customer to staff • Dealer knowledge about the customer (business or private use) • Socio-demographics	Service encounters Socio-demographics	Correlation analysis (partial correlation coefficients) of 416 questionnaires from different brands of one manufacturer in Japan.	Differentiation between private and business use, since this is an important indicator for satisfaction.

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Reference	Determinants	Concept	Empirical method	Comments
Jones and Sasser (1995)	• Picking up cars at home and leaving loan car • Follow up contact • Perceived repair quality (fix it right first time) • Cleanliness of the car	Service encounters Situational factors	Analysis of J.D. Powers results from 32 manufacturers.	Only completely satisfied customers are highly likely to stay loyal.
Keaveney (1995)	• Pricing • Inconvenience • Response to failed service • Competition • Ethical problems • Involuntary switching	Service encounters Situational factors Socio-demographics	Analysis of 526 interviews.	

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Reference	Determinants	Concept	Empirical method	Comments
Archer and Wesolowsky (1996)	• Staff handling of critical incidents (failed repairs) • Perceived repair quality	Service encounters	Logistic regression model of 4,500 questionnaires received from car owners from various Canadian branded dealers.	One critical incident was identified to have a much higher influence on the overall satisfaction than multiple positive visits.
Bei and Chiao (2001)	• Perceived service quality • Price fairness • Perceived product quality	Service encounters Situational factors	Analysis of 495 customers in 15 repair shops.	Perceived product, service and price were identified as equally important.

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Reference	Determinants	Concept	Empirical method	Comments
Devaraj et al. (2001)	• Age of customer • Prior experience • Perceived overall experience • Choice of dealer in future • Honesty and integrity • Ability to do the job right • Ability to do the job on time • Ease of getting an appointment	Service encounters Situational factors Socio-demographics	Factor analysis followed by a path analysis on survey response from 504 car owners from one dealer.	The authors also observed the influence of dealer data and found that warranty payment show a significant influence on satisfaction.

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Reference	Determinants	Concept	Empirical method	Comments
Yu et al. (2005)	• Overall evaluation of perceived quality experience • Reliability experience • Customization	Service encounters	Path analysis of 879 questionnaires received from Lexus owners.	Customer expectation on perceived quality is also determined by pre-purchase perceptions of quality.

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Reference	Determinants	Concept	Empirical method	Comments
Brito et al. (2007)	• Fix it right first time • Value of money service • Staff trustworthiness • Perceived skills • Keep to schedule and promises • Willingness to solve problems • Equipment condition • Employees' appearance • Image of being reliable • Equipment condition • Facility appearance	Service encounters Situational factors	Pure survey analysis and forward logistic regression of survey from 400 car owners.	Differentiation between branded and independent repair garages.

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Reference	Determinants	Concept	Empirical method	Comments
Yieh et al. (2007)	• Friendliness of staff • Time till first contact • Explanation of repair requirements • Price estimation • Information about repair time • Appearance of facility • Value for money service	Service encounters Situational factors	Responses from 495 surveyed car owners, structural equation model.	Perceived price fairness, perceived product quality, employee-customer interaction most important antecedents of satisfaction. Sociodemographics captured but not analyzed.

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Reference	Determinants	Concept	Empirical method	Comments
Hünecke and Gunkel (2012)	• Honesty and integrity • Do the job right first time • Friendliness of staff • Knowledge of staff • Socio-demographics • Country of residence	Service encounters Situational factors Socio-demographics	Path analysis of survey from 1,500 car owners and service customers in three countries (France, Italy, Spain).	After-sales satisfaction has no direct influence on loyalty. However, results differ in the three countries.

2.4.3 Literature review of the customer satisfaction determinants in the health care sector

The following literature review aims to identify the most important determinants of perceived customer satisfaction in the health care sector. Therefore, literate is reviewed according to the three main concepts: Service encounter, situational factors and sociodemographics. After a brief examination, the full overview of the relevant determinants is given in Table 2.2.

Service encounter

In health care, determinants from service encounters such as the communication or information transfer between patients and clinical staff show the highest relevance because they are mentioned most frequently. The health care literature recommends starting with administrative information, and providing information about forthcoming steps Björvell and Stieg (1991); Sun et al. (2001) or expected waiting time Sun et al. (2001). Satisfaction with information delivery in general is often included in empirical surveys in the health care sector Blanchard et al. (1990); LaVonne and Zun (2010); Sun et al. (2000); Walker et al. (2003); Yarnold et al. (1998).

Providing an explanation of diagnostic results shows transparency about the patients' current situation and was identified in the literature several times as predictor of satisfaction Jackson et al. (2001); LaVonne and Zun (2010); Sun et al. (2000).

The fundamental role of patient interaction was examined by Andaleeb (2001); Brody et al. (1989); Crawford et al. (2002); Saad Andaleeb (1998), who considered how to involve patients in the process to improve their perceived outcome. Brody et al. (1989) demonstrated that patients need to play an active role to increase their service satisfaction.

Bendall-Lyon and Powers (2004) described the importance of addressing and capturing service characteristics as perceived by patients. Beside communication, other issues are captured by the literature, with perceived quality determinants leading the way Boudreaux et al. (2000); Jha et al. (2008); Rhee and Bird (1996).

Situational factors

Situational factors are significantly relevant for the health care sector. Time-related determinants (such as waiting) are the most important

predictor of perceived consumer satisfaction among the situational factors. They are highly prominent in the health care literature. The highest satisfaction is achieved if the waiting time is shorter than the consumer expects Boudreaux et al. (2000); Sitzia and Wood (1997); Thompson et al. (1996). Waiting is a significant critical event, especially in urgent situations Mack et al. (1995). It means a reduction in perceived quality Pitrou et al. (2009); Sun et al. (2001). Thompson et al. (1996) examined the different effects of perceived (subjective and measured by survey) and actual (objectively measured) waiting time, and found that perceived waiting time was more important. This differentiation is also valid for the length of stay as another important situational factor Boudreaux et al. (2000); Hall and Press (1996).

Whether a visit was forced or voluntary was found to be highly significant, especially for health care Dabholkar and Thorpe (1994).

Sociodemographics

In most of the health care studies, sociodemographic information was captured by patient-satisfaction questionnaires Blanchard et al. (1990); Sun et al. (2000); Walker et al. (2003). Patient data such as age, sex, domicile, marital status, race, education level and level of income are influencing factors Venn and Fone (2005). Clear dependencies and correlations between these determinants and patient satisfaction were observed Blanchard et al. (1990); Sun et al. (2000); Walker et al. (2003). Especially in critical events, language barriers may result in service failures due to failed communication, especially in health care Carrasquillo et al. (1999). Thus, it is essential to capture sociodemographics when determining perceived consumer satisfaction in the health care sector.

The most significant determinants for perceived customer satisfaction in the health care sector are summarized in the following Table 2.2.

Table 2.2.: The most important concepts and corresponding determinants for perceived consumer satisfaction in the health care sector, ordered by ascending date.

Reference	Determinants	Concept	Empirical method	Comments
Brody et al. (1989)	• Integration of patients in treatment • Interaction with patient	Service encounters	Chi-square and t-tests on questionnaires given to 117 patients before and after visit.	Perception of patients and their role they play.
Blanchard et al. (1990)	• Perception that expectations are fulfilled • Physicians' perceived behavior • Emotional support received • Communication	Service encounters	Path analysis of results from Physician Behavior Checklist conducted from 366 cancer patients.	Identification of main predictors of overall satisfaction from cancer patients.

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Reference	Determinants	Concept	Empirical method	Comments
Björvell and Stieg (1991)	• Information delivered upon arrival	Service encounters	187 patients evaluated their perceptions of health care in a questionnaire.	
Bursch et al. (1993)	• Waiting time for first contact • Perception of care • Perceived skills of staff • Information delivery	Service encounters Situational factors	Multiple linear regression of 258 telephone surveys of patients from an emergency department (ED).	Main determinants for satisfaction in ED.
Mack et al. (1995)	• Urgency of visit • Ambulance use	Situational factors	Correlation analysis and multiple regression conducted from 1,316 mailed surveys.	Focus on urgency of visit and staff interaction.

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Reference	Determinants	Concept	Empirical method	Comments
Rhee and Bird (1996)	• Perceived technical skills • Perceived quality	Service encounters	Analysis of 618 telephone surveys conducted from patients 60 days after visit.	Overall satisfaction and quality.
Thompson et al. (1996)	• Perceived waiting time • Actual waiting time	Situational factors	Univariate analysis of 1,631 telephone surveys conducted with patients 2-4 weeks after visit.	Only focus on waiting time.
Yarnold et al. (1998)	• Managing perceived waiting time • Information delivery • Expressive quality of entire staff	Service encounters Situational factors	Nonlinear tree models of 3,564 mailed surveys from patients from an academic and a community hospital.	Expressive quality most important.

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Reference	Determinants	Concept	Empirical method	Comments
Carrasquillo et al. (1999)	• Language barriers of patients • Possibility of communication	Service encounters	Logistic regression and chi-square tests of 2,333 telephone surveys conducted with patients 10 days after visit.	Focus on language barriers.
Boudreaux et al. (2000)	• Perceived quality of the patients' treatment • Perception of safety • Quality of instructions	Service encounters	Logistic regression of 437 telephone surveys conducted with patients 10 days after visit.	Most relevant determinants for overall satisfaction and recommendation.

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Reference	Determinants	Concept	Empirical method	Comments
Sun et al. (2000)	• Willingness to return • Communication to patients • Responsiveness of staff	Service encounters Situational factors	Logistic regression of 2,333 telephone surveys conducted with patients 10 days after visit in 5 EDs.	Main determinants of overall satisfaction.
Jackson et al. (2001)	• Age, gender • Meet expectations • Duration of presenting symptom • Communication of causes • Outcomes (need for repeat visit)	Service encounters Situational factors Socio-demographics	Logistic regression of 500 surveys conducted with patients immediately after visit and 2 and 3 months after visit.	Focus on all aspects but reaction of patients differs with different time intervals of the survey.

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Reference	Determinants	Concept	Empirical method	Comments
Sun et al. (2001)	• Receive help when needed • Information about waiting time • Information about diagnostic results • Information about next steps • Age	Service encounters Situational factors Socio-demographics	Logistic regression of 2,373 mailed surveys conducted with patients from four different hospitals.	Focus on patient satisfaction measurement.
Walker et al. (2003)	• Communication with staff • Sociodemographics (especially young female patients) • Attention of staff	Service encounters Socio-demographics	58 patients reported their perceptions of medical specialties in a questionnaire, which also asked for some sociodemographics.	Focus on cancer patients.

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Reference	Determinants	Concept	Empirical method	Comments
Jha et al. (2008)	• Perceived clinical care • Socio-demographics	Service encounters Socio-demographics	Chi-square and t-tests on questionnaires given to patients from 4,032 hospitals via Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) survey.	Perception of hospital care.
Hekkert et al. (2009)	• Age • Health status • Education of staff	Situational factors Socio-demographics	Correlation analysis of 66,611 mailed surveys conducted with patients from 22 different hospitals.	Overall satisfaction.

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Reference	Determinants	Concept	Empirical method	Comments
Pitrou et al. (2009)	• Waiting time • Total length of stay	Situational factors	Multivariate analysis of 146 telephone surveys conducted with patients 1 month after visit.	Only focus on waiting time.
Isaac et al. (2010)	• Patient experience as an indicator to measure technical quality	Situational factors	Correlation analysis of service-line specific data from 927 hospitals.	Examine relationship between of HCAHPS and technical measures of quality and safety.
LaVonne and Zun (2010)	• Communication between physicians and patients • Information about diagnostic results	Service encounters	Analysis of variance of 287 surveys.	Focus on communication.

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Reference	Determinants	Concept	Empirical method	Comments
Yarris et al. (2012)	• Physicians' estimate of pain control • Perceived length of stay	Service encounters Situational factors	Logistic regression of 242 face-to-face interviews conducted with patients before leaving the hospital.	Estimation of patient satisfaction.

2.4.4 Conclusions from the conceptual framework

To generate a holistic overview about the concepts explained above, a full literature review was carried out. Tables 2.1 and 2.2 summarize the most prominent determinants for the determination of perceived consumer satisfaction in the automotive industry and the health care sector, according to the three concepts. To validate the determinants identified from the literature, the empirical methods, together with potential limitations, are listed. 20 studies from health care and 11 from the automotive industry were reviewed.

The key principle of this literature review was a systematic identification and consideration of the relevant studies and articles dealing with perceived satisfaction. The search strategy was based on established procedures Dickersin et al. (1994); Robinson and Dickersin (2002) using Ovid and PubMed. EBSCOhost was used for the literature review on the automotive industry. The search strategy was based on a three-phase procedure. In the first search phase, satisfaction determination based on consumer perceptions was used as a key identifier to find articles that provide a general overview. This literature was reviewed for the specific perceptions determining consumers' satisfaction. Those specific perceptions were based on the concepts service encounter, situational factors and sociodemographics. These were used as further identifiers for phase two. In the third phase, specific literature was identified to prove the specific hypothesis and gain in-depth understanding about specific issues. To improve the quality, highly ranked and frequently cited literature were preferred where possible.

Most of the examined determinants of perceived customer satisfaction are related to the service encounter concept in both sectors. In the automotive business especially, service encounters are strongly related to perceived quality and satisfaction because of the high levels of technical requirements, in terms of services and repairs Yu et al. (2005). The second most frequently examined concept was situational factors followed by sociodemographics. To examine the most significant determinants for the automotive sector, an empirical analysis on an existing survey from the German premium car manufacturer BMW was performed.

2.5 Improved satisfaction determination: Empirical test of literature comparison

Service industries have a significant impact on the economic situation in the United States. Around 60% of the annual gross domestic product (GDP) is from service industries and nearly 70% of jobs An and Noh (2009); McKee (2008). This section uses a survey from the automotive industry as a representative example for service industries to identify the need for action in determining perceived customer satisfaction. The most important determinants for the automotive industry are identified for each concept, employing a multiple linear regression, along with managerial implications.

First, the existing survey from the automotive manufacturer BMW is presented in detail. The raised questions are mapped to the examined three concepts from the literature review. Second, the sample selection for the conducted analysis is provided. Third, the analysis that is performed to measure the impact of the individual determinants is illustrated in detail.

2.5.1 Procedure and sample

An existing survey of BMW was used, an internationally operating premium automotive manufacturer. It determines customer satisfaction based on service visits in the United States. The questions were categorized into the three concepts identified from the literature review (service encounter, situational factors, and sociodemographics). A fourth concept defined as automotive-specific determinants captures the technical components of the survey. Survey data from 3,219 car users in the United States was used who responded to a questionnaire between January and March 2011. For each question, either Likert-type scales from 1 to 10 (1 = *very low performance* to 10 = *very high performance*) or a binary coding (yes or no) was employed. In total, 16 questions were asked that covered several categories of established processes a customer might notice during a service visit. The concepts, associated determinants, and scales are listed in Table 2.3. A variance inflation factor (VIF) value was calculated that provides an index to prevent multicollinearity in linear regressions.

Table 2.3.: Concepts, labels and scales from the BMW survey.

Concept	Label	Scale
Service encounter	SATISFACTION_SERVICE_ADVISOR*	Likert
	SATISFACTION_VALUING_SERVICE*	Likert
	RECOMMENDATION_PROB	Binary
	SATISFACTION_QUALITY_OF_WORK	Likert
	SATISFACTION_SERVICE_COMFORT	Likert
	INFO_DELAY**	Binary
Situational factors	LENGTH_OF_STAY	Individual
	SATISFACTION_CLEANLINESS	Likert
	READINESS_CAR_ON_TIME	Binary
	SATISFACTION_TIME_CASHIER	Likert
	SATISFACTION_APPOINTMENT	Likert
	SATISFACTION_ALTERNATE_TRANSPORTATION	Likert
Sociodemographics	DOMICILE**	Individual
Automotive specific	ALTERNATE_TRANSPORTATION_NEEDED	Binary
	REPAIRS_FIXED	Binary

* VIF-value over 4.0; **excluded from analysis

2.5.2 Sample selection

The distribution of customers' domicile was very imbalanced in the survey responses. The influence of the sociodemographic factor domicile therefore could not be analyzed immediately. A stratified sample selection was conducted that normalized the results so that every domicile in the survey appeared relatively similar. The optimal sample size with a power of 0.99 was calculated to be N = 379 Faul et al. (2007). The calculation of the power was based on the results of an F-test, with an effect size of $f^2 = 0.1$, a significance level of $\alpha = 0.05$, and $\beta = 0.95$.

2.5.3 Analysis

Multiple linear regression models were calculated for the sample set to determine the relationship between the overall satisfaction and the various concepts and corresponding determinants shown in Table 2.3. To prevent multicollinearity, a variance inflation factor (VIF) value was calculated within the multiple linear regression. Determinants were only considered where the VIF value was below 4.0. The assumption of the normality of the error distribution in multiple linear regression (regarding the proper calculation of test statistics) is supported by the central

limit theorem. This says that if many samples are randomly taken from a large observations, the arithmetic average of the observed values is normally distributed, independent of the original distribution. Even for small sets of samples, multiple linear regression is very robust Osborne and Waters (2002). Only one determinant within the service encounter concept captured the information transfer: Information about a delayed service. Because delaying the service of a car is a very infrequent event, the responses show a high number of missing values, making it necessary to exclude this determinant from the multiple linear regression and analyze its impact separately in an independent sample t-test. Finally, 11 determinants were used for the regression analysis. In the multiple linear regression, each concept was analyzed separately to identify its impact. The analysis was conducted with SPSS Statistics version 20.0.

Table 2.4.: Results of the multiple regression analysis of the concepts and corresponding determinants.

Concept	Variable	Model 1[a]	Model 2[b]	Model 3[c]
Situational factors	Constant	ns	-23.029***	-21.486***
	SATISFACTION_APPOINTMENT	0.285***	0.091*	0.090*
	SATISFACTION_TIME_CASHIER	0.307***	ns	ns
	READINESS_CAR_ON_TIME	0.164*	0.122***	0.120***
	SATISFACTION_CLEANLINESS	0.216**	ns	ns
	LENGTH_OF_STAY	ns	ns	ns
	SATISFACTION_ALTERNATE_TRANSPORT	ns	ns	ns
Service encounter	RECOMMENDATION_PROB		0.328***	0.346***
	SATISFACTION_SERVICE_COMFORT		0.184***	0.179***
	SATISFACTION_QUALITY_OF_WORK		0.398***	0.416***
Automotive specific	REPAIRS_FIXED			ns
	ALTERNATE_TRANSPORTATION_NEEDED			ns

R^2 final = .883; p < 0.001; *** p < 0.001; ** p< 0.01; * p < 0.05
a: F(6,117) = 20.269; ΔF = 20.269 ***; R^2 = 0.510; b: F(9,114) = 94.491; ΔF = 119.626***; R^2 = 0.882;
c: F(10,113) = 85.579; ΔF = ns; R^2 = 0.883; ns: not significant

2.6 Results of the survey analysis

Table 2.4 shows the results of the multiple linear regressions, including the beta estimates. The F-change (ΔF) expresses the effect of the significance increase that results from the parameters added to the model. It shows the impact of an added concept on the overall satisfaction. The R-square describes the amount of total variance that is explained by the general model. Table 2.5 shows the results of the independent t-test to

identify the impact of the communication within the service encounters concept.

Table 2.5.: Results of the independent sample t-test of the delay communication.

Group	Delay communicated = yes		Delay communicated = no		t-test	
Variable	Mean	SD	Mean	SD	t	p
Satisfaction	80.15	25.15	48.61	28.00	10.387[a]	0.000

a: Unequal variances; t-test corrected

2.6.1 Impact of concepts on the overall satisfaction

The first model of the multiple linear regression covers the determinants that are considered to be situational factors (model 1). The six corresponding questions of the survey showed an increase of significance of $\Delta F = 20.269$ and a total amount of explained variance of $R^2 = 0.510$. Adding service encounter (model 2), the performance of the overall model increased significantly by $\Delta F = 94.491$ and resulted in a $R^2 = 0.882$. In model 3, the automotive-specific determinants were added, which showed a non-significant change of the overall model. All three models resulted in the best performance of $R^2 = 0.883$.

The highest variance of the dependent variable overall satisfaction was explained by model 2, the service encounter. The situational factors consolidated in model 1 were also significantly relevant for the overall satisfaction. The automotive-specific determinants in model 3 were not significant in explaining overall satisfaction. The only sociodemographic determinant used by BMW was the state of domicile of the customer. This parameter was used for the stratified sampling to secure an equally distributed sample, and it was therefore not possible to analyze it in its own right. To get a deeper understanding of the most important determinants, the models were observed in detail.

2.6.2 Impact of the determinants on overall satisfaction

To identify the most significant and thus important determinants for overall satisfaction, the complete linear regression model were analyzed, including all three concepts (situational factors, service encounter, and

automotive-specific determinants), as shown in Table 2.3. The findings and key indicators for perceived overall satisfaction at BMW are covered below.

Model 1: Situational factors

The most important determinant of overall satisfaction among situational factors is the satisfaction with the time needed at the cashier (β = 0.307). The second most important issue is satisfaction with the ease of getting an appointment (β = 0.285). Both determinants are time-related. They are followed by satisfaction with the cleanliness of the car after the service visit (β = 0.216) and the readiness of the car on time as promised by the dealer (β = 0.164). The length of stay of the car at the dealer and satisfaction with alternative transportation showed no significant results.

Model 2: Situational factors and service encounters

The second model included all determinants that correspond to the concepts of situational factors or service encounters. The satisfaction with the time needed at the cashier was no longer significant, and neither was satisfaction with the cleanliness of the car. The significance and importance of satisfaction with the ease of getting an appointment decreased to β = 0.091. The importance of the readiness of the car on time as promised by the dealer decreased as well, but was still the most significant determinant among the situational factors in this model (β = 0.122). The length of stay of the car at the dealer and the satisfaction with the alternate transportation still showed no significant results.

However, the additional concept of service encounters increased the significance of the overall model. The quality of work performed was the most important determinant in this model (β = 0.398), followed by the willingness of the customer to recommend the dealer (β = 0.328). The third most important determinant was also part of the service encounters, the satisfaction with the service comfort that is provided by the dealer (β = 0.184).

Model 3: Situational factors, service encounters and automotive-specific determinants

The third model combined all the identified concepts in the questionnaire to explain the overall satisfaction. It had the highest value of

R^2 = 0.883, as already identified and shown in Table 2.3. The satisfaction with perceived service quality of work performed still showed the highest impact (β = 0.416), followed by the willingness of the customer to recommend the dealer (β = 0.346), and satisfaction with the service and comfort (β = 0.179). All three correspond to the service encounter concept. From the situational factors, like model 2, the readiness of the car on time as promised by the dealer (β = 0.120) and the satisfaction with the ease of getting an appointment (β = 0.090) were most significant. The automotive-specific determinants, about whether alternate transportation was needed and if the repairs were fixed the first time showed no significant impact on the overall satisfaction in the linear regression model.

2.6.3 Impact of the communication of a delay on overall satisfaction

The only determinant within the service encounters concept that covered the communication between customers and staff was information about the delay of a service. As described earlier, it was necessary to analyze the impact of this determinant separately because it was an optional question, answered only if the car was not ready when promised. The information transfer showed significant influence on overall satisfaction, shown in Table 2.5. The results revealed a significant difference between customers who were told about the delay of the service before they went back to pick up their car (average satisfaction of 80.15) and customers who were not told about the delay beforehand (average satisfaction of 48.61). The impact of a delay and the timing of the communication therefore seem to be important determinants in controlling critical events.

2.7 Implications for the automotive industry based on the findings from BMW

In the literature review, the hypothesis that the determinants to capture perceived consumer satisfaction in health care are closely related to those in the automotive industry was tested and confirmed. They can be split into the same three concepts: Service encounter, situational factors, and sociodemographics. However, analysis of the BMW survey

shows potential for improvements to capture satisfaction. In the following section, it will be examine how to make the necessary changes, and present the established benefits for this premium German car manufacturer based on the empirical and literature findings. The positive impact of an increase of consumer satisfaction on loyalty has already been identified for BMW Walter et al. (2013).

2.7.1 Options for improvement for the service encounter concept

Managers working in the after-sales segment of the premium car manufacturer BMW should focus intensively on the communication between service advisors and the customer, because these determinants were identified as the most important for customer satisfaction. The empirical analyses support the findings from the literature review, that service encounter is the most important concept to determine perceived consumer satisfaction because it shows the highest share of variance explained. At BMW, information about administrative issues and explanations of the results from the service is not currently covered by the survey. Especially in health care, these determinants are identified as significant predictors of perceived satisfaction. Therefore, BMW should capture this information to understand the most significant service process-related determinants. Willingness to recommend the dealer and satisfaction with service comfort were the second and third most significant items within this concept after the quality of work performed. Informed customers show much higher satisfaction levels. The significant impact of service failure and the effect of active communication are shown in Table 2.5.

Additionally, time-related service encounters are identified as highly relevant to prevent a decrease in satisfaction, for example, from having to wait. BMW already captures the communication of the delay and is therefore able to analyze the impact of this service failure. However, there is still room for improvement. The current time-related question is only asked if there is a delay. To understand how best to communicate any delays or additional waiting time, BMW should ask for customers' preferred communication channel. A personalized communication strategy could then be implemented, which is better for effective customer relationship management. The consequences of service failures in this case for BMW, and the importance of capturing these, was shown by the case of delayed spare parts delivery that increased waiting

times Maier and Weiss (2013). BMW could also benefit from asking a question about satisfaction with explanations of the invoice.

Perceived value for money plays an important role in the automotive sector. Particularly if customers are paying for their own service or repair, BMW should focus on a detailed explanation of the charges. This item is currently captured in satisfaction with the value provided by the service, which provides important information about how well the company meets consumer expectations of value for money. Based on the empirical analysis, the quality of work performed is the most important element of this concept, which matches the literature findings and the assumption that service quality is an antecedent of consumer satisfaction. BMW captures this information by asking about the quality of work performed, providing an insight into performance. They are also able to compare these findings with data received from other cars and dealers IBM (2013); Meinzer et al. (2012b). Consequently, BMW should continue and try to extend these capabilities.

2.7.2 Implications for an improved measurement of situational factors

Situational factors have the second highest impact on the overall satisfaction in the empirical analysis. The most important determinants identified for situational factors are time-related, with waiting time being the most prominent. The health care sector showed that waiting time is a critical factor in consumer treatment and needs to be seen as a service failure whenever it exceeds the customer's expectation. BMW captures this determinant in detail via questions about the readiness of the car when promised, the time with the cashier and satisfaction with how long it takes to get an appointment. The readiness of the car on time was the most important determinant to measure the overall satisfaction in the empirical model. However, there is still room for improvement. From health care, it was shown that the waiting time until first contact is also significant. It is therefore recommend asking about the waiting time after arrival as well, to cover the whole service process. In line with Thompson et al. (1996), it is also suggested that BMW should differentiate between perceived and actual waiting time. The perceived length of stay is already captured in the survey, but did not show a significant impact in the linear regression model. An improvement could be achieved

by differentiating between actual and perceived length of stay. This minor change would cover all the most important time-related items.

The perception of the appearance of service advisors and the service institution itself was considered important in the literature review, but did not show a significant impact on customer satisfaction. The BMW survey includes satisfaction with the cleanliness of the car. It is also suggested asking about the appearance of the service advisor and the dealership in general to understand whether this impact is important to perceived consumer satisfaction.

2.7.3 Better customer understanding through the concept of sociodemographics at BMW

The only sociodemographic determinant currently included is the state of residence of the customer, and it was used as the basis for stratified sampling. Therefore, separately evaluating its impact was not possible. To customize consumer treatment, a more precise knowledge of their sociodemographics is needed. BMW may therefore need to find a way to include more determinants from this concept. Bloemer and Lemmink (1992) identified the dealer's knowledge about the consumer's car use, whether private or business, as a significant determinant. Currently, BMW can only get such information from their own business fleets or potential public sources. It is recommended that this determinant be specifically included in the survey.

BMW should also capture the age and sex of their service consumers, which have been examined as significant determinants in the literature review. Such information would help BMW to steer their individualized customer treatment centrally and not only via the dealerships, which are currently the institutions that know the customers best. BMW should also find a way to measure customers' preferred communication channels to improve the customer relationship management. Cooil et al. (2007) and Keaveney and Parthasarathy (2001) observed that better-educated customers ask for additional information to support their decision-making. Therefore, it is recommended that this sociodemographic determinant is captured.

BMW should try to analyze more sociodemographic determinants, provided that their customers and dealers agreed to provide this information. The significance of sociodemographic factors in optimizing

customer care is supported by the literature unequivocally, and is especially important for the after-sales processes in the automotive industry. Sociodemographics is certainly a critical concept to analyze from a data-privacy perspective and it is therefore important to be aware of national policies.

2.7.4 Extending the capability to match automotive-specific determinants with internal BMW technical data

The BMW survey captures two automotive-specific determinants. Customers are asked whether they need alternate transport and if the repair was done right the first time. The automotive-specific determinants did not show a significant impact in the empirical analysis. However, the literature review proved that knowledge about previous repeat repairs was essential because these are seen as critical events. Consumers were especially dissatisfied when their cars had a high rate of repeat repairs, defined as repairs caused by a similar technical problem or a perceived identical cause Biehal (1983); Kohl et al. (2011); Meinzer et al. (2010). The gap between perceived service failures such as repeat repairs and the technical image that BMW wishes to convey is particularly important Meinzer et al. (2012b). BMW is already able to capture a huge amount of technical data, including warranty or diagnostic information IBM (2013), which enable the measurement of repeat repairs in the technical data. However, the repeat repair rate from a customer's perspective is significantly higher than the measures based on warranty or diagnostic data Meinzer et al. (2012b). Matching this automotive-specific determinant from the survey with the technical data transferred from the cars and the dealers, BMW is able to interpret technical measures from a customer's perspective Meinzer et al. (2012a). BMW should extend these capabilities to those processes that are measured by internal key performance indicators with high customer focus. This would reduce the gap between technical, objective measures and subjective customer-perceived feedback. An in-depth analysis about technical indicators for dissatisfaction could also be achieved.

2.8 Limitations and future research

In this chapter, an overview of the determinants that best measure the perceived consumer satisfaction in health care and the automotive industry has been provided. The results were derived from the literature review of both industries and an analysis of a survey conducted by the premium car manufacturer BMW and they confirm that findings from the health care sector can be adapted to the automotive industry. The practical implications were drawn out, particularly the possible adaptations and improvements based on the health care findings. However, some important general limitations should be considered when interpreting the findings.

First, BMW was chosen as a representative example of the automotive industry. The survey was an established questionnaire used to determine satisfaction. It represents the way to capture customer satisfaction today and thereby represents the practical state of the art. These kind of surveys are used to determine competitive benchmarks J.D.Powers (2013, 2014). The strategic importance of these surveys, the related results and the fact that these are public caused the use as a benchmark to determine satisfaction within the automotive industry. However, beside these public studies, internal questionnaires are used that differ throughout the automotive industry. Therefore, further research should include surveys from other companies to broaden the understanding of the findings and to verify their generalizability. These internal studies will differ with the companies. Based on the findings from this work, the general concepts are very likely to remain identical. As a consequence, further company specific determinants could be identified to enhance the customer understanding. Discrepancies of customer perceptions are expected if the value of the company and its products will differ significantly.

Second, the survey was carried out in the United States due to the availability of the results and underlying questionnaires. The literature review of this chapter has been conducted independent of the countries. Thus, the core concepts of perceived customer satisfaction will not vary with the country. However, there may be significant cultural differences of the individual determinants in other countries than the United States. Effects such as income, cultural preferences or product availabilities will differ. Therefore, further research is needed to analyze survey results from other countries to identify country specific determinants that are of significant importance for the automotive industry.

Furthermore, country specific regulations, such as emission laws for instance, should be considered. Independent of the particular company within the service industries, external factors are available public (such as OECD data OECD (2016) or data from the World Bank group Worldbank (2016), etc.) that can be analyzed for their influence on perceived customer satisfaction.

Third, the applicability of the knowledge transfer to the automotive industry was examined. Further research should also consider other industries to investigate the generalizability of the findings. The conducted literature review identified the three main concepts of perceived customer satisfaction: Service encounter, situational factors and sociodemographics. The identification of similarities within other service industries, such as the telecommunication sector, can be performed by analyzing these concepts in the individual business. Thereby, knowledge transfer may be applied for other service industries once these three main concepts are present for satisfaction determination. Furthermore, knowledge transfer can also be applied for the health care sector by transferring insights from other businesses. The retail as well as the telecommunication sector were identified to be representatives of applied data driven business models. For example, subjective customer information, received from call centers, were combined with objective data. Thereby, customer specific price models could be derived. The possibility to transfer these kind of data driven business models in a generic way and cross-industrial need to be further researched.

Fourth, the cross-industrial knowledge transfer has been examined and validated based on the literature review from the health care sector and the automotive industry. To validate the findings from literature, an existing survey from the automotive industry has been analyzed to identify the most important determinants of perceived customer satisfaction. In order to finally proof the success of the cross-industrial knowledge transfer from health care to the automotive industry empirically, a comparable survey would need to be conducted for the health care sector. Future research should conduct such a study with the goal to confirm the most important determinants of perceived patient satisfaction extracted from the literature. Comparing both survey results, the existing automotive study that has been used in this work and the outlined future survey from the health care sector, similarities of the main determinants can be proven. Thereby, the empirical validity of the cross-industrial knowledge transfer could be expressed for example by

correlation coefficients of comparable determinants and the overall satisfaction.

2.9 Conclusion

The results of this chapter demonstrate that insights about determination of patient satisfaction in health care can be transferred to the automotive industry. Three concepts were derived from the health care literature and analyzed for their applicability to the automotive industry. These were service encounter, situational factors, and sociodemographics. This cross-industrial knowledge transfer is possible because there are universally applicable determinants, which can be transferred from health care to the automotive sector. By transferring those determinants, it is possible to generate a description of status quo, detect potentials for change, and allow predictions of perceived satisfaction. This allows knowledge of the health care sector to be used by managers in companies in other industrial sectors. The automotive industry can enhance their determination of perceived consumer satisfaction by improving their established questionnaires. By adapting the presented approach, the missing determinants can be identified immediately. Therefore, all after-sales service processes can be monitored from the customers' perspective and be improved sustainably.

3 Can machine learning techniques predict customer dissatisfaction? A feasibility study for the automotive industry

3.1 Overview and structure of the chapter

The following chapter uses the insights derived from the previous chapter 2. The precisely determined perceived customer satisfaction indicators examined in chapter 2 are used as features to develop a model to classify dissatisfied customers within the ongoing service interaction. This chapter contributes to existing research as a methodology is developed to consolidate subjective customer perceptions with objective data.

A feasibility study for the automotive industry is performed. Features from service processes at the dealers and from the car itself have been extracted. Using results of an existing customer satisfaction survey, five different classification models were evaluated for their performance using various data preparation approaches. Thereby, the two main business questions could be answered: First, **can dissatisfied customers be classified before the customer service interactions ends based on data that is produced during a service visit?** Second, **can the indicators for dissatisfaction be derived from service process data?**

This chapter provides a solution the service industry to proactively react on potential service failures. Thereby, the customer satisfaction can be controlled and improved not only in terms of a better determination, but even more by the identification of critical elements of the service process. The chapter will provide a scenario to identify these elements

even before the customer-service interaction ends and the perceived satisfaction is generated. A sustainable increase of the overall satisfaction rate as a competitive advantage can thereby realized.

The chapter is structured as follows: First, the vast amount of data that is already available within the automotive industry is presented. A brief literature overview is provided that shows the principle feasibility of consolidating subjective customer feedback with objective data based on industrial examples. Furthermore, the lack of research within the automotive industry is examined. Second, the data sources, available within the automotive service process, are presented and the related features are extracted. Furthermore, the consolidation logic and the labeling is illustrated. The two different data preparation schemes and the three modeling approaches for the classifier evaluation are also provided in this methodological section. Third, the results of the experimental design are examined related to the data preparation schemes and the modeling approaches. Fourth, the results are critically discussed and their contribution on the automotive industry is shown. The chapter closes with a summary and a brief outlook regarding future research.

This chapter will be submitted to the Journal Artificial Intelligence Research Meinzer et al. (2017). Minor changes have been done that the submission properly fits to this work.

3.2 Introduction

Every hour, around 1 TB of data are produced by cars and dealers within the automotive industry today, growing to 1 GB in the future created by self-driving cars in every second Mearian (2013). Thus, the automotive industry is looking intensively for methods to handle this vast amount of data and analyze it to secure maximum customer benefit.

Increasing perceived customer satisfaction or, respectively, decreasing dissatisfaction was identified as the number one management target within the automotive industry Brito et al. (2007); Hünecke and Gunkel (2012). Knowing about dissatisfied customers is vitally important to create competitive leads, especially in the after-sales sector Gebauer et al. (2008). For the US service industries, an estimated revenue of 6-8 billion USD is annually created by the automotive after-sales environment Gaiardelli et al. (2007). Consequently, the classification of customer dissatisfaction is of great value to enable proactive actions before the customer actually gets dissatisfied. A satisfied customer will retain and thus

is of great interest from a business perspective. This is underlined by literature that shows that the costs for new customer acquisition are at least double Xia and Jin (2008) to 5-6 times higher than maintaining the customer Bhattacharya (1998). Reichheld and Sasser Jr. (1990) indicate that profits can be increased by almost 100% only by retaining 5% of the customers.

Traditionally, customer satisfaction with a dealer visit is assessed by customer surveys using questionnaires after the customer left the dealer Brito et al. (2007); Meinzer et al. (2010, 2016); Mueller (1991). The use of questionnaires to measure dissatisfaction has several drawbacks. First, the customer is already dissatisfied at this time as the customer-service interaction is already completed. Second, not every customer can be assessed as only a little sample of customers receives a survey. However, for every visit, service and repair data are produced and can be used for further analysis Chougule et al. (2013); Kohl et al. (2011).

Therefore, the essential question for the automotive industries is: **Can dissatisfied customers be classified in real time based on data that is produced during a service visit?**

Beside this customer value, the optimization of processes based on the knowledge of customer dissatisfaction would generate huge company benefits. Repair routines could be improved and potential service failures could be eliminated. In order to realize this company value, a second question arises: **Can the indicators for dissatisfaction be derived from service process data?**

The following literature review aims to identify existing approaches to increase customer satisfaction in the telecommunication, insurance, health care and automotive sector. The use of machine learning techniques was prevalent especially in the telecommunication business. The prediction of customer churn, as a consequence of dissatisfaction, using machine learning algorithms was thereby most prominent. Datta et al. (2000) developed a prediction model for churning customers in mobile phone services using a cascade neural network model. Customers that will discontinue using the cellular phone services were predicted. To predict the time of churn was the goal of Gopal and Meher (2008). They compared ordinal regression models with survival analysis for tenure prediction of mobile phone customers whereby the regression models showed most significant results. Hung et al. (2006) aimed to develop a propensity-to-churn score for mobile phone subscribers in Taiwan. They compared various data mining techniques and identified decision

trees as most promising to model churning customers. Predicting latent churn customers was the scope of Xia and Jin (2008). The authors investigated different techniques to predict customer churn and concluded that support vector machines (SVM) showed the highest accuracy.

In the health care sector, Yarnold et al. (1998) were among the first who used machine learning techniques to predict overall patient dissatisfaction. Nonlinear decision trees were used to classify patient satisfaction based on survey response data of emergency departments. Sun et al. (2000) had the objective to identify process measures that significantly influence patient satisfaction in emergency departments. Logistic regression models were applied based on questionnaire data, patient characteristics and process measures. Critical features of satisfaction, such as explanation of diagnostic results, could be identified. Boudreaux et al. (2000) investigated the main predictors of patient satisfaction in municipal emergency departments. Their results were based on telephone interview data and sociodemographics of hospital patients that were analyzed with logistic regression. The findings revealed the main indicators for overall patient satisfaction like patients perceptions of care and further features. An extensive overview on the determination of perceived patient satisfaction in the health care sector can be found in Meinzer et al. (2016).

Within the automotive industry, similar approaches were used for customer recommendations, targeted marketing leads and customer satisfaction. Mavridou et al. (2013) aimed to improve the car configurator. They used association rules based on customer choices to create an individualized recommendation system. Chan et al. (2011) focused on the product development process within the automotive industry. They mapped survey response data from customer studies to design attributes according to customer preferences. Lee and Park (2005) investigated the possibilities to create marketing leads from customer satisfaction, sociodemographic and accounting data. They used the techniques of self-organizing maps and decision trees for an individualized customer segmentation. Salini and Kenett (2009) aimed to make customer preferences more transparent. They applied Bayesian Networks solely on survey response data. For instance individualized pricing or region specific marketing concepts were derived. The work of Chougule et al. (2013), Bandaru et al. (2011) and Bandaru et al. (2015) focused on modeling customer satisfaction using vehicle failure data. They limited their focus on quality and reliability related satisfaction and extracted

features from warranty data Chougule et al. (2013). Bandaru et al. (2011) and Bandaru et al. (2015) used extracted and calculated features from service and sales data to model customer satisfaction.

Models that focus on the automotive industry are scarce, as pointed out by Chougule et al. (2013) and Meinzer et al. (2016). Machine learning techniques were not applied in order to classify overall dissatisfied customers or to identify the most critical indicators based on continuously created, objective data. Due to the limitations of determining subjective customer satisfaction using questionnaires and the overall customer satisfaction as a fundamental management target in the automotive industry, there is an unmet need for a system to classify dissatisfied customers from objective, technical data Meinzer et al. (2016). Such an approach has not been presented so far as the literature review expressed.

Customer satisfaction is one of the most important managerial goals in the automotive industry and helps to increase competitive advantages. To address this high revenue potential, dissatisfied customers need to be predicted and the indicators for dissatisfaction need to be identified. The large amount of data that is produced every day by dealers, customers and cars can be used to achieve this goal Brito et al. (2007); Hünecke and Gunkel (2012). This chapter investigates several machine learning approaches for their performance in predicting dissatisfied customers and identifying general indicators for customer dissatisfaction based on technical data. The presented concept can be transferred to other service industries, such as the health care sector where the customer satisfaction is an important management target and sensor data are continuously produced.

3.3 Materials and methods

This section describes the materials and methods to classify customer dissatisfaction and to identify indicators for customer dissatisfaction. First, the necessary data sources are described. Second, the consolidation of the data is presented. Third, the feature extraction is illustrated. Fourth, the data balancing procedure is shown. Finally, the experimental design to prepare and model the data is explained. The complete data analysis process is shown as an overview in fig. 3.1 and will be described in more detail.

3.3.1 Data sources

Since unique identifiers to aggregate all information for each car are not present, an automated way to consolidate and validate the data on an incident level was developed. Generally, warranty data, diagnostic data, dealer system data and general vehicle data have been consolidated.

A detailed description of the transfer of information to the automotive manufacturer's can be found in Kohl et al. (2011); Prenninger (2013). The data sources, used for labeling and feature extraction are illustrated in fig. 3.1.

Warranty data

Warranty claims identify all repairs that are performed and paid by the automotive company within the warranty period or as goodwill. Dealers have to claim for all work they do by using different codes. Those codes consider all parts that are replaced, mechanical work and the time needed for the several repair steps. All this information and the amount of money the dealer requests is transferred via the claims. An overview of the features are listed in Table 3.1.

Diagnostic data

The data transfer of diagnostic protocols is automatically triggered on each repair visit caused by an electronic related defect. The system captures details of the errors (stored as fault codes) set in the car. Repair plans are derived from these fault codes and provided to the mechanics. Diagnostic data comprises the results and errors that are read out from the car as well as the repair procedure steps. A detailed description can be found in Kohl et al. (2011). The features extracted from this sources are given in Table 3.1.

Dealer system data

Additional information about dealers' work is retrieved from the dealer management systems. Spare parts that were paid by the customer or regular maintenance information is provided. An overview about different exemplary features from this source is given in Table 3.1.

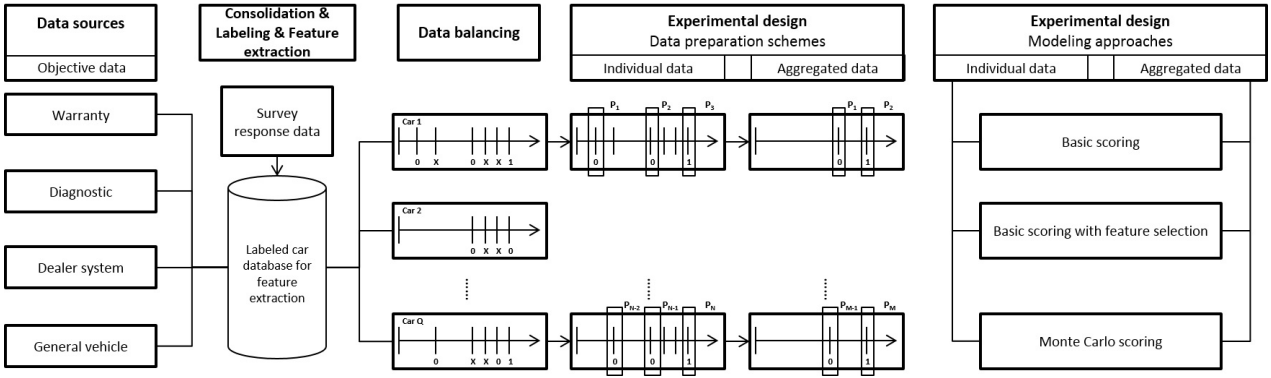

Figure 3.1.: Overview about the data sources for the consolidated database, the data balancing procedure, the resulting data preparation and modeling approaches. The label 0 was used for a satisfied and label 1 for a dissatisfied customer; Service visit without survey response are represented by X, and the patterns of data deduced from service visits by P.

General vehicle data

This data source covers all general car and dealer information such as car type, extras, power, etc. It is collected after a car is produced and sold to the customer. Examples for these car characteristics are presented in Table 3.1.

Survey response data

After each service visit the customer may be contacted for a customer satisfaction survey if he gives the dealer his approval. The survey is conducted by an external agency that collects data for the main automotive companies. A random sample of customers is asked to fill out a questionnaire. Thus, a representative set of service visits from all dealers is drawn assuming that this sample covers the different perceived quality levels of the visits. The sample size is based on various factors like the size of the dealer or the type of customer (business, private, etc.). There are regular maintenance interval visits included as well as repair incidents. The perceived overall satisfaction with a service visit is determined. A customer can receive a survey multiple times for different visits. This data source is needed in order to label the service visits as satisfactory or dissatisfactory.

3.3.2 Consolidation and labeling

Data consolidation

In order to analyze the data, the five different data sources needed to be combined as illustrated in fig. 3.1. All systems store the information of a service visit in combination with the vehicle identification number (VIN) and a time-stamp. However, the timestamp is not unique in all data sources. There can be multiple timestamps identifying different service visits (e.g. diagnostic readouts differ from warranty claiming). The data in the warranty and dealer management system is created manually, the others are automatically produced. This situation yields a biased timestamp. This bias needed to be integrated into the consolidation logic. A window of 5 days and 50 kilometers was tolerated to consider the data as one visit. Otherwise a new visit was assumed.

The aggregation procedure was split up in three steps and is explained in the following.

Step 1: Data sources consolidation

1. Data sets for all vehicles were extracted from the five data sources introduced in section 3.3.1.
2. Check all data sources for matching cars (VIN).
3. Vehicles with survey responses were selected.

Step 2: Specified matching

1. Data sets with identical timestamps and VIN were matched.
2. Vehicles with different timestamps but identical VIN were transferred to step 3.

Step 3: Tolerance matching

1. Biased timestamps with identical VIN were filtered and the difference between the timestamps was calculated.
2. Vehicles with a difference less than 5 days or 50 kilometers were consolidated into one service visit.
3. Vehicles that did not fulfill these criteria were considered as separate service visits.

Labeling

Each service visit can be identified with the unique timestamp of the survey and the VIN. The survey design requires to send out the questionnaire not later than 30 days after a service visit. Thus, survey data and repair visits using a tolerance window of 30 days were mapped. The overall satisfaction of the particular customer was considered to be the class label. The overall satisfaction rate was measured using a likert scale from 1 - 5 (where 5 is best). In order to guarantee a two-class classification problem, the results of this question have been transferred into a binary coding. Service visits with satisfaction rates of 1 to 3 were identified as dissatisfactory and labeled with 1 whereas 4 and 5 represent the service visits of satisfied customers that were labeled with 0. This is a common way of interpretation and presentation in a management manner as shown for example by Boudreaux et al. (2000).

3.3.3 Feature extraction

Features were derived from the consolidated and labeled data sources. In order to provide a holistic overview, the features were categorized as presented in Table 3.1. Generally, the features provide an encompassing view about the service visits of the car. Technical information such as the repair cause, repair results, affected parts or general vehicle characteristics were included. Furthermore, features that may potentially be perceived by the customer were calculated, such as repeat repairs, the length of stay or the time between actual and previous visit. In total 105 features were extracted for the analysis and presented in Table 3.1.

3.3.4 Data balancing

Dissatisfied customers were underrepresented in the dataset. For the analysis, too many patterns about satisfied customers were included during the learning process. The class imbalance challenge has gained attention previously in research on machine learning Li and Mao (2014). In the dataset, 5,048 events with label 1 corresponded to 13,960 service visits with label 0. As the minor group of dissatisfied customers should be classified as good as possible, strategies to cope with this class imbalance were needed. Thereby, the probability of False Negatives, meaning dissatisfied customers were classified as satisfied, should be reduced to a minimum. Various machine learning algorithms that do not take class imbalance into account tend to be biased Kotsiantis et al. (2006); Li and Mao (2014). In order to increase the performance of the classification of dissatisfied customers, a random undersampling of the satisfied customers according to Garcia et al. (2007) was used. Compared to alternative solutions, such as cost functions, that was shown to be an easy and effective procedure.

In order to achieve equal populations of the two classes, a selection probability of roughly 36.1% within the satisfied customer group was needed to achieve a subsample of 5,048 observations. Thereby, an optimal population of car owners whose satisfaction level changed from satisfied to dissatisfied within a service history has been generated.

3.3.5 Experimental design

The experimental design of this study contained two data preparation schemes: Individual and aggregated data. Three modeling approaches

Table 3.1.: Overview of the features used for classification, corresponding feature categories and data sources

Feature	Feature category	Feature description	Data sources	Category information	Exemplary feature
1	SV_CNT	Amount of service visits per car	Warranty Diagnostic Dealer system	Calculated	Visits = 5
2 - 57	CHARACS	General characteristics of the car	General vehicle	Extracted	Milage = 12,000 miles
58	LENGTH	Length of stay in workshop per service	Warranty Diagnostic	Calculated	Length of stay = two days
59 - 62	SOURCE	Identifier of data sources	All	Calculated	Data source = Diagnostic
63 - 65	RR	Identification of repeat repairs	Warranty Diagnostic	Calculated	Warranty repeat repair = true
66 - 69	WGS	Description of warranty level of repair	Warranty	Extracted	Warranty stage = Goodwill
70 - 95	DIAG	Repair details from diagnostic data	Diagnostic	Extracted	Result = Software update
96 - 104	WTY	Repair details from warranty data	Warranty	Extracted	Repair = Engine part replaced
105	DIFF	Time gap to previous service visit	Warranty Diagnostic Dealer system	Calculated	Previous visit = 197 days

were used: Basic scoring, basic scoring with evolutionary feature selection and a Monte Carlo scoring. The two data preparation schemes aimed to provide insight into whether the performance of the classification can be increased by considering the individual service visits or combining them as a history of events. The three modeling approaches addressed the question about the derivation of potential indicators of dissatisfaction. In the experimental design five classifiers were compared using different parameter settings: AdaBoost, k nearest neighbor (kNN), SVM with linear and RBF-kernel and Random Forest. These five classifiers were chosen as they were evaluated to be suited as state-of-the-art classifiers for industrial applications Reif et al. (2014).

Data preparation schemes

Two different data preparation schemes consisting of individual and aggregated data were applied. Individual data means that training and scoring was based on the original longitudinal data structure of cars and service visits. Consequently, the dataset consisted of multiple dealer visits per car. This approach is typically used today to analyze survey results.

Aggregated data means, that all service visits of one customer (represented by the VIN_ID) that remain the customer as satisfied were aggregated to one observation. Means were used for numeric features and modes for categorical features. The following, second record identified the visit that is labeled as dissatisfactory if available.

An exemplary overview on one car, its general characteristics and the corresponding service visits is given in fig. 3.2. The figure illustrates the two data preparation schemes.

Modeling approaches

The three benchmarked modeling approaches were: Basic scoring, basic scoring with evolutionary feature selection and a Monte Carlo scoring. In general, constant and quasi constant items, meaning features with very low entropy (for example high amount of null values), were eliminated. Furthermore, features with a correlation coefficient of more than .95 were removed.

Basic scoring compared different classifiers for their performance on customer dissatisfaction classification. The complete feature set was used.

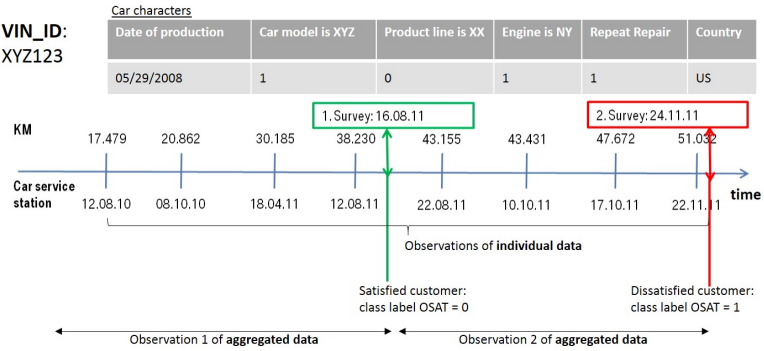

Figure 3.2.: Overview about the two data preparation schemes illustrated by one exemplary car.

The **basic scoring with evolutionary feature selection** Wang and Huang (2009) experiment had the main goal to identify the discriminant features and thus the main indicators for customer dissatisfaction. The feature selection must be fast in calculation to secure a practical implementation. Therefore, it was performed using a simple decision stump that uses only one split, therefore being fast and avoiding overfitting Shah et al. (2012). The initial feature set is randomly generated, whereby each feature set had a feature activation probability of p_i = .50. During the next maximum 50 iterations a population of 5 individual feature sets competed for the best classification accuracy using mutation. Mutation means the random activation and deactivation of features with p_m = 1 / random of features. Furthermore, features can interchange within the individual feature sets with the probability of p_c = .50. One of the five feature sets will result in the highest accuracy and remain for the next iteration. If the accuracy of one of the new feature sets is better than before, the algorithm proceeds to the next iteration. Once there was no improvement over 10 iterations, an early stopping rule was applied and the final subset of features was reported.

A **Monte Carlo** resampling approach was conducted in order to evaluate the classification variances of the applied predictions. Thereby, 500 random subsamples, each consisting of 1,000 balanced observations (500 satisfied and 500 dissatisfied customers), were drawn and evaluated

using the grid search from the basic scoring approach. In each iteration the respective classification results and parameter sets were stored.

All experiments were conducted using RapidMiner toolbox version 5.3.013 (RapidMiner, Cambridge, MA, USA). A PC with 32 cores and 512 GB RAM was used for the analysis.

Experimental setup and evaluation

In order to achieve the intended goal of differentiating satisfied from dissatisfied customers during a service visit, a specific selection of machine learning approaches was chosen. An overview of the most common machine learning techniques can be found in Duda et al. (2000); Hastie et al. (2011). In this chapter, the focus is on the following five classifiers based on the above described design. First, the performance of the AdaBoost classifier was investigated with $N_{it} \in$ [10,20,..., 100] which corresponds to literature findings Polikar (2007); Schapire et al. (1998). Second, the performance of the kNN classifier was investigated with number of nearest neighbors [k = 1,2,..., 10]. Third, the performance of the SVM was investigated using the linear kernel and fourth, using the RBF kernel. According to Wu and Wang (2009) both SVM classifiers were investigated with kernel parameter C in the range $[2^{-5},\ 2^{-4}, ...,\ 2^{5}]$. For the RBF kernel the parameter space $[2^{-5},\ 2^{-4}, ...,\ 2^{5}]$ was used for γ. Fifth, the performance of the Random Forest according to Oshiro et al. (2012) was investigated using 10 to 1,000 trees increasing with 10 steps on a quadratic scale [10,20,50,...,1000]. Each set of free parameters was evaluated.

From the current dataset, a training (.70), test (.20) and validation (.10) sample was conducted and the accuracy for test and validation was reported. For each parameter set, the classification rate of the five classifiers was investigated. For the feature selection approach, the partitioning was performed after the evolutionary feature selection has been done on the full feature set. Within the Monte Carlo Scoring, the partitioning has been done within each iteration before the classification models were applied to the feature set resulting from the Monte Carlo iteration.

3.4 Results

The results of the experimental design are presented in Tables 3.2 - 3.4. The classifiers in the tables are sorted in alphabetic order where the

classifiers with the highest accuracy in test and validation partition are marked. For the results of the Monte Carlo scoring in Table 3.4 the standard deviation σ is given in brackets over all iterations.

Table 3.2 presents the results for the basic scoring. The SVM using the RBF kernel was the best performing classifier for the individual as well as for the aggregated data with a test and validation accuracy of 77.2% (76.4%) and 88.8% (88.8%) respectively.

Table 3.2.: Results of basic scoring on individual and aggregated data.

	individual data		aggregated data	
Classifier	Test	Validation	Test	Validation
AdaBoost	50.0	68.8	82.9	82.9
kNN	57.0	58.0	55.1	54.9
SVM (Linear)	72.3	70.8	80.4	81.7
SVM (RBF)	**77.2**	**76.4**	**88.8**	**88.8**
Random Forest	75.0	74.7	81.5	78.3

Table 3.3.: Results of basic scoring with feature selection on individual and aggregated data.

	individual data		aggregated data	
Classifier	Test	Validation	Test	Validation
AdaBoost	70.0	70.7	83.3	79.3
kNN	55.8	55.9	84.2	80.9
SVM (Linear)	73.2	72.1	78.9	80.7
SVM (RBF)	72.6	74.9	**86.1**	**88.3**
Random Forest	**75.0**	**74.6**	87.2	82.5

Table 3.3 summarizes the results of the basic scoring with evolutionary feature selection. Based on the individual data the Random Forrest showed best results with an accuracy of 75.0% for the testing and 74.6%

Table 3.4.: Results of Monte Carlo scoring on individual and aggregated data.

	individual data		aggregated data	
Classifier	Test	Validation	Test	Validation
AdaBoost	66.0 (0.06)	66.6 (0.06)	79.5 (0.06)	79.7 (0.04)
kNN	54.6 (0.05)	54.5 (0.04)	55.0 (0.05)	55.6 (0.03)
SVM (Linear)	69.6 (0.04)	69.9 (0.03)	80.3 (0.04)	80.2 (0.03)
SVM (RBF)	**75.0 (0.04)**	**72.2 (0.03)**	**84.1 (0.04)**	**83.3 (0.03)**
Random Forest	71.2 (0.05)	71.8 (0.03)	79.9 (0.04)	79.8 (0.03)

for the validation data. The SVM with RBF kernel performed best for aggregated data with an accuracy of 86.1% (88.3%). In order to secure the practical application of the feature selection approach, a fast computing time is required. Therefore, decision stump has been applied within the feature selection procedure using one split. This approach secures the necessary computing performance but has the disadvantage that interaction effects of the features are limited to the one split criteria and thereby may decrease the accuracy.

Results for the Monte Carlo scoring are given in Table 3.4. The SVM with RBF kernel showed the best classification results for individual data with an accuracy of 75.0% and 72.2% for test and the validation partition respectively. For the aggregated dataset, it was also the SVM with RBF kernel that achieved highest accuracy with 84.1% and 83.3% for test and validation partition. Both show a standard deviation of the accuracy over all iterations of σ = 0.04 and σ = 0.03.

Overall, best classification rates with 88.8% for test and validation were achieved with the basic scoring approach on the aggregated dataset performing the SVM with a RBF kernel with a parameter set of C = 16, γ = 0.03125 (Table 3.2). The second best results with a classification rate of 88.3% were returned by the SVM using a RBF kernel based on the basic scoring with evolutionary feature selection using the aggregated data with an optimal parameter set of C = 4, γ = 0.03125 (Table 3.3). The feature selection selected 46 features. Thereby, 23 features were selected from the category CHARACS, 15 from DIAG, 5 from WGS, 2 from RR and 1 feature was selected from the category SOURCE (Table A.1).

3.5 Discussion

There is a significant cross-industrial need to identify dissatisfied customers, since companies are no longer competing only on product quality but even more on a service quality level Corbin et al. (2001); Sivakumar et al. (2014); Yarris et al. (2012). This chapter showed a method to classify dissatisfied customers from the automotive industry based on data produced within a service process with a maximum classification rate of 88.8%. Generally, the approach is designed to secure the practical implication by considering high accuracy and fast computing power as necessary success factors.

The paper contributes to the existing research as it predicts customers dissatisfaction solely based on objective data. This allows a proactive customer treatment in the future in order to achieve the management target to increase the overall customer satisfaction. Furthermore, sustainability to keep satisfaction high can be achieved once the indicators for dissatisfaction could be identified. The complexity of the presented data analysis was caused by isolated data sources and the resulting need for consolidation was shown. A stepwise data consolidation logic to overcome this challenge was derived and proven for the automotive industry. This methodology is not limited to the car sector but can be transferred to service industries, such as the health care or the telecommunication sectors.

The presented work answers two questions. First, can dissatisfied customers be classified in real time based on data that is produced during a service visit? Overall, the schema that aggregates the service events achieved best results throughout all experiments. Thereby, the SVM classifier (RBF kernel) outperformed the other classifiers and showed best results of 88.8% accuracy for test and validation data. Consequently, dissatisfied customers could be classified based on a service visit. Furthermore, the results showed that it is not a single event that turns a customer from satisfied into dissatisfied but rather the whole history of experiences the customer had. This is based on the fact that the aggregation of the service history yielded higher classification rates in all modeling approaches. This result matches previous findings in literature Keaveney and Parthasarathy (2001).

Second, can the indicators for dissatisfaction be derived from service process data? This question is answered by the results from the experimental design that achieved results of 86.1% for the test and 88.3% for

the validation partition based on basic scoring with evolutionary feature selection on aggregated data. Specific features that are highly important for the perceived dissatisfaction of a customer could be derived. The selected features were investigated in more detail. Most of the features were related to technical information from general car characteristics, warranty and diagnostic data. Furthermore, two features were related to the category of repeat repair parameters, as illustrated in Table A.1. Based on these findings the potential indicators of dissatisfaction could be deduced from the technical data that were created when the car is still at the dealer. Additionally, repeat repairs in general are critical events that could be important to identify customers that may need specific care. This matches to the literature findings that showed repeat repairs to be highly influential for the perceived satisfaction Biehal (1983); Meinzer et al. (2010).

Generally, the presented method of linking technical data to customer perceptions is a novel approach that could be used in individual business sectors and thus create value for the service industry in the future. For instance, the need in the health care sector has already been identified by Holgers et al. (2005) and Yarnold et al. (1998). With the consolidation of diagnostic results with the subjective patient expectations, a personalized patient treatment could be developed. The knowledge about potential dissatisfaction indicators generates huge business value as it prevents customer churn and thus reduces reacquisition costs as shown by Xia and Jin (2008). A proactive approach which takes special care of potentially dissatisfied customers has a very low effect in case of false positives. If satisfied customers are classified as dissatisfied, the business result will be a more specific treatment. Thus, only the dissatisfied customers that are not identified have a real negative impact.

3.6 Summary and Outlook

This chapter provided an approach to answer two important questions that help the automotive industry to increase the customer satisfaction and thus securing competitive leads. Can dissatisfied customers be classified in real time based on data that is produced during a service visit? Can the indicators for dissatisfaction be derived from service process data? In the presented data analysis procedure, the challenge of combining technical data from various sources with subjective survey responses

was solved with a specific data consolidation logic. An experimental design consisting of three modeling approaches combined with two data preparation schemes was performed to answer the above questions. The methodology that classified customer dissatisfaction best was the SVM classifier with a RBF kernel, which resulted in an accuracy of 88.8%. The indicators for dissatisfaction were identified within the feature selection experiment and the SVM with a RBF kernel achieved best results. Knowing these indicators allows a proactive customer treatment as dissatisfied customers can directly be identified even before the customer-service interaction is completed. Thus, actions to increase the satisfaction can be implemented immediately and secure a competitive advantage.

Furthermore, managerial implications can be derived based on the dissatisfaction indicators that have been identified by the feature selection. In total, 46 indicators that have a high influence on dissatisfaction were identified. Most of them are related to car characteristics, such as the car model. Thereby, individual customer treatment campaigns can be designed according to this information. Additionally, 21 indicators were related to technical processes (diagnostics, warranty and data source information). Management can use this information to optimize the internal technical processes as these have a significant influence on the perceived service quality. Furthermore, these technical indicators need to be analyzed in detail in order to avoid service failures. Repeat repairs can be one of these service failures. They were identified as a main dissatisfaction indicator. Management should develop campaigns to reduce the rate of repeat repairs, especially the customer perceived ones. Therefore, a transparent and detailed explanation of the conducted work by the service advisors may be one opportunity. In general, the management of the automotive industry can benefit significantly from the derived indicators for dissatisfaction.

The presented method was designed for the automotive industry and will be of high importance for other service industries. A closely related business that the approach might be suitable for is the health care sector. Corbin et al. (2001) showed that satisfying patient-physician interaction is highly important to survive in the tough competition. Diagnostic data that were collected during the treatment could be consolidated with patient satisfaction survey responses. Thus, dissatisfied patients may be classified and indicators for dissatisfaction may be derived. The adaptation of the method for the health care sector and further industries should be investigated. Therefore, survey responses from other service

industries are needed and should be combined with service process data using the presented consolidation logic and the experimental design.

4 Practical impact of this work

The perception of customers are key resources in order to create new products and services Mahr et al. (2014). The involvement of customers in innovative processes helps to create new customer oriented features Poetz and Schreier (2012). A critical need exists to process knowledge with the aim to create maximum customer value based on individualized treatments Gordon et al. (2011). Service industries, the automotive industry in particular, are in a changing process. As new competitors arise with individualized customer relationship models, existing companies need to adapt. They strive towards an active supporter of the customer Saarijärvi et al. (2014). Consequently, effective service-based business models are needed to create competitive leads.

Today, customer satisfaction campaigns are developed within departments that use survey results as input factors. On the other hand, service optimization campaigns that affect technical procedures (such as failure diagnostics) are based on objective, technical data and are developed in other departments. Consequently, customers' perceptions and even more generic, customers' data has widely been separated from objective service process information today Saarijärvi et al. (2014). However, customer data indeed increases power and brings along undiscovered possibilities. All these potentials should have the common goal of creating maximum customer value Hendler (2014). A contribution to this goal is addressed by this work.

Chapter 2 provides an approach for cross-industrial knowledge transfer for perceived customer satisfaction determination. Adapting the methods from the health care sector, implications for the automotive industry to improve the customer understanding by better designs of questionnaires are derived. Furthermore, the most relevant determinants according the the three main concepts service encounter, situational factors and sociodemographics are examined. The first section of

this chapter addresses the implications gained by this cross-industrial knowledge transfer.

A business-model based on the consolidation of customer and technical data is derived in chapter 3. Thereby, the automotive industry is able to identify potentially dissatisfied customers in real time. Data that is generated within each service visit combined with historical customer perceptions is used as the basis for this approach. Furthermore, the most critical service processes that have the highest chance to create dissatisfied customers can be identified. Using this information, the service quality and thus, customer satisfaction can be improved sustainably. The second section of this chapter addresses the implications gained by such kind of data driven business model.

4.1 Implications from cross-industrial knowledge transfer

In the highly competitive environment of the automotive industry, it is not the product itself anymore but the services around the product that will yield competitive leads. This phenomenon is known as the servitization-paradox Kastalli and Van Looy (2013). Thereby, the customer and his perception of service is in the middle of interest. Consequently, the automotive industry needs to enhance their knowledge about customer perceptions. Transferring existing knowledge from other service industries is therefore a fast and effective procedure and also proven to be successful by literature Gebauer et al. (2012). In the health care sector for instance, the phenomenon of customer focused services is already a core business requirement, known as patient centricity Curro et al. (2013); Steel (2015). As the core product of the medical environment is the care of patients', the need for an encompassing patient understanding is obvious. Therefore, the determination of perceived patient satisfaction has been examined in detail in chapter 2. The main concepts of perceived satisfaction has been examined to be service encounter, situational factors and sociodemographics. While the health care, the hospitality as well as the retailing sector is already well researched, studies for the manufacturing industry and in particular the automotive are scarce Kastalli and Van Looy (2013). In health care, diagnostic results are combined with subjective patient perceptions in order to increase the perceived success of the medical treatment Corbin et al.

(2001). The treatment of Tinnitus patients is one example of the application of subjective and objective data analysis. A major part of health care professionals are already in a changing process towards a data-driven strategy Groves et al. (2013). The knowledge about patients' perceptions is thereby one of the key principles. Thus, the cross-industrial knowledge transfer has been performed for the automotive industry considering the health care sector as a benchmark.

The implications resulting from this cross-industrial knowledge transfer are far reaching. The following components can be extracted based on an existing survey analysis from chapter 2.6 as contributions to the existing research and as managerial implication. For all three concepts of perceived satisfaction determination (service encounter, situational factors and sociodemographics), implications were derived in chapter 2.7.

Generally, satisfaction determination within the automotive industry can be improved by adding the relevant determinants of each concept that were derived from the analysis of the health care sector.

The concrete implications and benefits have been worked out in chapter 2.7. In summary, these were the following: First, the highest adaption needs to be done within the sociodemographics as there are currently the fewest determinants established. Second, within the concept of service encounter, determinants related to the communication need to be added according to the findings from the health care sector. Furthermore, time-related determinants were only covered if there was a delay. However, in order to reduce the negative perceptions of such service failures, the preferred communication in case of delays should be asked. Third, within the concept of situational factors, the automotive industry needs to differentiate perceived and objective waiting time in the questionnaires in order to evaluate customers' perception. Fourth, the automotive-specific determinants should be extended in a way that data-driven business models can be established that use this information. Fifth, the automotive industry should increase their use of customer data in general to create value on both sites, for the company and the customer. Most of the customers are willing to share their data once the value is transparent to them and meets their individual needs Roeber et al. (2015). Technical data, that is generated while servicing a car, have been analyzed in chapter 3.4 in order to enrich the subjective customer feedback by objective data. Using these technical data combined with customer information allows the real-time classification of probably dissatisfied customers (see chapter 3.5). Even more, the key indicators that

cause dissatisfaction could be identified which allows proactive actions to avoid dissatisfaction (see chapter 3.4 and Table A.1).

Even if the benefits arising from the knowledge about customers' needs are obvious, still the limitations due to data privacy and legal restrictions remain. Certainly country- and business-specific issues have to be considered. This is why this section focuses on general topics that are independent of the afore mentioned issues. The main general topics are: Transparency, customers' trust, customers' perception of control and customers' trust in the value arising of their data being analyzed.

A prominent way to overcome this challenge is via service-outsourcing Kastalli and Van Looy (2013). However, customers still connect their perceptions with the core company. Consequently, this action does not release the company from their obligations of developing customer trust. Furthermore, this decision brings additional difficulties as service should be a core element and provided by the company itself Johnson (2007). While online platforms such as Google or Facebook make the most asset out of user data Andrejevic (2015), the service industry needs to find another way to develop customers' trust. Users of online platform expect the use of their "digital footprint" from the companies, while customers of the automotive industries do not. The most important implication for the service industry and in particular the automotive industry is that customers always need to know what happens with their personal information Spiekermann et al. (2015).

Consequently, full transparency towards the customer regarding the use of their data is the key to generate value for both sites, the customer and the service industry Roeber et al. (2015); Spiekermann et al. (2015). Furthermore, customers should have full control over their degree of data sharing Roeber et al. (2015).

The knowledge transfer from health care to automotive and the developed classification model based on the data consolidation approach enable the automotive industry to create competitive advantages as shown in chapter 2.7 and 3.5. The main benefits arising from this work are the encompassing understanding of customer perceptions and the enrichment with technical, objective data. Thereby, the following competitive advantages can be realized: First, customers and their needs will be better understood. Second, an individualized treatment based on these needs is possible. These two are the basic requirements to realize optimal customer focused services in the automotive industry. This will help to close the existing gap to other business sectors within the service

industries, such as the health care or the retail sector. Even more important, these implications help to create market leads compared to existing competitors. Furthermore, new competitors will enter the market of the automotive industry, that follow data driven business models. Using the implications from the cross-industrial knowledge transfer combined with the implications from the developed data consolidation logic, further leads can be generated.

4.2 Implications for data driven business models

It is obvious tat especially the automotive industry is in a disruptive change. That means, new competitors such as Google enter the market that follow data driven business models to reach high customer satisfaction results. Consequently, a precise knowledge about critical success factors and thus, the main determinants that drive customer satisfaction get even more important to survive in this tough competition. The key success factors may change in the future faster than ever before. Therefore, management always needs to ensure to address the customer needs not only by their products but more and more by services. Traditionally, manufacturing industries, like automotive, focus on their products rather than on services. A reorientation of the manufacturing industries towards service is needed and this change is currently in process Kowalkowski et al. (2012). In most of the times, customer data is generated as an output of measuring service performance. However, in the future it needs to be used the reverse way Saarijärvi et al. (2014, 2015); customer data as an input for improved and personalized services. In chapter 3, a data-driven approach to increase competitive advantages by optimizing customer service is presented according to this reverse use of customer data.

Entry barriers of new competitors and entrepreneurs are lower than ever before due to rapid growth of importance of the internet as a distribution platform for connected cars. Furthermore, new ideas will emerge that provide customers with more convenient services around their car and is the basis for new competitors such as Uber or OnStar. The trend of connected cars is kind of misleading already, as the actual trend goes beyond, towards a connected ecosystem, including transportation. Fig. 4.1 illustrates the disruption of the automotive industry

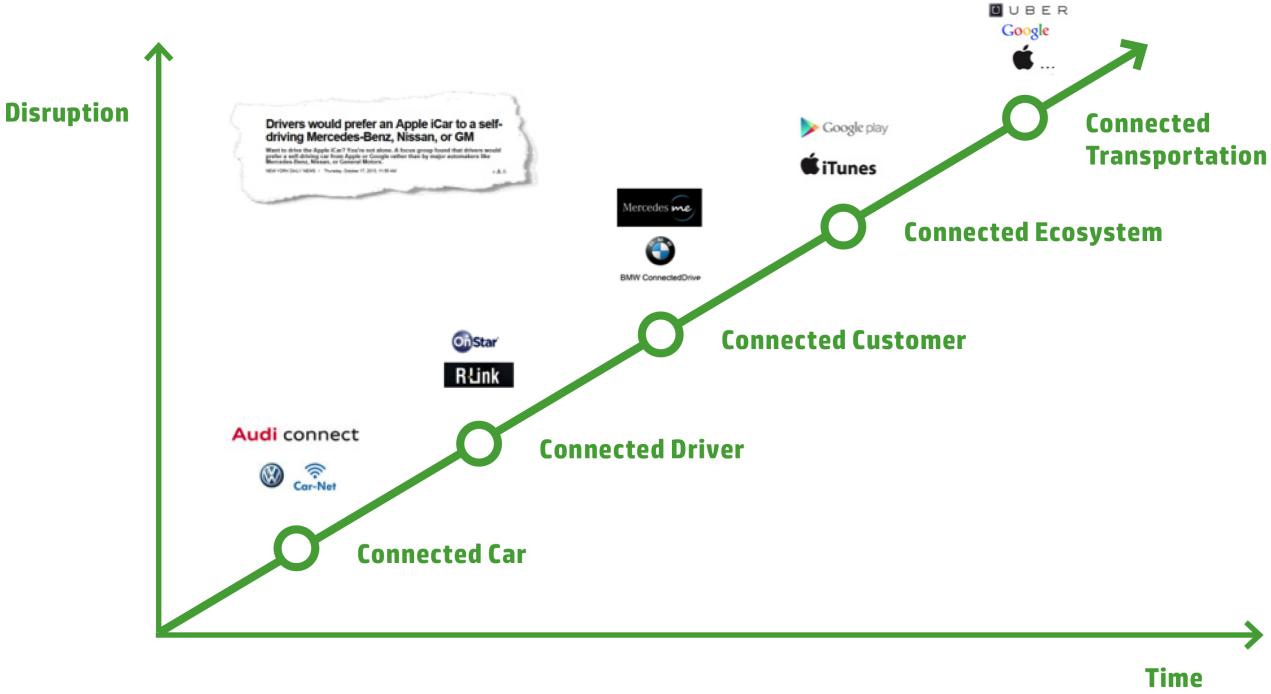

Figure 4.1.: Illustration of the disruption of the traditional automotive industry and the new competitors entering the market with new customer services Seiberth (2015).

over time due to connected services and the new competitors that already entered the market Seiberth (2015). The most important consequence resulting from this graph is the fact that the traditional automotive manufacturers are not illustrated as the most important service providers for transportation anymore. Fig. 4.1 shows platform providers, such as Uber, Google and Apple to be the most important companies in the area of connected transportation Seiberth (2015), while the traditional automotive companies are represented in the area of connected cars and customers. The study of Seiberth (2015) and the Fig. 4.1 show the automotive disruption and the need for the traditional automotive industry to change their service portfolio applying data driven business models.

In future, services will not only be offered by the dealers in the traditional way, but directly by the manufacturers due to connected services Hirsh et al. (1999); Seiberth (2015). The classical repair and maintenance business is just one example that will change in the future. Companies like Openbay or RepairPal (both based in the U.S.) are two representatives that already sell plug in devices online that read out failures from the car and thereby provide an optimized service plan based on the identified failures Singh (2015). Using a smartphone application, the next located dealer that is able to do this service is listed and the resulting costs are calculated, independent of the manufacturer. These facts make the need for new data driven business models obvious. Even more, it shows that also the traditional B2B business models of the automotive industries need to change towards direct B2C models Singh (2015). More than one third of the customers would prefer to buy a car online instead of going to a dealer for this process Mohr et al. (2014). This example shows that significant change will affect not only the after-sales sector but the whole value chain of the automotive industry Lao et al. (2015).

Further requirements come along that need to be addressed by companies in order to differentiate themselves from the competition. A business strategy is needed in order to identify the most relevant company data to focus on Acito and Khatri (2014); Davenport et al. (2001). The most relevant customers need to be known in order to ensure targeted marketing. Business decisions need to be supported and evaluated by company data. In consequence, data driven models are required to increase customer satisfaction Tallon (2013) and the profitability, in particular for the automotive industry. Individualized customer services will be one of the key differentiators. The traditional automotive industry

will disruptively turn into a service business Huang and Rust (2013) with the goal to fulfill the individual customer needs. Beside data driven business models, a sustainable customer understanding is of fundamental importance. The main concepts to ensure this customer understanding were presented in chapter 2. The resulting managerial implications were presented in chapter 4.1.

New service models can be derived from customer data Matthing et al. (2004); Saarijärvi et al. (2014) that were determined in chapter 2.4.2. Proactive customer campaigns can individually be derived. Therefore, perceived customer dissatisfaction indicators derived from technical data can directly be used, as shown in chapter 3.5. To realize individualized customer actions on demand, the customer care process must be fully transparent. The output of the data analysis must be transparent to those members of the company that are involved in the customer interaction process. Thereby, fastest and highest customer value can be generated. This transparency certainly yields less centralized steering capabilities but allows more individualized treatment and thus new service features to be adapted.

Specifically, this work provides concrete implications towards data driven business models in the automotive industry. First, the enhancements of the current perceived customer satisfaction determination were examined in chapter 2.7. Various components need to be considered, for instance sociodemographics Cooil et al. (2007), to find the best communication strategy. Regarding situational factors, for instance waiting time, the dealers would be able to identify the crucial customers that have the highest probability to get dissatisfied as a consequence. The benefit resulting from capturing the sociodemographics need to be mentioned in this respect, as worked out in chapter 2.7.3. Using this information, individually suited incentives may be offered that fit to potential customers' needs. Generally, precisely established determinants to capture customer perceptions are the basis for data driven service models.

Second, service encounter is known as the most relevant concept from literature review in chapter 2.4.4 and the empirical part that is based on the literature review in chapter 2.6.1. In particular, the communication aspect could be significantly improved. Furthermore, technical indicators for potential dissatisfaction are known from chapter 3.4. Based on this knowledge, dealers will be enabled to communicate to customers in a personalized way, especially in critical situations. Thereby, customers

still feel accepted and well-treated. Affected customers could be identified even before they return back to the dealer to get their car returned. For specific service failures, individual ways of communication could centrally be defined.

In order to be able to realize these benefits, several requirements need to be fulfilled. First, the collection of customer data and its kind of use must be transparent. Second, it must be secured that customers understand their own value resulting from the use of their data. Third, every involved party within the service interaction must be able to access the results and consequences of the data analysis. Examples are service advisors, technicians, staff at the counter or the central customer satisfaction units of the company. Fourth, findings from the service interaction need to be transferred back to the organization in oder to centrally improve service processes continuously. Fifth, the use of customer data should be flexible. Adaptations should be easily possible. Thereby, changing customer needs can be identified based on additional customer information that might get available and processes can be adapted accordingly.

Summarizing, the power of customer data and its need to create better services is clearly obvious. The more transparency about customers' needs is provided to the involved parties of a service interaction, the better customers can be satisfied. Consequently, knowledge about customer' perceptions is a key requirement to create competitive advantage. The approach developed by this work provides a possibility to map the most relevant subjective, customer perception determinants with objective, internal service process data. A data driven business model that directly arises from this approach allows to identify dissatisfied customers within an ongoing service interaction and second, identifying the main dissatisfaction indicators of a service process from a customers' perspective. This specific approach is the main contribution of this work.

5 Outlook

The findings of this work show a wide range of possibilities for the industry to increase the performance of customer services. The results are examined based on existing industrial technologies and processes that produce a vast amount of data. The trend towards digitalization of the service industry and in particular the automotive industry is more important than ever before as shown in chapter 1.2.3 and 4.2 and the reason for a paradigm shift regarding the customer relationship models. Until today, it is the dealer with direct customer interaction. Due to connected cars and digital services, this situation will change. The automotive industry will not only be the manufacturer of the tangible product but even more a service provider. This change result in the need for new business models towards the customer. In this final chapter, the opportunities resulting from this thesis are presented. Directions for further enhancements and open research questions are shown.

5.1 Possibilities for customer service enhancements arising from trend towards connected cars

The trend towards connected cars is undisputed and the resulting consequences for all included parties within the automotive industry are extensive. The amount of produced data is continuously growing. Current studies calculate 25 Gigabytes of data to be generated every hour within the actual modern car models Hansen (2015). For autonomous driving cars the amount of data is estimated to be 1 Gigabyte per second Mearian (2013). The new generated data is the basis for new possibilities. The main implications are given below:

- Individualized customer services: Beside the car itself, information about the customers driving the car and the locations around the car will be captured Hansen (2015). This offers a wide range of scenarios for new customer services. In particular, it is of significant importance to provide personalized services based on customer needs. One example is proven by latest studies, that more than 50% of the customers expect an pick-up of their car at their preferred destination that is arranged online Accenture (2015).

- Real-time services: New service offers can be realized based on continuously generated information about the status of cars due to connected services, such as condition based maintenance Mikusz et al. (2015). Business models that realize these services on the basis of service data need to be developed. Predictive maintenance is an application that is already established as a competitive advantage with the aircraft industry leading the way Nadarajan (2014).

- Downtime reduction and mobility maximization: Using sensor data offers the possibility to predict electronic failures within the car. Based on on-board diagnostic services, failures that may cause a potential breakdown of a car can be predicted Siegel et al. (2014). Such offers target the reduction of downtimes and maximize customers' mobility. Different companies of the automotive industry are working on these services already in different implementation stages Mikusz et al. (2015). Furthermore, suppliers offer tools to generate data and thus allow these services, such as OnStar or Openbay Siegel et al. (2014); Singh (2015).

- New safety features: The analysis of driving patterns and current locations can be used to increase safety conditions Lim et al. (2015). Thereby, "risk clusters" according to the type of driver can be calculated. Using these results combined with their current location, individualized routings can be calculated in order to minimize the probabilities for accidents. Especially in big cities the optimization of the traffic flow is another benefit beside improved safety.

The automotive industry gets disrupted Viereckl et al. (2015) as studies show. While traditional companies such as BMW or Volkswagen used to lead the automotive sector, new competitors will arise due to the trend

of digitalization. Within the next five years, individualized and significantly improved services arising from connected cars will be the main differentiator Mearian (2013); Viereckl et al. (2015). Furthermore, new features and customer services will arise, mainly in the following areas: Autonomous driving, safety, entertainment, drivers' health, mobility and vehicle management and integration into the complete digital ecosystem Viereckl et al. (2015). Consequently, existing automotive manufacturers need to invest significantly in digitalization and connected car solutions. For selected manufacturers this is already the case like the Volkswagen Group who initiated various digitalization labs, such as the Volkswagen Data:Lab Gehrke et al. (2016); Volkswagen (2014).

This work illustrates already available data, generated within the aftersales environment and second, the benefits arising from the use of this data. Determined customer perceptions can be matched with objective service process data, received from the dealers and cars. An in depth customer understanding is resulting from this joint data that is generating new knowledge. Thereby, the most accepted customer features which secures investments in the most promising services can be identified by the company.

Furthermore, data that is today still unknown will be generated by connected cars in the future. However, this data will generate new possibilities. An example is the revolution of the definition of mobility. Today, the automotive industry defines mobility by owning a car. However the future will be mobility as a service in semi-autonomous cars Janota and Spalek (2016). The quality of services and the personalization will be key success factors to differentiate automotive manufacturers in terms of profit and customer loyalty. These services will be based on combined data from connected cars, biometric data, health conditions, customer perceptions and many more Janota and Spalek (2016). Consequently, the ability to handle data in the most effective way will be a key element to generate competitive leads.

5.2 Limitations and further research

Based on the findings of this work, several new opportunities arise for the health care sector and the automotive industry. Generally, customer perceptions were identified to be one of the most important indicators to optimize customer services. Based on the knowledge transfer from the

health care sector, the key determinants of perceived customer satisfaction were defined. These should be continuously captured, for instance by questionnaires, in order to generate an encompassing customer understanding. This work presented a method to map subjective customer perceptions with objective service and process data within the automotive industry. Further research may be applied in order to transfer the findings to other service industries.

The following subsections provide an overview about open research that could be applied according to the findings of this work and the related industrial sectors. First, further research opportunities within the health care research, arising form the performed literature review, are presented. Second, open research within the automotive industry, based on the developed model to predict dissatisfied customers and identify the key indicators of dissatisfaction, is presented. Third, the open research that could be applied to the service industry in general is provided. Thereby, opportunities are presented to generalize the arising benefits from this work.

5.2.1 Further research within the health care sector

In this work, an encompassing literature review on the determination of perceived patient satisfaction has been performed. Based on the extracted information, the most important concepts required to measure satisfaction are known. This knowledge can be used to improve the determination within other service industries. However, in order to generate more insights for the health care sector, the following additional research is possible:

- Subjectively varying diseases: The health care sector would benefit from the application of combining subjective patient responses with objective data, according to chapter 3. Medical concerns that may vary with the individual patient perception are the main application fields. Tinnitus is chosen as an example, as the severity varies subjectively from patient to patient Cima et al. (2012); Crummer and Hassan (2004). Furthermore, there are objective consequences, such as hearing loss Crummer and Hassan (2004). There are various potential causes for Tinnitus, such as neurologic or metabolic diseases, that can objectively be measured. In order to secure the best medical outcome, subjective patient feedback about their perceived severity of Tinnitus is determined in

a first step. Therefore, existing questionnaires, such as the Tinnitus Questionnaire or the Tinnitus Handicap Inventory are commonly used Kamalski et al. (2010). Further research should make use of this historical patient feedback. Existing objective diagnostic results and resulting treatments of potential causes should be mapped to the patient feedbacks. The goal is to secure, the patient outcome and thus the perceived quality of life by using the subjective feedback as an input. Existing research focusing on the use of cognitive behavior as input for the medical is already available within the area of Tinnitus Cima et al. (2012). However, further research should investigate the application of the developed experimental design in chapter 3.3.5. Thereby, the objective features that are related to medical causes may be identified which have the highest chance for an optimized perceived treatment outcome. Furthermore, future research should not only focus on Tinnitus as a representative example, but on subjectively varying diseases in general.

- Patient specific communication: This work showed that mapping diagnostic results to perceptions allows a better communication. Compared to the automotive industry, a well established communication strategy towards patients is even more important within the health care sector. The better patients are integrated into the communication channel, the higher the perceived outcome Brody et al. (1989); LaVonne and Zun (2010); Sun et al. (2000). Further research should investigate how to generate an encompassing understanding about patients' preferred communication. This knowledge is of relevance, especially in order to communicate diagnostic results towards the patient Groves et al. (2013); Kvedar et al. (2014); Meinzer et al. (2017); Yarnold et al. (1998). Learning from historical patient feedback, the preferred way of communicating diagnostic results and explaining the next medical steps could be derived.

- Medical unit specific treatment: This work is predominantly concentrating on general patient perceptions that are relevant for most kind of medical institutions. In order to optimize the patient satisfaction determination to specific sectors, such as emergency departments or cancer ward, further specific determinants

should be examined. This would allow a better treatment within these specified care units on an individual level. Especially for middle and long-term treatments, like in palliative stations or rehabilitation centers, these specific determinants may play a highly significant role for high satisfaction of patients and their families. Further research should investigate how to derive the best treatment strategies for the individual medical units based on subjective patient outcomes.

- New data driven services: Every day vast amount of data is generated that can be used for new patient services, for example resulting from smart health devices Marr (2016). Further research should address how the get this data combined with existing patient information within the health care sector. The realization of additional patient offers should be analyzed. An example could be the treatment not in a clinical department but at home of the patients, for non critical treatments. Using connected devices and wearable technologies, services can be realized that allow to transfer for instance pictures of affected areas to a dermatologist for initial diagnosis Ratchinsky (2016). Summarizing, such new services will target to improve patients' comfort on the one hand and making medical treatments more effective on the other hand. However, only these patients that really benefit from such new services should be identified by subjective patient perceptions together with their specific expectations and medical needs.

5.2.2 *Further research within the automotive industry*

The developed approach of this work focuses on optimizing the performance of service processes in order to increase customer satisfaction. Therefore, data generated by service processes that are established already have been combined with subjective customer feedback from conducted surveys. The presented trend towards digitalization in section 5.1 results in recommendations for further research for the automotive industry.

- Services embedded in the car: Service processes will partly shift from dealers into cars. Service appointments, the replacement of

fixed service intervals defined by dealers with driving pattern analysis by the car, or individualized price offers are just three examples. These examples of services were tied to dealers, in future they will be directly result from the analysis of connected car data. As this work focuses on the processes at the dealer, further research should investigate the performance of new services embedded in the car along the value chain Gehrke et al. (2016). Features such as advanced driver assistance systems or concierge services should be analyzed regarding their customer value. Therefore, data that track the usage of these services can be combined with customer feedback using the developed method in this work. The perceived benefits of these new services can thereby be monitored. In consequence, adaptations can be done according the analysis of this combined dataset of subjective perceptions and objective use of services.

- Integration into digital ecosystem Hofmann and Meinzer (2018): External services such as the integration into the digital home ecosystem will play an important role. The combination of data arising from connected cars with smart thermostats can be one example. Combining location data with customer profiles of the smart home interface, the thermostat could recognize the car moving away from home and thus control the thermo-regulation accordingly. The presented methodology can be used to identify the preferred services customers want to ingrate into their connected cars. Further research should address this potential.

- Data partnering: The value of data from the automotive industry for other businesses should be analyzed. One example are the insurance companies. Today, several insurances already offer solutions to collect data from the cars and to match them to existing driver contracts. They offer individualized services and bonus programs for safe driving. Customer rates will thereby get cheaper in the most cases as the clients driving behavior and thus, the risk for insurance companies is more predictable. The automotive industry can benefit from this trend by offering individualized services in cooperation with these insurances. The automotive sector can be the provider of the information, such as driving patterns

received from connected cars. It is important to maintain customers' privacy but offer best rates to the customer at the same time. Furthermore, transparency about the information transfer of customer data and the purpose of analyzing this data towards the customer must be secured at any time. Customers need to see the benefit arising from such partnerships for themselves. Further research should address the determination of the relevant driving patterns needed to provide individualized insurance services at the best customer rates.

- Safety enhancements: Driver health assistance services may play an important role in the future. Brands such as Volkswagen will offer emergency functions (Volkswagen Emergency Assist) to alert medical services in case of accidents automatically Viereckl et al. (2015). Further research should identify the relevant data from the car and the driver that need to be available to medical services in emergency situations. Beside the most necessary first information, such as location data and amount of passengers in the car, hospitals would benefit from more details. Based on detailed driver information that are already available for the according automotive company, hospitals could map the medical histories to the affected drivers already before they are arriving at the emergency unit. Further research should investigate the usage of the consolidation logic from this work for this purpose.

5.2.3 *Further research within the service industry in general*

Findings from the health care sector and the automotive industry resulting from this work allow service industries in general to benefit. Further research is illustrated in the following areas.

- Cross-industrial use: The way of determining perceived satisfaction vary across different businesses. However, cross-industrial measures of customer satisfaction can be applied also for specific industries Gilbert and Veloutsou (2006). The well established and cross-industrial benchmark measures, such as he American and the European Customer Satisfaction Indexes (ACSI and ECSI) Deng et al. (2013); Fornell et al. (1996); Kristensen et al. (2000),

are useful but do not provide enough transparency regarding customer perceptions for management Gilbert and Veloutsou (2006). To ensure an encompassing customer understanding, this work identified three main concepts of perceived satisfaction determination for the health care sector and the automotive industry: Service encounters, situational factors and sociodemographics. Further research should address potential similarities and differences across the service industries, such as the hospitality, banking or telecommunication sector.

- Variation of styles for satisfaction determination: The influence of the type of survey, such as mailed, face-to-face or online questionnaires, should be investigated. In this work, classical questionnaires were used and analyzed in order to identify the main determinants of perceived customer satisfaction. However, results and thus the business impact of satisfaction determination may depend on the way the customer is surveyed. Therefore, future research should intensify the use alternative methods, such as face-to-face satisfaction determination. This observation should provide the insight about the generalizability of the identified main concepts (service encounters, situational factors and sociodemographics) and in consequence the independency of the type of surveying a customer across the different service industries.

- Enhancing internal customer knowledge by data consolidation: Today, the service industry owns several customer characteristics already for targeted marketing or to establish an efficient customer relationship model for example. Combining this internal customer information with subjective perceptions from surveys will provide additional value generally for the service industries. For instance call-centers benefit from this combination in real time while they talk to customers. Telecommunication providers already target to propose an individualized rate based on user profiles. Further research should address the identification of the most valuable customer information in order to understand their perceptions more thoroughly. The sources, respectively business areas where these information could already be available should be identified. Even more, ways to capture these data may be examined.

- Cross-industrial knowledge transfer in other businesses: The cross-industrial knowledge transfer is shown for the health care sector to the automotive industry. Future research should investigate more industries to enhance the determination of perceived satisfaction and to prove the generalizability. The studies need to be statistically investigated. Once the individual determinants within the three main concepts show comparable importance across different industries, for example expressed by the correlation or regression coefficient, the cross-industrial knowledge transfer in general could be proven.

A Feature selection results

A.1 Identified features from evolutionary feature selection based on aggregated data

Table A.1.: Results of evolutionary feature selection based on aggregated data.

Feature	Feature description	Feature Category
BAUREIHE = A	Car model is A	CHARACS
BAUREIHE = B	Car model is B	CHARACS
BAUREIHE = C	Car model is C	CHARACS
BAUREIHE = D	Car model is D	CHARACS
BAUREIHE = E	Car model is E	CHARACS
BAUREIHE = F	Car model is F	CHARACS
BAUREIHE = G	Car model is G	CHARACS
BAUREIHE = H	Car model is H	CHARACS
BAUREIHE = I	Car model is I	CHARACS
BAUREIHE = J	Car model is J	CHARACS
MOTORBAUREIHE = MB1	Engine is MB1	CHARACS
MOTORBAUREIHE = MB2	Engine is MB2	CHARACS
MOTORBAUREIHE = MB3	Engine is MB3	CHARACS
MOTORBAUREIHE = MB4	Engine is MB4	CHARACS
MOTORBAUREIHE = MB5	Engine is MB5	CHARACS
MOTORBAUREIHE = MB6	Engine is MB6	CHARACS
MOTORBAUREIHE = MB7	Engine is MB7	CHARACS
MOTORBAUREIHE = MB8	Engine is MB8	CHARACS
MOTORBAUREIHE = MB9	Engine is MB9	CHARACS
PRODUKTLINIE = COMPACT	Product line is COMPACT	CHARACS
PRODUKTLINIE = LARGE	Product line is LARGE	CHARACS
BEF_20	Repair group 20	WTY
BEF_50	Repair group 50	WTY
BEF_70	Repair group 70	WTY
DC5_10	Diagnostic group 10	DIAG
DC5_20	Diagnostic group 20	DIAG
DC5_30	Diagnostic group 30	DIAG
DC5_40	Diagnostic group 40	DIAG
DC5_50	Diagnostic group 50	DIAG
DC5_80	Diagnostic group 80	DIAG
DC_PART_00	Part group 00 from diagnostics	DIAG
DC_PART_20	Part group 20 from diagnostics	DIAG
DC_PART_30	Part group 30 from diagnostics	DIAG
DC_PART_60	Part group 60 from diagnostics	DIAG
DC_PART_70	Part group 70 from diagnostics	DIAG
DC_PART_90	Part group 90 from diagnostics	DIAG
DC_RESULT_0	Diagnostic result code 0	DIAG
DC_RESULT_2	Diagnostic result code 2	DIAG
DC_RESULT_4	Diagnostic result code 4	DIAG
FLAG_KEY	Key reader identifying flag	SOURCE
KULANZSTUFE = 3	Warranty stage 3	WGS
KULANZSTUFE = 4	Warranty stage 4	WGS
PRODUKTFELD_BDR	Product field BDR	CHARACS
PRODUKTFELD_OFI	Product field OFI	CHARACS
Wiederholer_BEF2	Repeat repair based on warranty	RR
Wiederholer_DC5	Repeat repair based on diagnostics	RR

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The automotive industry is in the middle of a disruptive change in which a competitive differentiation based on the car as a product itself is not sufficient anymore. Customer centricity is one of the most important management goals in this industrial sector. The consequence is a shift from a product-focused company towards a service provider where the car is just one element to achieve the target of maximum customer satisfaction. Understanding subjective customer perceptions in this complex service environment is the resulting challenge.

In order to achieve the highest outcome of a medical treatment perceived by the patients, patient centricity is the core focus of the health care sector since years. The determination of perceived patient satisfaction has been well researched and various measurement approaches exist.

This work focuses on the knowledge transfer of perceived satisfaction determination from the health care sector to the automotive industry. A case study has been conducted that illustrates the managerial implications and recommendations for improvement of the established customer satisfaction determination in the automotive industry. Each service process of a car is generating a vast amount of data. This work shows how to make maximum use of this value by answering these two questions: 1. Can dissatisfied customers be classified before the customer service interaction ends based on data that is produced during a service visit? 2. Can the indicators for dissatisfaction be derived from service process data? Based on the knowledge derived in this work, new data-driven service and business models can be developed for the automotive industry to really achieve customer centricity.

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