Master Thesis

Using text-mining-assisted analysis to examine the applicability of unstructured data in the context of customer complaint management

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Abstract

In quest of gaining a more holistic picture of customer experiences, many companies are starting to consider textual data due to the richer insights on customer experience touch points it can provide. Meanwhile, recent trends point towards an emerging integration of customer relationship management and customer experience management and thereby availability of additional sources of textual data. Using text-mining-assisted analysis, this study demonstrates the practicality of the arising opportunity with means of perceived justice theory in the context of customer complaint management. The study shows that customers value interpersonal aspects most as part of the overall complaint handling process. The results link the individual factors in a sequence of 'courtesy → interactional justice → satisfaction with complaint handling', followed by behavioural outcomes. Academic and managerial implications are discussed.

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1. Introduction

Companies operating within the telecommunication industry are facing a multitude of industry drivers, which they try to master on a daily basis. The drivers range from deregulation, to technology advances, to competition in general (Lee & Stewart, 2014). These drivers are dynamic by nature, which makes it difficult to maintain any competitive advantage that was previously achieved. In addition, when considering the net promoter score, which is a common customer loyalty metric, the industry average of the telecommunication industry ranks among the lowest overall (*Net promoter benchmarks report*, 2013). Consequently, a focus on improving customer experience can be a starting point for future advances with respect to the competitive position of a company.

Customer experience combines a number of facets that are all shaped through the offerings by a company, which can range from advertising and packaging to customer care and service performance (Meyer & Schwager, 2007). Thus, customer experience represents a central role for a variety of important company metrics. For example, customers infer their subsequent satisfaction from a series of experiences that result from using the services by a company (Maxham III & Netemeyer, 2003). In turn, customer satisfaction links to a variety of other outcomes such as word-of-mouth and trust (van Doorn et al., 2010). As a result, starting from the experience that is provided by a company to the customer an entire functional chain is put into motion. Improving the customer experience can ultimately influence loyalty and customer retention, which are essential prerequisites for a profitable brand positioning (Rust & Zaborik, 1993).

As part of the overall value creation process by a company, which is compiled through multiple company-customer interactions, potential customer experience improvements are dependent on the insights from frequent customer feedback (van Doorn et al., 2010). Companies are facing a mix of different kinds of customer feedback, which can be either structured and of quantitative nature or unstructured and of qualitative nature (Meyer & Schwager, 2007). For example, a study by Ordenes, Theodoulidis, Burton, Gruber, and Zaki (2014) analysed customer experience feedback from an airport car park and transfer service. Based on the information within textual data it was possible to gain a more holistic view of the underlying service process and to identify previously unknown improvement factors. For instance, management realised that a previous change in the park's name had caused service process failures and that customers were unable to find the designated parking spaces. Thus, once customer feedback is successfully organized and analyzed it can subsequently create value for a firm (van Doorn et al., 2010).

Data that resides within existing company systems can provide additional sources of information for companies. Furthermore, recent trends forecast an integration of customer experience management (CXM) into existing customer relationship management (CRM) structures (Goldenberg, 2013). CRM captures information on things like customer inquires and service requests, whereas CXM aims at capturing customers' opinions (Meyer & Schwager, 2007). The inherent textual data can thereby be of value as it may reveal novel insights by means of text mining methods. Although previous works have acknowledged the power of text mining analysis within the context of CRM and CXM (Chang, Lin, & Wang, 2009; Ordenes et al., 2014), overall text-mining-assisted analysis research specifically aimed at complaint management remains scarce. For example, an academic literature review by Ngai, Xiu, and Chau (2009) on the use of data mining techniques in CRM revealed that out of the relevant 87 selected articles only two linked to complaint management. Despite the fact that customer satisfaction is a well-researched topic in the context of service recovery (Bitner, Booms, & Tetreault, 1990; Smith, Bolton, & Wagner, 1999; Tax, Brown, & Chandrashekaran, 1998) to date research neglects the current changes that direct towards a more integrated approach of CRM and CXM (Goldenberg, 2013).

The purpose of the study is to help bridge the gap between CRM and CXM data by linking former research and recent developments in the realm of CRM with means of text-mining-assisted analysis. Correspondingly, the study aims at answering the research question: Can unstructured CRM and CXM data be used to infer succeeding customer evaluations within the context of complaint management? Moreover, additional sub-questions aim at investigating the influence of recovery attributes on perceived justice evaluations, the impact of perceived justice dimensions on customer satisfactions with complaint handling, and the relationship between customer satisfaction with complaint handling and behavioural intentions by the customer. It is expected that the findings on the initially unlinked and unexamined textual data contribute to the overall goal of gaining a more holistic view on customer experiences by building on recent developments within CRM. Consequently, improvements in customer experience and resulting practical implications can be achieved.

The study begins with a review of existing literature related to satisfaction with complaint handling including adjacent theories on behavioural outcomes, perceived justice, and recovery attributes. The corresponding hypotheses are derived along the studied literature. The methodology behind the study is presented in chapter three. Chapter four presents the empirical results from the data analysis. A discussion of the research findings including practical implications, limitations, and future research is presented in chapter five. Finally, chapter six presents the conclusion.

2. Literature review and theory development

The following section develops a model along with the corresponding hypotheses in order to describe the underlying relationships for customer satisfaction with complaint handling in the context of complaint management. The goal is to explain how selected recovery attributes (compensation, speed, courtesy) affect post-complaint behaviour intentions (continued use and positive word-of-mouth) by means of perceived justice and customer satisfaction with complaint handling. The model also incorporates various failure context conditions (total number of service encounters and service failure severity) and a moderating variable (complaint status).

2.1 Satisfaction with complaint handling and behavioural outcomes

Effective customer complaint handling and thus also satisfaction with complaint handling is a crucial opportunity for companies to influence future customer behaviour by rectifying preceding service failures (Bijmolt et al., 2010). Therefore, complaint handling has the power to transform dissatisfactory encounters into satisfactory ones through the creation of positive feelings (Andreassen, 2000; Bitner et al., 1990). Based on a subjective evaluation of emotions, satisfaction can be defined as a positive feeling of fulfilment that follows the evaluation (Andreassen, 2000). Although the construct of satisfaction has also been conceptualized as overall satisfaction (e.g. Karande, Magnini, & Tam, 2007), satisfaction with complaint handling (Tax et al., 1998) is commonly used for particular complaint handling experiences (Gelbrich & Roschk, 2011).

Customer satisfaction links to a variety of valuable outcomes that follow the initial complaint filing. If looked at from a profitability perspective, customer satisfaction is found to ultimately positively influence market share through increased loyalty and customer retention (Rust & Zaborik, 1993). The behavioural perspective offers a wide continuum that includes actions ranging from filing the complaint itself to recommendation to word-of-mouth to pure exit (van Doorn et al., 2010). Consequently, one can conclude that new customer experiences eventually lead to an adaptation of existing customer attitudes towards the respective company and their products or services depending on the quality of service recovery and the satisfaction with complaint handling. The following sections will focus on continued use and positive word-of-mouth as two potential outcomes of satisfaction with customer complaint handling.

Continued Use Continued use refers to the willingness of doing business with the company in the future after a service recovery occurred (Liao, 2007; Weun, Beatty, & Jones, 2004). It is one of the most important constructs when measuring customer behaviour on an intentional level as it offers an indication for future purchases by the customer (Gelbrich & Roschk, 2011; Orsingher, Valentini, & Angelis, 2010). Due to the distinct differences in customer satisfaction levels, which can be elevated or exacerbated in both directions (Bitner et al., 1990), subsequent customer behaviour also ranges from continued use to switching intentions and exit (Chih, Wang, Hsu, & Cheng, 2012). Numerous similar references are found in the literature including repurchase intent, loyalty (Ruyter & Wetzels, 2000), and return intent (Orsingher et al., 2010). Moreover, it is important to emphasize that commitment is only an attitudinal aspect and thus differs from customer engagement behaviours (Orsingher et al., 2010).

Similarly to most other behavioural intentions, customer satisfaction with complaint handling is found to have a positive relationship with continued use (Kumar Piaralal, Kumar Piaralal, & Awais Bhatti, 2014; Tax et al., 1998). Although Kau and Loh (2006) find support for the positive relationship, they also find that the impact on continued use is relatively low when compared to word-of-mouth behaviour and trust. Another study, investigating the relationship between satisfaction and switching intentions, found a significant negative relationship between these two variables (Chih et al., 2012). The results thereby indirectly contribute to the proof of the proposed relationship. The consistency across studies and various research setups leads to the following hypothesis:

H1: Satisfaction with complaint handling will lead to continued use.

Word-of-mouth Similarly to commitment, word-of-mouth (WOM) is also a customer behaviour that is frequently defined at the intentional level (Gelbrich & Roschk, 2011). WOM consist of two parts; the likelihood to spread information and the valence of the respective information (Davidow, 2003). Consequently, WOM can be constructed as the likelihood of either positive or negative WOM (Maxham III & Netemeyer, 2003). Furthermore, WOM can be a powerful tool for companies to lower the cost of customer attraction as well as improve the company's image (Anderson & Mittal, 2000), which can eventually positively affect company revenues (Bijmolt et al., 2010).

Research in the context of post-complaint behaviour and service recovery often links positive WOM to the antecedent satisfaction with complaint handling (Kumar Piaralal et al., 2014; Wirtz & Mattila, 2004). The results show that satisfied customers are more likely to engage in positive WOM than customer who are dissatisfied with the complaint handling (Gelbrich & Roschk, 2011; Kumar Piaralal et al., 2014). In other words, being satisfied with the complaint handling stimulates customers to share their positive experience with others and promote the company. Interestingly, when distinguishing between complainants and non-complainants, Kau and Loh (2006) find that complainants are more likely to engage in WOM than non-complainants. The study thereby emphasizes the importance of carefully handling customer complaints and paying extraordinary attention to the group of complainants. Overall, following hypothesis can be formulated:

H2: Satisfaction with complaint handling will lead to positive word-of-mouth.

Solved Complaint Another crucial aspect of customer complaint handling is the question whether the complaint has ultimately been resolved. Although customers might be satisfied with the handling of their complaint, the fact that it is not yet completely resolved might influence future behaviour and decisions. A study by Kolodinsky (1992), researching complaint behaviour, found that the probability of a complaint being solved was significantly positively related to the number of complaints by a respondent. The same study also found a significant relationship between the probability of a complaint being solved and future purchases. Hence, being dissatisfied with the primal complaint handling, but additionally being disappointed by unresolved complaints might exacerbate any effects on behavioural outcomes. Thus, the hypothesis reads as follows:

H3: Complaints with the status 'solved' moderate the relationship between satisfaction with complaint handling and behavioural outcomes.

2.2 Perceived justice and satisfaction with complaint handling

With respect to the antecedents of satisfaction with complaint handling, justice theory has been used in marketing for investigating service encounters in situations of both service failure and recovery (Orsingher et al., 2010). While the theory of justice originated in social psychology (Adams, 1965), the concept has been applied in several contexts including organizational and legal context (e.g Greenberg, 1990). The theory is based on the notion of balance that should exist in the relation between the company and a customer. Exchanges that are being made as part of a service encounter will lead to imbalance if the interaction is unsatisfactory or the outcome is not perceived as appropriate by the customer (Chebat & Slusarczyk, 2005).

Despite occasional deviations, for example conceptualizing justice theory based on a monistic perspective (Liao, 2007) or the inclusion of informational justice (Nikbin, Ismail, & Marimuthu, 2013), in research justice theory is most often conceptualized with three dimensions of distributive, procedural and interactional justice (Chebat & Slusarczyk, 2005; Orsingher et al., 2010). Moreover, the characteristics of justice theory enable the linkage to customer satisfaction with a particular complaint handling incident, as customers tend to assess the actual complaint handling performance with respect to their prior expectations (Orsingher et al., 2010; Tax et al., 1998). Hence, if customer expectations are not being met, this will negatively affect subsequent evaluations by customers.

Due to the comprehensive nature of justice theory, it is suitable for examining complaint handling across various procedural stages ranging from initiation to completion (Tax et al., 1998). Individuals are thus enabled to assess both the outcome of a filed complaint and the underlying process, which aims at resolving the conflict (Conlon & Murray, 1996). Consequently, the present study uses justice theory in order to investigate the applicability of text-mining tools in the context of complaint management on the grounds of the theory's established validity and applicability.

Distributive Justice Among the three different dimensions of perceived justice, distributive justice is the only dimension specifically referring to the outcome of an exchange (Gelbrich & Roschk, 2011). The outcome in this context is an equation of rewards and losses that are weighted against any investments that have been made. If the relation between two such ratios is perceived as unbalanced then a feeling of injustice arises from the exchange (Adams, 1965). It is therefore important for companies to prevent any feeling of injustice in order to prevent negative customer evaluations. Coupons, reimbursements (Conlon & Murray, 1996), or the replacement of the good or service (del Río-Lanza, Vázquez-Casielles, & Díaz-Martín, 2009) are some of the examples of how companies can try to restore distributive justice towards their customers.

If done successfully, numerous empirical studies showed that this will result in a positive effect on the satisfaction with complaint handling (Homburg & Fürst, 2005; Smith et al., 1999). Moreover, distributive justice is often found to exert the most significant relationship with complaint handling satisfaction (Homburg & Fürst, 2005; Orsingher et al., 2010). However, there are also studies that find a weaker correlation of the relationship between distributive justice and complaint handling satisfaction (del Río-Lanza et al., 2009). Consequently, customers perceive outcomes as either fair or unfair. While favourable outcomes are perceived as fair and lead to higher satisfaction, unfavourable outcomes that are perceived as unfair lead to lower satisfaction with the complaint handling process (Andreassen, 2000). This leads to the following hypothesis:

H4: Perceived distributive justice will lead to higher satisfaction with the complaint handling process.

Procedural Justice In contrast to distributive justice, procedural justice "concerns the way that decisions are made rather than the nature of those decisions themselves" (Lind & Tyler, 1988, p. 5). Processes also include complaint handling policies and rules that are used by a company to solve customer complaints (Smith et al., 1999). Due to the fact that procedural justice looks beyond outcome measures, it is particularly valuable when researching customer journeys in its entirety, as it adds valuable insights to the overall understanding of customer journeys. Procedural justice within the complaint handling process refers to the cost of effort and time invested by the customer before a complaint is resolved (Chebat & Slusarczyk, 2005). On a more detailed level, Tax et al. (1998) identified several other elements relevant for complaint evaluation, which include convenience, flexibility and control over the process, as well as easy access.

Chebat and Slusarczyk (2005) found in their study on perceived justice that the factor of timeliness is one that acts as a basic requirement in service recovery situations. Consequently, customers are expecting a speedy handling of their complaint. But there are also numerous studies that prove a self-contained positive effect of perceived procedural justice on satisfaction with complaint handling (e.g. Kau & Loh, 2006; Wirtz & Mattila, 2004). In other words, if customers need to deal with time-consuming and complex processes this will eventually also affect the satisfaction with complaint handling. Thus, the corresponding hypothesis is formulated as follows:

H5: Perceived procedural justice will lead to higher satisfaction with the complaint handling process.

Interactional Justice Closely related to the procedural justice is interactional justice, which refers to the enactment of the complaint handling procedure (Bies & Shapiro, 1987). Together with procedural justice it is therefore also part of the process dimension (Kumar Piaralal et al., 2014). At the centre of interactional justice is the quality of interpersonal treatment and communication (Greenberg, 1990) and the perceived fairness of the employee behaviour that customers experience (Homburg & Fürst, 2005). With respect to the company-customer relation, there are several factors influencing the interactional justice that is perceived by the respective customer. Examples of these factors are politeness and employee’s empathy perceived by the customer (Orsingher et al., 2010) as well as the willingness to achieve service failure recovery (Homburg & Fürst, 2005). Additionally, the appropriateness of the language used during the conversation can also impact interactional justice (Chebat & Slusarczyk, 2005).

In line with the other two justice dimensions, interactional justice is also found to have a positive effect on satisfaction with complaint handling. Hence, the interaction with customer service represents a direct touch point with the company that is being evaluated by the customer. Although inferior to the effect size of distributive justice, Smith et al. (1999) prove a positive relationship to satisfaction with service encounter across two different studies. In addition to a joint effect of perceived justice on service recovery satisfaction, Wirtz and Mattila (2004) also demonstrate the effectiveness of interactional justice (e.g. an apology) for recovery strategies that are targeted at satisfying customers in a timely manner. Consequently, it is hypothesized:

H6: Perceived interactional justice will lead to higher satisfaction with the complaint handling process.

2.3 Recovery attributes and perceived justice

Although the various customer reactions (e.g. post-complaint behaviour and justice perceptions) have been subject to numerous studies in the past, relevant antecedents are often being ignored (Maxham III & Netemeyer, 2003; Tax et al., 1998). Thereby, the potential value of analysing the immediate recovery phase and the generated social and economic interactions between a company and a customer is neglected (Miller, Craighead, & Karwan, 2000; Smith et al., 1999). In order to account for the effect of social and economic interactions of service failure processes (Smith et al., 1999), some studies include organizational responses and recovery attributes, which refer to the reactions by a company (Conlon & Murray, 1996; Smith et al., 1999). Although the number of categories varies across studies, a higher order construct of three categories covering characteristics of timeliness, compensation, and employee behaviour is commonly found to have empirical relationships with customer perceptions (Estelami, 2000; Gelbrich & Roschk, 2011). Thus, customers take these characteristics into account when evaluating their overall customer service experience. Consequently, the present study examines the influence of three different recovery attributes (compensation, promptness, and courtesy) on perceived justice evaluations (Tax et al., 1998).

Compensation Compensation refers to the types of financial indemnification that customers receive in order to indemnify incurred losses (Lariviere & Vandenpoel, 2005).

Compensation can have the form of discounts, coupons, product replacements, refunds, or similar measures (Conlon & Murray, 1996). The goal of the company is to restore the customer's confidence in the firm that was damaged as a result of a perception of loss by the customer (Estelami, 2000). Research shows that the recovery attribute compensation is associated with perceived distributive justice (Tax et al., 1998). Therefore, compensation affects the outcome of the exchange, which results in the following hypothesis:

H7: Compensation will lead to a higher level of perceived distributive justice.

Promptness Within customer complaint handling processes the issue of timing is another important recovery attribute. Promptness refers to the speed by which a service failure was recovered (Lariviere & Vandenpoel, 2005). In the case that customers file a complaint due to a perceived failure by the company a slow recovery can reinforce the initial negative picture of the company and add to the level of dissatisfaction (Bitner et al., 1990). Promptness can further be extended to the efficient control of complaint handling processes (Gelbrich & Roschk, 2011). In addition, the consequent link with procedural justice is empirically tested (Tax et al., 1998) and proves the importance of timely complaint handling with respect to process evaluations. Thus, the hypothesis reads as follows:

H8: Promptness will lead to a higher level of perceived procedural justice.

Courtesy Courtesy acts as a higher order construct for various employee behaviour characteristics that can be identified during the interpersonal communication (Davidow, 2003). Examples for employee behaviour are empathy, politeness, and informative behaviour (Estelami, 2000). With regard to perceptions of fairness, it is found that the presence of explanations for the service failure has a positive effect (Bies & Shapiro, 1987). Moreover, apology is found to have a positive relationship with interactional justice (Ruyter & Wetzels, 2000; Smith et al., 1999). Employee behaviour characteristics are important elements when evaluating the interactions with customer service, which leads to the following hypothesis:

H9: Courtesy will lead to a higher level of perceived interactional justice.

2.4 Boundary conditions for effectiveness of recovery attributes

Although the aforementioned recovery attributes are hypothesized to individually influence customers' justice perceptions as well as several behavioural outcomes, there are also additional factors that indirectly alter the effects of recovery attributes.

Total number of service encounters In research the total number of service encounters can be examined in numerous ways. Low, Lee, and Lian (2013) for example found proof of a moderating effect of transaction frequency on loyalty and the tolerance of service failure. According to Tax et al. (1998) poor complaint handling can be mitigated by prior positive experiences. In the context of granting recovery voice, results by Karande et al. (2007) show a greater impact of recovery voice on perceived procedural justice with longer customer transaction histories. Additionally, the length of a relationship can also alter customer engagement behaviour and customer satisfaction over time (van Doorn et al., 2010). Although transaction frequency and the overall length of a relationship are found to generate higher levels of service failure tolerance (Low et al., 2013), the commonly negative nature of customer service encounters should lead the opposite relationship with lower service failure tolerance over time. Thus, the hypothesis reads as follows:

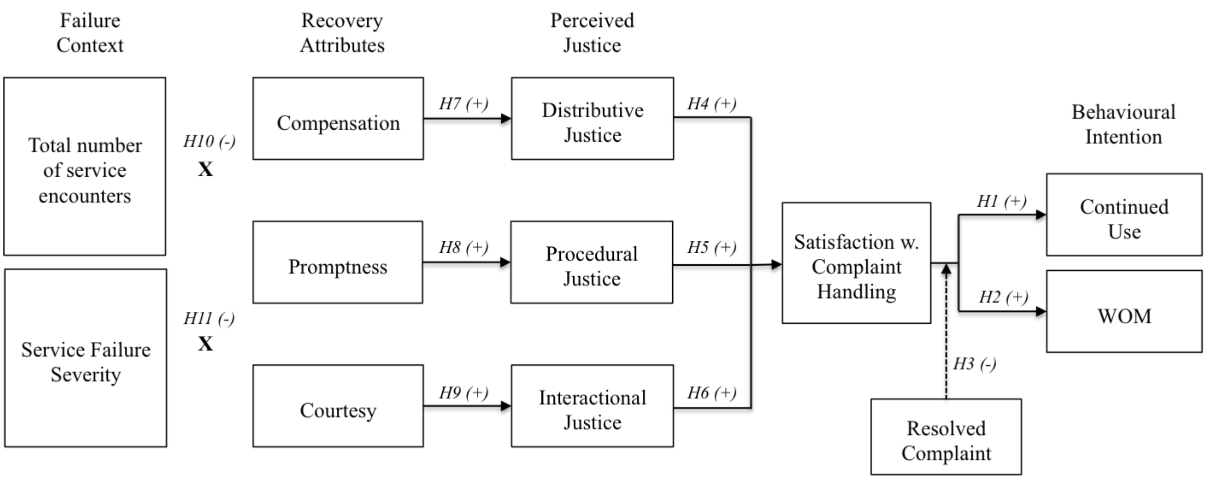
H10: A greater number of service encounters will lower the positive effect of recovery attributes and perceived justice evaluations.

Service Failure Severity Because customer evaluations of complaint handling experiences differ with the magnitude of failure, service failure severity represents another boundary condition that should be taken into account (Liao, 2007). Several studies found support for the moderating effects of service failure severity (Kumar Piaralal et al., 2014; Smith et al., 1999; Weun et al., 2004). A study by Conlon and Murray (1996) researched problem severity by using the measure of product price and their results showed a negative relation to satisfaction with the explanations by the company and repurchase intention. This shows that for example the effect of explanations provided differs across different service failure severity levels and is thus limited. Because in the context of customer complaint handling it can be assumed that not all incidents are equally severe (Lariviere & Vandenpoel, 2005), it is hypothesized:

H11: Increased service failure severity will lower the positive effect of recovery attributes and perceived justice evaluations.

Figure 1 is a representation of the underlying processes that are part of service recovery and complaint handling. The figure summarizes all relevant variables and their hypothesized interactions in accordance to their development in chapter 2.

Figure 1 Research model



Note: WOM = word-of-mouth

3. Method

The research was initiated in collaboration with a major German telecommunication company. The marketing department of the company provided the data for conducting the research. The data set consisted of secondary data that was gathered prior to the research (between 2012 and 2013) and combined two different internal sources of data: internal customer relationship management (CRM) system and customer feedback questionnaires. In order to ensure the usefulness of the data both the information and sample quality were checked (Blumberg, Cooper, & Schindler, 2011).

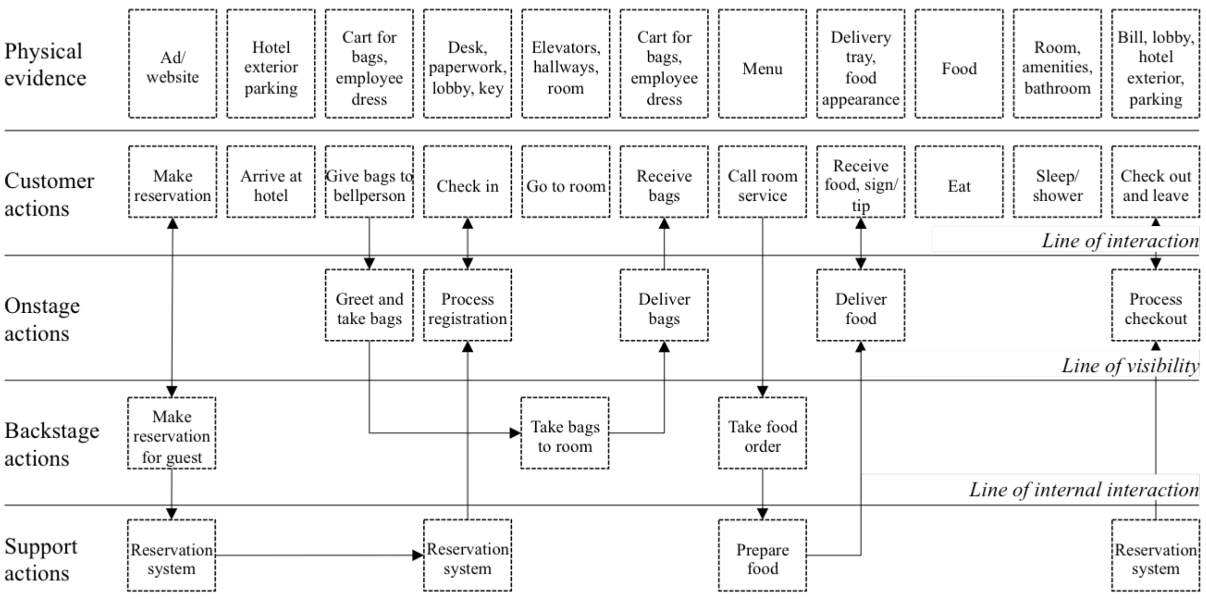
Although the data was investigated previously, it was decided to use the data for another research based on two main arguments. First, the data set links two previously separate data sets, thus making it possible to combine collected data from the internal CRM system with the customer experience management (CXM) system. The approach is in line with recent developments, which advocate a shift in focus from CRM to one that manages customer experience holistically as part of their integration (Ab Hamid & Akhir, 2013; Goldenberg, 2013). Second, both data sets include unstructured data that originate from open text fields and thereby allows the use of text-mining-assisted analysis for information extraction (Ordenes et al., 2014). In contrast to structured data that results from standardized customer feedback questionnaires and thereby primarily measures predefined dimensions (Caemmerer & Wilson, 2010), rich textual data enables the extraction of more in-depth information (Khare & Chougule, 2012).

3.1 Context

With regard to the topic of service recovery, the telecommunication industry was the industry of choice for numerous research studies in the past (e.g. Chih et al., 2012; Kau & Loh, 2006). Setiawan (2014) used text mining to measure customer satisfaction based on data from social medium Twitter. The research method enabled him to make inferences on the service quality of telecommunication companies. Iwashita, Shimogawa, and Nishimatsu (2011) proposed a classification technique in order to analyse customer enquiries that were stored by agents of a telecommunication company. As a result, it was possible to efficiently analyse large amounts of unstructured textual data. The examples show that text mining can be of great value when analysing unstructured textual data by providing additional insights. However, when analysing an industry such as the telecommunication industry it is important to keep in mind the structural factors that characterize an industry. Examples of structural factors can be contracts, switching costs, and the availability of alternatives, which can influence behavioural customer intentions (Kau & Loh, 2006; Tax et al., 1998) and are present in the context of most telecommunication services. Switching costs for example are able to positively influence repurchase intentions despite a relatively low level of customer satisfaction (Jones, Mothersbaugh, & Beatty, 2000). Hence, the characteristics of the industry play an important role for any conclusions to be made.

As part of the research a specific focus was put on complaint handling, which represents one of the many services typically provided by a telecommunication company. The interactions with customers are not limited to one particular instance, but instead service providers are subject to multiple interactions with customers over time (van Doorn et al., 2010). Furthermore, those interactions vary with respect to their importance. For example, companies whose core part of the offering is a service need to pay particular attention to their service interactions in general (Meyer & Schwager, 2007). Consequently, in order to provide high-quality services it is crucial to be aware of all touch points that a particular service consists of. At each individual touch point customers make a comparison between their prior expectations and the actual experience, which ultimately leads to customer satisfaction or dissatisfaction (Meyer & Schwager, 2007). One way to visualize customer-company interactions is by means of service blueprints, which separate a service process into individual structural elements (Shostack, 1987). The technique provides a visible overview of often times complex service processes (Shostack, 1987). Figure 2 is an exemplary representation of a service blueprint for an overnight hotel stay (Bitner, Ostrom, & Morgan, 2008). The figure illustrates the respective touch points in simplified terms and differentiates between the visible and invisible layer, thereby highlighting the complexity of many services. Similarly, the overall complaint handling experience and consequent service recovery is a process of multiple interactions that trigger discrete outcomes (Tax et al., 1998). For companies operating in the context of services it is therefore important to keep in mind that the customer's overall experience is a sum of multiple contact points. As a result, it is difficult for companies to improve customer experience in a targeted fashion.

Figure 2 Exemplary service blueprint for overnight hotel stay. Adapted from Bitner et al. (2008, p. 9)



3.2 Sample and procedure

The sample provided by the company combined two different sets of data. The first source consisted of a total of 1,893 customer service entries that were extracted from the internal CRM system. An agent originally entered the data as part of customer enquiries, which were made via various channels (i.e. in-store and by correspondence), but mainly through the company's customer service hotline. Although the input by an agent is based on some general guidelines that specify required information for input, the actual description still varies a lot between individual agents (Iwashita et al., 2011). It is important to note that the data does not provide a complete transcript of the conversation between the customer and the agent. Instead it is a personal summary by the agent, which describes the specific customer enquiry and the actions that were taken in response. For instance in one specific case the agent noted that he called back the customer upon their request, informed the customer that there were no news regarding the current enquiry, and asked the customer for patience. Consequently, the available information is limited to the actual input of the agent.

The second source consisted of a total of 299 customer feedback questionnaires, which the company collected through a survey method in order to monitor the quality of their complaint handling practices. Several studies made use of a survey method in order to examine service recovery (Kau & Loh, 2006; Kumar Piaralal et al., 2014) and thus proving its applicability. All questionnaires had been sent out to customers six weeks after a complaint was recorded within the company systems. Thus, the fact that a complaint was filled represents a precondition for all questionnaires used in this research. Moreover, the sample depicts a subsample of the original sample, because the selected customer feedback questionnaires represent the 299 customer feedback questionnaires with lowest customer satisfaction ratings. Although the use of a non-probability sample prohibits inferences about the general population (Blumberg et al., 2011), it does not compromise the objective of the research. First, the development of accurate effect sizes can be neglected because the research employs individual scales instead of common scales for most of the variables and focuses on proving their positive or negative effect (Blumberg et al., 2011). Second, a focus on the most negative evaluations may lead to better insights on the specific cases studied. The customer feedback questionnaires consisted predominantly of structured data as Likert-type questions were employed on a five-point scale. In order to account for the restricted sample all relevant discrete variables were dichotomized with a median split, which resulted in high/low groups for each variable (MacCallum, Zhang, Preacher, & Rucker, 2002). Moreover, the data set also provided textual data, as one of the relevant questions asked customers to describe negative aspects relating to the handling of their complaint.

In order to transform the textual data into numerical data the process of content analysis was used, which establishes a framework based on measurable and quantifiable categories (Chang et al., 2009). Thus, content analysis enables both valid and replicable inferences from the textual data (Krippendorff, 1980). First, the available data within both sources was screened and selected based on the research objectives. All CRM data entries were restructured in order to conform to the structure of customer feedback questionnaire data. Additional data cleansing further improved the quality of the data and resulted in a final sample of 273 unique customer feedback questionnaires, which could be matched with an average of about four CRM data entries (total of 1,068) for each customer. Second, all textual data was coded based on the themes and theories identified. As part of the prescriptive analysis individual dictionaries with keywords were created manually for each of the respective variables (Blumberg et al., 2011). Because of the limited size of the two data sets, Microsoft Excel software was used for the coding process. Third, all relevant variables were imported into IBM Statistical Package for Social Science Statistics for statistical analysis.

The statistical analysis was conducted by means of binary logistic regression in order to assess the hypothesized relationships. This type of model was applied due to the fact that all dependent variables, which are part of the research study, are dichotomous variables as they were dummy coded prior to analysis. In comparison to other types of analysis for categorical dependent variables (i.e. discriminant function analysis or logit analysis) logistic regression is generally employed for predictor variables that are a combination of both categorical and continuous variables (Wuensch, 2014). The resulting function indicates the probability that the studied subject will end up in the respective category (Wuensch, 2014).

3.3 Measures

The majority of the variables were coded as dummy variables, thus taking values of 0 or 1. The reason behind this decision originates from the nature of researched constructs, which represent either high or low conditions of categories or the presence or absence of categorical dimensions. Only one variable (total number of service encounters) was measured as a discrete variable. Table 1 presents an overview of all variables used in this research along with their corresponding labels and description. Due to the fact that both the data from CRM as well as from the customer feedback questionnaires was recorded in German, the dictionaries were also generated in German (see appendix A for a list of dictionaries). Additionally, one element of textual data, both within CRM and customer feedback questionnaire data, was the source for multiple variables and several dimensions of theoretical constructs.

Table 1 List of variables

Description	Label
Independent Variables	
Total number of service encounters	SEN
Service failure severity (where 0 = low and 1 = high)	SEV
Compensation (where 0 = not offered and 1 = offered)	CMP
Promptness (where 0 = complaint forwarded and 1 = complaint not forwarded)	PRT
Courtesy (where 0 = not present and 1 = present)	CRT
Solved complaint (where 0 = complaint not solved and 1 = solved complaint)	SOC
Dependent Variables	
Distributive justice (where 0 = not achieved and 1 = achieved)	DJUST
Procedural justice (where 0 = not achieved and 1 = achieved)	PJUST
Interactional justice (where 0 = not achieved and 1 = achieved)	IJUST
Satisfaction with complaint handling (where 0 = low and 1 = high)	SATCOM
Continued use (where 0 = no probability and 1 = probability of future commitment)	CON
Word-of-mouth (where 0 = no probability and 1 = probability of future positive word-of-mouth)	WOM

Behavioural intention Both continued use as well as word-of-mouth (WOM) are based on the original customer feedback survey, which employed a five point Likert-scale for their measurement. In order to account for the range restrictions of the sample the variable was dichotomized with a median split. Consequently, for continued use the value 0/1 represents a low/high probability for the future use of the company's products and services based on the experience by the customer. For WOM the value 0/1 represents a low/high probability for recommending the company to friends and acquaintances based on the experience by the customer.

Satisfaction with complaint handling Satisfaction with complaint handling is based on the original customer feedback survey, which employed a five point Likert-scale for measurement. In order to account for the range restrictions of the sample the variable was dichotomized with a median split. Consequently, the value 0/1 represents a low/high satisfaction with the experience with respect to the complaint.

Perceived justice All dimensions of perceived justice and the respective variables are based on the original customer feedback survey, which asked customers to describe negative aspects relating to the handling of the complaint. Separate dictionaries were used for each justice dimension in order to code dummy variables that represent the non-fulfilment/fulfilment of the respective dimension. Because the original question asked for negative aspects of the complaint handling, it was assumed that customer comments relating to a specific justice dimension manifest its non-fulfilment and were therefore coded with 0. Similarly, customer comments neglecting a specific justice dimension manifest its fulfilment and were therefore coded with 1. The dictionary for distributive justice consists of words that relate to the outcome of the exchange, including coupons and various forms of reimbursements (Conlon & Murray, 1996; Gelbrich & Roschk, 2011). The dictionary for procedural justice is a collection of words that relate to both the time and effort invested by the customer as part of the complaint (Chebat & Slusarczyk, 2005). The dictionary for interactional justice consists of words that describe the interpersonal treatment and communication (Greenberg, 1990), including aspects of politeness, employee's empathy (Orsingher et al., 2010), and explanations (Bies & Shapiro, 1987).

Recovery attributes The variables that are used to represent the selected recovery attributes originate from textual data entries by the agents within the company CRM system. All variables are dummy coded with values of 0/1, which represent the absence/presence of the respective recovery attribute, and employ separate dictionaries. The dictionary for compensation combines various forms of financial indemnification (Lariviere & Vandenpoel, 2005), including coupons, discounts, refunds, and product replacements (Conlon & Murray, 1996). Although the variable promptness refers to a speedy handling of the complaint (Lariviere & Vandenpoel, 2005), its dictionary consists of words that describe situations where the complaint processing was postponed or internally forwarded. Consequently, for this variable the coding was reversed in order to match the direction of the other two variables. The dictionary for courtesy consists of words that describe positive aspects of employee behaviour like politeness, empathy, informative behaviour (Bies & Shapiro, 1987; Estelami, 2000), and apology (Smith et al., 1999).

Total number of service encounters The number is based on the original customer feedback survey, which employed a question asking about the total number of times the customer made contact with company regarding the complaint. Although this discrete variable relies on customer judgement, internal company investigation proved that the responses represent a valid measurement. Moreover, including the total number of service encounters complements the research objective of accomplishing a holistic view.

Service failure severity The variable service failure severity was generated based on the textual data entries by the agents within the company CRM system. In order to enable judgements about the service failure severity a list of originally 47 company-specific words was rated on a seven point Likert-scale (1 = extremely low to 7 = extremely high) by two experts from the company with respect to the level of severity. The underlying assumption is that certain company-specific processes or databases are more likely to be used in severe complaint cases than others. Moreover, the inclusion of domain information can improve the effectiveness of text mining (Ordenes et al., 2014). Because inter-rater agreement was low (Cohen's Kappa coefficient of -0.93, see appendix B), it was decided to select only words that have been rated to signal high severity by both raters. The respective dictionary was then used to develop a dummy variable with values of 0/1, which represent the absence/presence of at least one highly severe company-specific word.

4. Results

The results of the study are presented in the same order as the hypotheses were developed within the literature review and theory development. Inter-correlations and descriptive statistics including mean values and standard deviations are presented in table 2. The magnitude of the correlation coefficients indicates a low correlation between the independent variables. The results of the binary logistics regression analyses are presented in this chapter.

Table 3 Binary logistic analysis for continued use (H1, H3)

Variable	B	S.E.	Wald	Sig.	Exp(B)
SATCOM	1.410	.391	13.028	.000	4.097
SOC	.854	.325	6.920	.009	2.348
SATCOM x SOC	-.625	.578	1.170	.279	.535
Constant	-.791	.207	14.642	.000	.453
Omnibus Chi-Square (df=3, Sig.=.000)	25.491		Cox & Snell R Square		.096
Hosmer-Lemeshow (df=2, Sig.=.000)	1.000		Nagelkerke R Square		.129

Table 4 Binary logistic analysis for word-of-mouth (H2, H3)

Variable	B	S.E.	Wald	Sig.	Exp(B)
SATCOM	1.912	.396	23.299	.000	6.769
SOC	.826	.334	6.102	.014	2.285
SATCOM x SOC	-.932	.568	2.689	.101	.394
Constant	-1.219	.223	29.835	.000	.295
Omnibus Chi-Square (df=3, Sig.=.000)	37.316		Cox & Snell R Square		.131
Hosmer-Lemeshow (df=2, Sig.=.000)	1.000		Nagelkerke R Square		.177

Influence of satisfaction with complaint handling on behavioural outcomes The results for testing hypothesis 1-3 are presented in table 3 and 4. The hypotheses 1 and 2 predicted that both continued use and positive word-of-mouth (WOM), which are used as indicators for behavioural intentions by the customers, are positively influenced by satisfaction with complaint handling. The omnibus test of model coefficients for both analyses report significant chi-square values (p-value of 0.000), thereby indicating significant effects for the combined predictors. Moreover, the models classify 63.9 % (for continued use) and 69.3 % (for WOM) of cases correctly. The results indicate a positive relationship with continued use

Table 2 Inter-correlations and descriptive statistics

	SEN	SEV	CMP	PRT	CRT	DJUST	PJUST	IJUST	SATCOM	CON	WOM	SOC	Mean	SD
SEN	1.00												7.71	8.56
SEV	.21	1.00											.18	.38
CMP	.08	.10	1.00										.18	.39
PRT	-.21	-.34	-.15	1.00									.73	.45
CRT	.06	.19	.12	-.20	1.00								.60	.49
DJUST	.03	.05	.00	.01	.01	1.00							.83	.38
PJUST	.01	.03	-.02	.05	.00	.02	1.00						.35	.48
IJUST	-.17	.02	.08	-.02	.03	.10	-.34	1.00					.33	.47
SATCOM	-.10	-.01	-.04	.09	.04	.01	.04	.15	1.00				.32	.47
CON	-.07	-.07	-.10	.00	-.01	.05	-.02	.02	.27	1.00			.48	.50
WOM	-.09	-.05	-.06	.06	-.11	.10	.02	.09	.35	.33	1.00		.41	.49
SOC	.09	.08	.00	.06	-.01	.14	.08	-.09	.13	.18	.14	1.00	.41	.49

Note: N=272; correlations greater than .12 are statistically significant (p>.05) and WOM with significance at the 0.01 level and thereby providing support for hypotheses 1 and 2. Consequently, high satisfaction with the complaint handling increases the likelihood of the two behavioural outcomes by a factor of 309.7 % for continued used and 576.9 % for WOM. Hypothesis 3 predicted a moderating effect by the status of the complaint on the relationship between satisfaction with complaint handling and behavioural outcomes. The results indicate that the interaction variable is not significant (p-value of 0.279 for the dependent variable continued use and 0.101 for the dependent variable WOM), which provides no support for hypothesis 3. However, table 3 and 4 also indicate a significant positive relationship of the status of the complaint with the two behavioural outcome variables at the 0.05 level.

Table 5 Binary logistic analysis for satisfaction with complaint handling (H4, H5, H6)

Variable	B	S.E.	Wald	Sig.	Exp(B)
SEN	-.012	.021	.350	.554	.988
SEV	.063	.537	.014	.907	1.065
DJUST	.001	.351	.000	.997	1.001
PJUST	.374	.298	1.573	.210	1.454
IJUST	.730	.299	5.960	.015	2.076
SEN x SEV	-.005	.041	.017	.897	.995
Constant	-1.048	.391	7.168	.007	.351
Omnibus Chi-Square (df=6, Sig.=.251)		7.828		Cox & Snell R Square	.029
Hosmer-Lemeshow (df=8, Sig.=.639)		6.075		Nagelkerke R Square	.040

Influence of perceived justice on satisfaction with complaint handling Table 5 shows the results for hypotheses 4-6, which predict higher levels of satisfaction with the complaint handling for cases with established distributional justice, procedural justice, or interactional justice respectively. Although the omnibus test of model coefficients fails to report significant chi-square values (p-value of 0.251), additional backwards stepwise logistic regression analyses reports a significant test (chi-square of 5.474, df of 1, and p-value of 0.019). Thus, there is support for the significance of the predictor as part the original analysis. Furthermore, the model classifies 67.7 % of cases correctly. Of all three dummy variables created for each perceived justice dimension only interactional justice appears to be significant (p-value of 0.015) and thus providing support for hypothesis 6. Consequently, cases where interactional justice was achieved from the customer perspective increase the likelihood of a high level of satisfaction with the complaint by a factor of 107.6 %. Hypothesis 4 (p-value of 0.997) and 5 (p-value of 0.210) are not supported.

An extension of the research model further corroborates the results for interactional justice and its importance within the complaint handling context. In order to investigate the effect of interactional justice on a more detailed level the original three-dimensional justice theory model was extended into a four-dimensional model with the inclusion of the informational justice dimension (Badawi, 2012; Nikbin et al., 2013). Informational justice describes the level of adequacy of communication and information that is provided to the customer (Liao, 2007). A study by Badawi (2012) shows that clear information as well as informing the result to the customer significantly increases complaint handling satisfaction. The model extension required a split of the original dictionary for interactional justice into two different dictionaries that individually describe interactional and informational justice (see appendix C). The dictionary for the interactional dimension describes the particular behaviour by the agent and the dictionary for the informational dimension describes the extent to which customers are provided with information by the agent. The results of the binary logistics regression analysis for satisfaction with the complaint handling on the basis of a four-dimensional model show that only the dummy variable interactional justice significantly influences satisfaction with the complaint handling at the 0.05 level (see appendix D). This result is further supported by additional backwards stepwise logistic regression analysis with a significant chi-square value (chi-square of 3.434, df of 1, and p-value of 0.064). Consequently, within a four-dimensional justice theory model interactional justice increases the likelihood of higher satisfaction with the complaint handling by a factor of 78 %.

Table 6 Binary logistic analysis for perceived distributive justice (H7, H10, H11)

Variable	B	S.E.	Wald	Sig.	Exp(B)
SEN	.015	.024	.362	.548	1.015
SEV	.571	.733	.608	.436	1.771
CMP	.086	.936	.009	.927	1.090
PRT	.206	.433	.227	.634	1.229
CRT	.169	.365	.215	.643	1.185
CMP x PRT	-.269	.912	.087	.768	.764
CMP x CRT	.205	.894	.053	.818	1.228
SEN x SEV	-.017	.051	.114	.735	.983
Constant	1.118	.502	4.955	.026	3.058
Omnibus Chi-Square (df=8, Sig.=.982)		1.952		Cox & Snell R Square	.007
Hosmer-Lemeshow (df=8, Sig.=.421)		8.182		Nagelkerke R Square	.012

Table 7 Binary logistic analysis for perceived procedural justice (H8, H10, H11)

Variable	B	S.E.	Wald	Sig.	Exp(B)
SEN	-.019	.020	.979	.322	.981
SEV	-.432	.539	.644	.422	.649
CMP	-.072	.600	.015	.904	.930
PRT	.811	.652	1.550	.213	2.251
CRT	.414	.654	.401	.527	1.513
CMP x PRT	.016	.739	.000	.983	1.016
PRT x CRT	-.516	.716	.518	.472	.597
SEN x SEV	.064	.038	2.745	.098	1.066
Constant	-1.164	.637	3.345	.067	.312
Omnibus Chi-Square (df=8, Sig.=.704)		5.488		Cox & Snell R Square	.020
Hosmer-Lemeshow (df=8, Sig.=.299)		9.541		Nagelkerke R Square	.028

Table 8 Binary logistic analysis for perceived interactional justice (H9, H10, H11)

Variable	B	S.E.	Wald	Sig.	Exp(B)
SEN	-.053	.026	4.099	.043	.949
SEV	.201	.565	.127	.722	1.223
CMP	1.198	.645	3.448	.063	3.314
PRT	.762	.680	1.257	.262	2.143
CRT	1.261	.729	2.990	.084	3.529
CMP x CRT	-1.027	.763	1.811	.178	.358
PRT x CRT	-1.230	.763	2.602	.107	.292
SEN x SEV	-.004	.048	.006	.937	.996
Constant	-1.238	.693	3.195	.074	.290
Omnibus Chi-Square (df=8, Sig.=.095)		13.528		Cox & Snell R Square	.049
Hosmer-Lemeshow (df=8, Sig.=.527)		7.094		Nagelkerke R Square	.067

Influence of recovery attributes on perceived justice The results for testing hypotheses 7-11 are presented in the tables 6-8. The hypotheses 7-9 predicted that recovery attributes compensation, promptness, and courtesy positively influence the respective perceived justice dimensions of distributive, procedural, and interactional justice. The omnibus test of model coefficients only reports a significant chi-square value for the perceived interactional justice model (p-value of 0.095), but fails to do so for the models of perceived distributive justice (p-value of 0.982) and perceived procedural justice (p-value of 0.704). Similarly, additional backwards stepwise logistic regression analyses do not report significant omnibus tests of model coefficients. However, two of the three models show improved classification percentages and classify 65.8 % (for procedural justice) and 66.9 % (for interactional justice) of cases correctly. In the context of distributive and procedural justice none of the recovery attributes are found to significantly influence the respective perceived justice dimension, thereby providing no support for hypotheses 7 and 8. However, both compensation and courtesy appear to significantly influence interactional justice at the 0.1 level (p-value of 0.063 and 0.084 respectively), which provides support for hypothesis 9. Consequently, the existence of the recovery attribute courtesy increases the likelihood of interactional justice by a factor of 252.9 %. Hypothesis 10 and 11 anticipate that the total number of service encounters and service failure severity represent boundary conditions of the failure context and negatively influence the perceived justice dimensions. The discrete variable total numbers of service encounters indicates a negative significant effect (p-value of 0.043) on perceived justice only in the context of interactional justice and thereby providing only partial support for hypothesis 10. The dummy variable service failure severity appears not to be significant (p-values of 0.436, 0.422, and 0.722), thus providing no support for hypothesis 11. Additionally, the results show a significant moderation effect of total number of service encounters and service failure severity in the context of procedural justice (p-value of 0.098), which indicates that high severity increases the negative effect of total number of service encounters on procedural justice by a factor of 6.6 %.

Following the extension to a four-dimensional perceived justice model the recovery attributes were adapted in order to fit the four-dimensional structure. In line with the other recovery attributes, explanations are hypothesized to lead to higher ratings of fairness (Bies & Shapiro, 1987). According to a study by Estelami (2000) adequate information also leads to consumer delight compared to consumer dissatisfaction. Consequently, the original dictionary for the recovery attribute courtesy was split into courtesy and explanations with courtesy referring to apologetic actions and explanations referring to informative actions (see appendix C). The omnibus test of model coefficients was performed for the models of interactional and informational justice, but fails to report significant chi-square values (p-value of 0.247 for interactional justice and p-value of 0.427 for informational justice). However, additional backwards stepwise logistic regression analyses reports a significant test for interactional justice (chi-square of 9.420, df of 4, and p-value of 0.051) and for informational justice (chi-square of 7.813, df of 1, and p-value of 0.005). Thus, there is support for the significance of the predictors as part the original analyses. Furthermore, the models show improved classification percentages and classify 58.5 % (for interactional justice) and 71.0 % (for informational justice) of cases correctly. The results of the binary logistics regression analysis show that none of the hypothesized recovery attributes significantly influences interactional or informational justice. However, the results show that the discrete variable total numbers of service encounters negatively affect interactional justice (p-value of 0.033) and informational justice (p-value of 0.007), thereby adding further support for hypothesis 10. Additionally, as part of the four-dimensional model a significant interaction effect of the recovery attributes promptness and courtesy exists on interactional justice at the 0.1 level (p-value of 0.085). Thus, promptness decreases the effect of courtesy on interactional justice by a factor of 70.6 % (see appendix D).

5. Discussion

The main objective of this research is to investigate the question whether unstructured data collected from customer relationship management (CRM) and customer experience management (CXM) systems can be used to infer succeeding customer evaluations. By identifying specific recovery attributes from CRM data and linking those to their complementing dimensions of perceived justice as part of CXM data, it was found that the individually composed hypothesized sequence of 'courtesy → interactional justice → satisfaction with complaint handling' is significant and positive. In this sequence there is a negative effect of the number of total service encounters on the justice dimension of interactional justice. In addition, satisfaction with the complaint handling leads to the behavioural intentions of continued use and positive word-of-mouth (WOM). The results show that there is predictive power resulting from the combination of unstructured CRM and CXM data into one overarching construct. Consequently, under the proposed research setup the findings partially affirm existing theoretical principles in the context of complaint handling experiences (e.g. Colquitt, 2001; Smith et al., 1999; Tax et al., 1998).

5.1. Interpretation of findings

The study shows that as hypothesized satisfaction with complaint handling is positively related to behavioural outcomes in terms of continued use and WOM. Although the results are in line with previous works (Kumar Piaralal et al., 2014; Tax et al., 1998), it should be emphasized in light of the sample used as part of this research, which consists of highly dissatisfied customers. For example Kau and Loh (2006), who distinguished between satisfied and dissatisfied complainants, report significantly higher mean values of WOM and loyalty for satisfied complainants. Despite this characteristic for dissatisfied customers, the study finds highly significant effects for both behavioural outcomes. Additionally, when compared with each other, the impact of satisfaction with complaint handling is stronger on WOM than on continued use, which is consistent with another finding by Kau and Loh (2006). In contrast to what was hypothesized, complaints with the status solved are not found to moderate the relationship between satisfaction with complaint handling and behavioural outcomes, but instead there is a significant direct relationship to both behavioural outcome variables. An explanation could be nature of the variable, which relates to the outcome of a complaint and should therefore be seen as an antecedent to succeeding customer evaluations. Support is provided by the significant correlation, although low in value, between the variable of complaint status and distributive justice (see table 2), which is the only perceived justice dimension that links to the outcome of the exchange (Gelbrich & Roschk, 2011).

One of the main findings of this study is the positive effect of interactional justice on satisfaction with complaint handling. There are numerous examples of studies which either find a relative low effect of interactional justice (Homburg & Fürst, 2005; Weun et al., 2004) or no significance for the effect on satisfaction with the complaint handling (Maxham III & Netemeyer, 2003). Nonetheless, this study adds to the findings of previous studies, which assert interactional justice a predominant role in the context of complaint handling (Chebat & Slusarczyk, 2005; Wang, Wu, Lin, & Wang, 2011). An explanation could result from the situation that highly dissatisfied customers find themselves in. It can be assumed that there are cases where reimbursements cannot make up for the damage already done and where customers are trapped within a lengthy procedural system, thereby making it difficult for companies to achieve either distributive or procedural justice. Consequently, in those situations interactional justice could be the only perceived justice dimension that can still be influenced by the company during the interaction. The results of the four-dimensional perceived justice model provide additional support for the importance of interactional justice. With interactional justice broken down into parts of behavioural aspects for interactional justice and informational aspects for informational justice, notwithstanding interactional justice is still the only dimension with a significant effect on customer satisfaction with complaint handling. In accordance with findings by Colquitt (2001), who reports differential effects of interactional and informational justice in the organizational context, the results of this study suggest a breakdown into interactional and informational justice for the context of service recovery.

The study shows that only for the case of interactional justice the recovery attributes compensation and courtesy have a significant effect on the justice dimension. In comparison to each other there is a slightly stronger impact by courtesy (factor of 252.9 %) than by compensation (factor of 231.4 %), which shows that the main effect is generated by the hypothesized effect of courtesy on interactional justice. Smith et al. (1999) come to a similar conclusion as they find different proportional effects by individual recovery attributes. The fact that compensation also has a significant positive effect on interactional justice can be explained by the circumstance that news of reimbursements or coupons are often times delivered by the agent himself, which is then attributed towards interactional justice by the customer. Within the context of interactional justice there is also a significant negative effect by the total number of service encounters. Although there are examples where transaction frequency is found to positively impact loyalty and tolerance of service failure (Low et al., 2013), the fact that most service centre request are based on negative circumstances as for example reports on defects calls for a negative effect of the number of service encounters, which is in line with reported findings. For the case of procedural justice there is also a moderation effect of severity on the relationship between number of service encounters and procedural justice. The conclusion is that in cases of high severity the damage by additional numbers of service encounters is even greater, making it more difficult to achieve procedural justice. Thus, in accordance with previous studies (Kumar Piaralal et al., 2014; Smith et al., 1999) service failure severity should be taken into account when investigating cases of service recovery. With regard to the impact of the total number of service encounters the results of the four-dimensional model are in line with the results of the main model and provide additional support for its negative effect on perceived justice (i.e. interactional and informational justice). Interestingly, the results of four-dimensional model also present a significant negative interaction effect of promptness on the relationship between the recovery attribute courtesy and interactional justice. Given the hypothesized positive direct effect of promptness on procedural justice the results are contradictory to the original expectations. Previous findings hint towards the ambiguity of promptness. Wirtz and Mattila (2004) for example argue that speedy recovery can also induce customers to think the service provider had control over the failure in the first place, thus increasing customer's attributions of controllability and generating negative associations with speedy recovery. Similarly, a prompt customer complaint handling limits the opportunity to bring forth signals of courtesy, which ultimately will limit the impact of the recovery attribute of courtesy (Chebat & Slusarczyk, 2005). Thus, although a prompt complaint handling might be of positive nature on an individual level, it can damage and decrease the effect of other recovery attributes that require some time to be established.

5.2 Practical implications

In line with the main objective of the study, which was to test whether unstructured data previously collected from CRM and CXM systems can be used to infer succeeding customer evaluations, one major implication is the validated value of unstructured data for the company. Although the findings are limited to both the selection of theories and constructs tested and the quality of the data, the fact that significant relationships are found points to the predictive power residing within the analysed unstructured data. Consequently, the identified predictors demonstrate the ability to classify customers to the right category with respect to both perceived interactional justice as well as satisfaction with complaint handling.

Furthermore, this opens up additional measuring possibilities within the realm of service recovery for the company, because unstructured data often times carries multiple factors for analysis (Ordenes et al., 2014), which enables the discovery of more latent knowledge (Chang et al., 2009). Consequently, it is worthwhile to investigate the possibility of extending the scope of data collection. For example, one option might be to record conversations between the agent and the customer word-for-word. This would allow for a more extensive analysis, which could for example include sentiment analysis (Setiawan, 2014).

Another source that offers a multitude of practical implications is presented by the findings of tested theories itself. Firstly, it offers the company the opportunity to streamline existing structures and procedures. For example, when comparing all analysed perceived justice dimensions including the selected recovery attributes it turns out that only interactional justice significantly impacts satisfaction with the complaint handling, which in turn is influenced by the recovery attribute courtesy. Consequently, there seems to be a limit with respect to the impact that reimbursements and a speedy service recovery process can bring to the company. Therefore, the primary focus of the company should be on the establishment of interactional justice when dealing with customer complaints. A similar implication is stated by Gelbrich and Roschk (2011) who advocate to focus on interactional justice in cases of nonmonetary failures or failures in service industries. An adapted focus frees up financial means that would otherwise have been spend on factors relating to the other two perceived justice dimensions. Secondly, the findings offer some guidance for future company trainings and development programmes, which should teach agents how to effectively deal with dissatisfied customers in such a way that they feel treated fairly as part of the conversation. Next to shifting the attention towards interactional justice, it is worthwhile to also place attention on the sub-dimensions of interactional justice. For example, the findings of the model extension show that although informative actions were originally included as part of interactional justice it is only the particular behaviour by the agent (e.g. courtesy, making an apology), which has a significant impact. In light of the underlying setup of the research study at hand, which was limited to a sample of the most dissatisfied customers, the implications and insights could potentially make the difference between exit of a customer and continuation of business.

Despite the fact that the focus of the study is on analysing unstructured data, there is also room for drawing implications with respect to structured data in the form of customer feedback questionnaires. Standardized customer feedback questionnaires tend to rely on predefined quality dimensions, which can lead to superficial information in case the standards for the measures are not set properly (Caemmerer & Wilson, 2010; Ordenes et al., 2014). However, through the analysis of unstructured feedback it is possible to gain better insights on customer experiences (Ordenes et al., 2014) and adapt existing standard questionnaires accordingly. Based on the fact that the company currently is not measuring the agent's courtesy in any dimension it is advisable to add a comparable dimension in the future. This will allow the company to track courtesy ratings over time and to take actions accordingly.

5.3 Limitations and future research

This research is subject to several limitations, which by extension provide direction for future research. Firstly, the sample used to conduct the research imposes one of the main limitations for the present study. Due to the fact that the sample consisted of only the most dissatisfied customers and was thereby very extreme, the quality of the data was considerably decreased and generalizations for the entire population are not possible. Consequently, in combination with the relatively small sample size it is important to point out that the presented results are mainly of tentative nature. For example, this can be shown with the partial lack of significance for the reported absolute measures of validity (i.e. omnibus chi-square test) for some of the presented models, which could only be achieved with additional model adaptations. Thus, future research should extent the present study, which can be seen as a pilot study due to the mentioned constraints, with more balanced data.

Secondly, all dictionaries used for the coding of the variables were generated by manual categorization, which limits the quality of the dictionaries to the subjective assessment of the coder. Furthermore, the quality of the data itself imposes an additional constraint on the analysis. In contrast to the unstructured data from the customer feedback questionnaires, the unstructured data extracted from the CRM system was limited with respect to its richness. One reason is that the agents generated the transcripts under time pressure, which also leads to the increased use of abbreviations. Consequently, the dictionary for the service recovery attribute variable promptness consists of only seven individual terms (see appendix A) due to the fact that the measure of time was difficult to identify as part of the provided data. In addition to the use of word-by-word recordings of conversations between the agent and the customer, future research should consider the use of linguistic techniques that analyse text with respect to natural language characteristics, which could improve the quality of categorization (Ordenes et al., 2014).

Finally, the research was based on two backdated data sets that originated from the CRM and CXM systems respectively. Firstly, for the data that originated from the CXM system one of the preconditions was that a complaint was recorded within the company system. However, the complaint could be both filed by a customer or classified as such by the respective agent. Consequently, there might have been a mismatch in the respective perceptions of customers and agents. Thus, future research should try to control for any potential mismatch within the sample. Secondly, in order to gain a more dynamic understanding of customer experiences future research should take into account additional communication channels. The analysis of additional contact points can result in greater insights and establish novel links to existing findings (Ab Hamid & Akhir, 2013).

6. Conclusion

This study builds upon the need for companies to react to recent trends, which indicate an emerging integration of existing CRM and CXM systems (Goldenberg, 2013). Traditionally, CRM systems stored basic information about individual customers that resulted from their history with the company. In contrast, CXM systems focus on mapping and storing data on customer experiences (Meyer & Schwager, 2007). Consequently, there is a need for integration of the two systems in order to capture customer experience holistically. Compared to the majority of previous studies, which utilized experimental designs to investigate the antecedents of satisfaction with complaint handling, this study used secondary data from existing company databases to test existing theories on service recovery. The aim was to first establish the grounds for the practicability of utilizing existing data storage system and second to employ text-mining-assisted analysis to examine underlying relationships in greater detail. The main finding is that the hypothesized sequence of 'courtesy → interactional justice → satisfaction with complaint handling' is significant and positive. This means that the interpersonal treatment during the customer-agent interaction as part of the overall service recovery process significantly influences succeeding customer evaluations and related behavioural outcomes. Moreover, the results provide support for an integration of unstructured CRM and CXM data into one overarching construct. Therefore, the study also contributes to the current discussion on reshaping customer experience frameworks into total customer experience models (Ab Hamid & Akhir, 2013) and its practicality with respect to legacy company systems. For all that, the quality of the data as well as the sample itself represented major constraints on the present analysis. Thus, it is anticipated that future research building on the insights gained in this article will overcome initial difficulties and arrive at more definite conclusions.

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Appendices

A. Dictionaries

Table 9 Dictionaries used for 3-dimensional model

Variable	Words
Failure context	
Service failure severity	rückabwicklung; nimbus; nimbusticket; rollback; rollbackbearbeitung; ressourcenmangel
Recovery attributes	
Compensation	Versandaustausch; Grundentgelte erstattet; Routertausch; erstattet; Jahreslos; Kochbuch; Rücküberweisung; Korrekturgutschrift; GGB erstattet; Sachleistung veranlasst; Aktion Mensch Los; Uhrenradio; getauscht; kostenfrei gebucht; Gutschrift erstellt; gutgeschrieben; Gutschrift veranlasst; Auszahlung per Scheck angewiesen; erstattung gutschreiben; gutschreiben
Promptness	weiter geleitet; neuer Termin; weitergeleitet; wtl; weitergefaxt; Weiterleitung; erneut
Courtesy	AB gesprochen; informiert; erklärt; Rückmeldung; Rücksprache; inf.; hingewiesen; erläutert; gebeten; entschuldigt; Erläuterungen; KD beruhigt; geduld gebeten
Perceived justice	
Distributive justice	Kulanz; Gutschrift; Summen; abgebucht; alles; Schulden; Abbuchung; kostenpflichtig; Rechnung; verrechnet; Angebot; Geld; kostet; teuer; Sondergenehmigung; Verrechnung; Router; Media-Receiver; Mahnung; zurückerstattet; Ergebnis; bezahlen; Wiedergutmachungsgutschrift; kaufen; Kosten
Procedural justice	zugesichert; lange; Wartezeit; Automat; Antwort; Bearbeitung; Ansprechpartner; Mitteilung; alles; reagiert; Erreichbarkeit; bearbeitet; Dauer; lange; Warteschleife; warte; Datenteufel; Zeitaufwand; Verzögerung; immer noch; Hand; noch nicht; Wochen; Tage; Handhabung; bis heute; spät; erledigt; bestellt; nichts getan; schnell; Jahr; Reaktion; Klärung; Bearbeitungszeit; Mal; Vorgang; Zentrale; Bearbeitungszeit; Terminabsprachen; erreicht; Termin; Beantwortungszeit; Koordination; passiert; nochmals; Kontaktperson; Zeitspanne; Ablauf; bis jetzt; hinzieht; wiederholen
Interactional justice	Mitarbeiter; Lust; Leuten; Auftreten; frech; Dame; kompetent; alles; unfreundlich; Auskunft; Auskünfte; beraten; Information; Rückinformation; Rückruf; freundlich; Inkompetenz; Beratung; versprochen; Erklärung; Kommunikation; kompetent; Rückantwort; unpersönlich; Behandlung; Ahnung; zickig; gekümmert; Kundenservice; eingehen; Reaktion; Zusagen; zugesagt; reagiert; Rückmeldung; Unverschämtheit; zugesichert; eingehalten; inkompetent; eingegangen; Verhalten; gelöchert; Rücksprache; Entgegenkommen; Gefühl; vermittelt; vertröstet; geschult; Kündenwünsche; kompetenz; Service; abgearbeitet; weiß; Auskünfte; kundenunfreundliche; zuständig; abgewiesen; helfen; Unverständnis; Hilfe; Versprechnung; ernst; gelaunt; bemüht; forsch; Erpressung; weiterhelfen; Aufklärung; Entgegennahme; behandelt; interessiert; Aussagen; hinhaltend; arogant

B. Inter-rater agreement for severity measure

Table 10 Inter-rater agreement for severity

	Value	Assymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Measure of agreement (Cohen's Kappa)	-.093	.039	-1.692	.091
N of valid cases	47			

a. Not assuming the null hypothesis
b. Using the asymptotic standard error assuming the null hypothesis.

C. Dictionaries for model extension

Table 11 New and altered dictionaries used for 4-dimensional model

Variable	Words
Recovery attributes	
Courtesy	gebeten; entschuldigt; KD beruhigt; geduld gebeten
Explanations	AB gesprochen; informiert; erklärt; Rückmeldung; Rücksprache; inf.; hingewiesen; erläutert; Erläuterungen
Perceived justice	
Interactional justice	Mitarbeiter; Lust; Leuten; Auftreten; frech; Dame; alles; unfreundlich; freundlich; versprochen; unpersönlich; Behandlung; zickig; gekümmert; Kundenservice; eingehen; Reaktion; Zusagen; zugesagt; reagiert; Unverschämtheit; zugesichert; eingehalten; eingegangen; Verhalten; gelöchert; Entgegenkommen; Gefühl; vermittelt; vertröstet; Kündenwünsche; Service; abgearbeitet; kundenunfreundliche; zuständig; abgewiesen; helfen; Unverständnis; Hilfe; Versprechnung; ernst; gelaunt; bemüht; forsch; Erpressung; weiterhelfen; Entgegennahme; behandelt; interessiert; Aussagen; hinhaltend; arogant
Informational justice	kompetent; Auskunft; Auskünfte; beraten; Information; Rückinformation; Rückruf; Inkompetenz; Beratung; Erklärung; kompetent; Rückantwort; Ahnung; Rückmeldung; inkompetent; Rücksprache; kompetenz; weiß; Auskünfte; Aufklärung; geschult; Kommunikation; Unwissen; Wissensstand

D. Logistics regression analysis for model extension

Table 12 Additional variables for 4-dimensional model

Description	Label
Independent Variables	
Explanations (where 0 = not present and 1 = present)	EXP
Dependent Variables	
Informational justice (where 0 = not achieved and 1 = achieved)	INFJ

Table 13 Binary logistic analysis for satisfaction with complaint handling (4-dimensional model)

Variable	B	S.E.	Wald	Sig.	Exp(B)
SEN	-.010	.021	.220	.639	.990
SEV	.100	.541	.035	.853	1.106
DJUST	-.007	.352	.000	.985	.993
PJUST	.305	.291	1.102	.294	1.357
IJUST	.577	.286	4.057	.044	1.780
INFJ	.392	.310	1.598	.206	1.481
SEN x SEV	-.008	.042	.041	.839	.992
Constant	-1.364	.504	7.331	.007	.256
Omnibus Chi-Square (df=7, Sig.=.406)		6.706		Cox & Snell R Square	.025
Hosmer-Lemeshow (df=8, Sig.=.621)		6.316		Nagelkerke R Square	.034

Table 14 Binary logistic analysis for perceived interactional justice (4-dimensional model)

Variable	B	S.E.	Wald	Sig.	Exp(B)
SEN	-.044	.021	4.538	.033	.957
SEV	.053	.520	.010	.919	1.054
CMP	.381	.387	.970	.325	1.463
PRT	.040	.346	.013	.908	1.041
CRT	-.165	1.025	.026	.872	.848
EXP	.090	.277	.105	.746	1.094
CMP x CRT	-.123	.848	.021	.885	.884
PRT x CRT	-1.225	.712	2.961	.085	.294
EXP x CRT	.874	1.001	.762	.383	2.395
SEN x SEV	.014	.039	.126	.722	1.014
Constant	.283	.396	.511	.475	1.327
Omnibus Chi-Square (df=10, Sig.=.247)		12.604		Cox & Snell R Square	.045
Hosmer-Lemeshow (df=10, Sig.=.565)		6.740		Nagelkerke R Square	.060

Table 15 Binary logistic analysis for perceived informational justice (4-dimensional model)

Variable	B	S.E.	Wald	Sig.	Exp(B)
SEN	-.051	.019	7.291	.007	.950
SEV	-.209	.547	.146	.703	.812
CMP	-.200	.622	.103	.748	.819
PRT	-.073	.573	.016	.898	.929
CRT	1.193	1.194	.999	.318	3.298
EXP	.000	.654	.000	1.000	1.000
EXP x CRT	-1.149	1.259	.833	.361	.317
EXP x PRT	-.122	.688	.031	.859	.885
EXP x CMP	.048	.753	.004	.949	1.049
SEN x SEV	.027	.037	.532	.466	1.027
Constant	1.334	.573	5.416	.020	3.798
Omnibus Chi-Square (df=10, Sig.=.427)		10.160		Cox & Snell R Square	.037
Hosmer-Lemeshow (df=8, Sig.=.715)		5.388		Nagelkerke R Square	.052