Analyzing Customer Experience Feedback Using Text Mining: A Linguistics-Based Approach

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Authors:

Francisco Villarroel Ordenes[1], Jamie Burton[2], Babis Theodoulidis[3], Thorsten Gruber[4], Mohamed Zaki[5],

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[1] Doctoral Candidate, Marketing and Supply Chain Management Department, School of Business and Economics, Maastricht University, Tongersestraat 53, 6211 LM Maastricht, +31 43 38 84820; f.villarroelordenes@maastrichtuniversity.nl

[2] Senior Lecturer in Marketing and Director of Research for the Customer Management Leadership Group, Manchester Business School; Booth Street West, Manchester, M15 6PB, UK, +44 (0) 161 275 6508; Jamie.Burton@mbs.ac.uk

[3] Senior Lecturer in Information Systems, Manchester Business School; Booth Street West, Manchester, M15 6PB, UK, +44 (0) 161 306 1320; b.theodoulidis@manchester.ac.uk

[4] Professor and Chair in Marketing and Service Management, School of Business and Economics, Loughborough University; Loughborough LE11 3TU, UK, +44 (0) 1509 228274; t.gruber@lboro.ac.uk

[5] Research Associate at Cambridge Service Alliance, Institute for Manufacturing, University of Cambridge, CB3 0FS, mehyz2@cam.ac.uk. I have done this research as part of my research activities with Manchester centre of service research while I was doing my PhD in Manchester Business School.

BIO

Francisco Villarroel Ordenes is a PhD. Candidate at the Marketing and Supply Chain Management Department at the School of Business Economics in Maastricht University. His research interests include social media conversations, customer experience feedback, sentiment analysis, value co-creation and the development of text mining methods for marketing research.

Dr. Jamie Burton is a senior lecturer and head of the Marketing Group at Manchester Business School (MBS). He is research director for MBS's Customer Management Leadership Group, publishes in a number of journals including the Journal of Marketing Management and the Journal of Service Management and his research interests include customer experience and feedback, transformative service research including service marketing, servitization, relationship marketing and customer profitability. Jamie is lead author of a 2013 British Quality Foundation report and is co-author of Murphy, J., et al. (2006), Converting Customer Value: from Retention to Profit, Chichester: John Wiley and Sons, Ltd.

Babis Theodoulidis is an associate professor in Information Management at Manchester Business School, University of Manchester. His research has been published in both science and social science journals such as International Journal Services Technology and Management, Journal of Information Systems, Knowledge Management Research & Practice, Expert Systems with Applications, International Journal of Information Management, International Journal of Data Warehousing and Mining and Journal of Visual Languages and Computing. His most recent research interests focus on the design of service-based information systems, the temporal and spatial aspects of information, the analysis of information using data and text mining techniques, the visualization of information, and service information management issues within organizations.

Thorsten Gruber is a Co-Director of the Centre for Service Management and a Professor of Marketing & Service Management at Loughborough University. His research interests include consumer complaining behavior, services marketing and the development of qualitative online research methods. His work has been published in journals such as Journal of the Academy of Marketing Science, Journal of Product Innovation Management, Journal of Business Research, Journal of Service Management, and Industrial Marketing Management.

Dr Mohamed Zaki is a research associate at Cambridge Service Alliance, University of Cambridge. Mohamed's research lies in the field of Information Governance, Business Intelligence and Big Data Analytics. He has many publications in these areas. His experience in the Business Intelligence/Data Analytics and service innovation areas enables him to consult in various projects to investigate business Intelligence issues in different domains within a service-oriented architecture. Currently, he investigates" How Big data could play a role in improving and optimising services within complex service network organisation" in different sectors such as education, asset heavy and defence.

Abstract

Complexity surrounding the holistic nature of customer experience has made measuring customer perceptions of interactive service experiences, challenging. At the same time, advances in technology and changes in methods for collecting explicit customer feedback are generating increasing volumes of unstructured textual data, making it difficult for managers to analyze and interpret this information. Consequently, text mining, a method enabling automatic extraction of information from textual data, is gaining in popularity. However, this method has performed below expectations in terms of depth of analysis of customer experience feedback and accuracy. In this study, we advance linguistics-based text mining modeling to inform the process of developing an improved framework. The proposed framework incorporates important elements of customer experience, service methodologies and theories such as co-creation processes, interactions and context. This more holistic approach for analyzing feedback facilitates a deeper analysis of customer feedback experiences, by encompassing three value creation elements: activities, resources, and context (ARC). Empirical results show that the ARC framework facilitates the development of a text mining model for analysis of customer textual feedback that enables companies to assess the impact of interactive service processes on customer experiences. The proposed text mining model shows high accuracy levels and provides flexibility through training. As such, it can evolve to account for changing contexts over time and be deployed across different (service) business domains; we term it an "open learning" model. The ability to timely assess customer experience feedback represents a pre-requisite for successful co-creation processes in a service environment.

INTRODUCTION

Collecting and analyzing customer feedback is important because it allows organizations to learn in a continuous manner, to adapt their offerings to customer preferences (Sun and Li 2011). Increasingly, customers use multiple communication channels to provide feedback, making it cumbersome for organizations to develop efficient and effective processes to collect and analyze all the information. Companies that can manage customer feedback data regularly are, on average, 5% more productive and 6% more profitable than their competitors (McAfee and Brynjolfsson 2012). Technological advances have expanded the choice of channels available for companies to collect customer feedback. Structured feedback, such as quantitative surveys, is now increasingly considered alongside unstructured feedback, such as telephone calls, e-mails, and social media, in which customers describe their experiences more freely (Witell et al. 2011). The latter contain information in a verbatim format and are characterized by a higher level of detail, describing the most critical elements for customer experience (Ziegler, Skubacz, and Viermetz 2008). However, the variety of content and the time and resources required to analyze textual feedback create barriers to uncovering meaning in these data.

Marketing departments have become increasingly aware of the importance of textual feedback and have used manual or automatic approaches to analyze this information. Companies that run analysis on a manual basis can gain a deeper understanding of customer feedback, but if their analysis lacks procedural models, they tend to be inconsistent when reviewing large quantities of data (Ziegler, Skubacz, and Viermetz 2008). At the same time, companies that have adopted automated analysis of textual feedback (e.g., text mining) have failed to realize their expectations in using this method (Fenn and LeHong 2012). Specifically, a lack of accuracy in predicting customer sentiments (positive/negative/neutral) and the inflexibly of methods in adapting to different business domains represent the main causes of this disillusionment (Fenn and LeHong 2012). The deployment

of text mining models has clear managerial implications, including the availability of accurate and timely information, for better informed decision making.

Academic research on these problems remains scarce. Customer feedback analysis using text mining has largely focused on developing more accurate models for automatically predicting the sentiment embedded within text (Gräbner et al. 2012). The majority of these studies have emphasized how different text mining methods (linguistic and nonlinguistic; Taboada et al. 2011) contribute to better predicting the overall sentiment in a customer review. Despite the importance of identifying sentiments, more specific information is contained in textual customer feedback. Critical elements of an organization's offering that trigger sentiment evaluations have largely been ignored. For example, in the customer feedback "Extremely friendly and helpful staff. Disappointed that the bar wasn't open full time! A lovely, quiet, and relaxing place to stay!" the first sentence is positive, the second is negative, the third is positive again, and more than three different aspects of a service are covered. With sentiment analysis, the focus would rest solely on the final sentiment output, but with multiple emotions in the comment, this is uncertain, providing little guidance for managerial response. However, if the focus of the automated analysis were on the service components and related customer interactions (e.g., with the staff, the bar, and the atmosphere), sentiment outcomes would offer greater value for decision-making purposes.

Service literature has long recognized that customer evaluations of service experience are an outcome of the interactions among companies, related systems, processes, employees, and customers in a service context (Bitner et al. 1997). These elements, recurrent in areas such as service blueprinting, service encounters, and service quality (Fisk, Brown, and Bitner 1993), indicate that services consist of activities between customer and company in a *cocreation process* (Payne, Storbacka, and Frow 2007). Despite their managerial and theoretical relevance, these elements are largely absent in operationalizations of automated models to analyze customer feedback (Taboada et al. 2011; Ur-Rahman and Harding 2011). In particular, there is no evidence of a framework that can

aggregate relevant aspects of the service process and operationalize them in a text mining model to help companies analyze customer textual feedback and conversations. At the same time, research has increasingly recognized the need to understand the holistic nature of customer experiences to design improved service systems (Patrício et al. 2011; Verhoef et al. 2009). We contend that insights into customer experiences are more likely to be identified in rich customer comments than through company-designed surveys, and thus the lack of text mining focusing on customer service experience is a significant oversight. In the context of these omissions, this article makes the following contributions.

First, the study fills a gap in the text mining literature by proposing a framework that provides a holistic approach for analyzing customer feedback by accounting for three key components of the value (co)creation process: activities, resources, and context (ARC). Through this framework, customer textual feedback not only can be classified as positive or negative in terms of a specific attribute (i.e., friendliness) (Feldman 2013) but also can be mapped onto a chain of activities and resources that describes how value is (co)created in a particular context (Grönroos and Voima 2013). The ARC framework departs from simple output-based analysis (e.g., attribute assessment and sentiment analysis) by offering a new processes and interactions approach that can be applied with linguistic text mining, which captures key elements of service in customer feedback, to better represent how value is (co)created.

Second, we contribute to text mining research by expanding the scope of automation from existing approaches to more flexible models. Implementing the ARC framework, we develop and propose a linguistics-based text mining model to extract detailed information about customer experiences from textual feedback. We explain how the ARC framework guides the utilization of linguistics-based text mining features in developing a text mining model for customer feedback analysis. This process enables the development of a model that captures customer context (personal and situational), activities and resources (pertaining to both customer and company), and the

sentiment associated with these constructs. Thus, a more complete and holistic picture of customers' interactions in service encounters is automatically captured. Moreover, the text mining model can be enriched over time with evolving customer terminology about changing service resources and activities and can also be adapted and applied in different (service) business domains. We call this characteristic an "open learning" model to describe a text mining model that can be enhanced over time and adapted.

CONCEPTUAL FRAMEWORK

Development of a Modeling Framework

Service literature has considered the process nature of services, especially the effect of customer–company interactions on customers' evaluations of a service experience (Fisk, Brown, and Bitner 1993). According to Bitner, Brown, and Meuter (2000), adequate mapping of these interactions facilitates the identification of *encounters*, which Shostack (1985, p. 243) defines as "a period of time during which a consumer directly interacts with the service." These encounters are critical for customers' service evaluations in terms of satisfaction (Bitner, Booms, and Mohr 1994; De Ruyter et al. 1997), service quality (Parasuraman, Zeithaml, and Berry 1994), and customer loyalty (Gremler and Brown 1999). Critical encounters among customers, employees, and physical facilities can occur through multiple channels—at the actual service setting, by telephone, through e-mail, and through the Internet (Bitner, Brown, and Meuter 2000). To increase the consistency of these encounters, Shostack (1987) defines the concept of *service blueprints* as visible portraits designed by the company to realize detailed customer–company interactions. Such blueprints help managers control critical elements of a service system (Shostack 1987). Service quality literature has also highlighted the interactive nature of services, in which customers' service evaluations are considered the result of various *activities* performed and *resources* used during the service (Grönroos 1984). Indeed, service quality measures, such as SERVQUAL (Parasuraman, Zeithaml, and Berry 1988), are based on the premise that service quality comprises various dimensions (i.e., reliability,

assurance, tangibles, empathy, and responsiveness) that derive from specific interactions required for the service (e.g., a conversation with an employee can affect the empathy dimension). Similarly, recent service research has proposed that services involve a *cocreation process* (Payne, Storbacka, and Frow 2007), in which the flow of customer and company processes influences customers' value perceptions of a service.

In summary, service literature highlights key aspects of the service process that facilitate customers' realization of value. Grönroos (2011, 2012) regards service as a means to an end, such that value, the desired end state, results when customers are better off after a service process than before. When using services, customers integrate resources provided by the company with other *resources* and apply skill to create value for themselves. During direct interactions with customers, companies have the potential "platform" to influence customers' value creation (Grönroos 2011, p.290). This value cocreation platform provides both parties with access to resources that enable certain activities, and different outcomes are possible depending on how the interaction progresses. The role of companies is to help customers in their value creation by providing them with necessary resources and processes (e.g., information, goods, service activities). Therefore, companies are "value facilitators" that assist customers in their value creation (Grönroos 2008, p.308).

To provide the right offerings to make customers better off (Grönroos 2011), a company must gain insight into customers' assessments of their experiences and their perceived value from the company's service processes, occurring in a context defined by the customer (Heinonen et al. 2010). Companies can achieve this by gaining access to customer feedback, through online and offline channels, during or following interactions (Rust and Chung 2006). Such feedback does not result in value for the company per se; it only leads to internal developmental processes that then result in actionable information, if internal support systems (e.g., reporting systems) are in place. Tronvoll (2007, p. 613) terms this process a "service adjustment process," because responding to customer feedback helps reduce any negative discrepancies, or increase any positive ones, that customers

signal. Improved systems and resources can then lead to better value experiences for customers in the future (Grönroos 2012). However, empirical studies analyzing customer feedback by systematically examining the resources and activities constituting the value (co)creation process and the context in which it is embedded remain scarce. Therefore, this study adopts a linguistics-based approach.

Customer Feedback Processes

The nature of customer feedback can be classified as *explicit* or *implicit* depending on whether customers consciously or unconsciously provide a third party with information about their experiences. Companies have traditionally collected explicit feedback through platforms (e.g., surveys, e-mail, online reviews), on which they directly solicit information from customers. Customers give implicit feedback through determined actions, without the firm requesting the information (i.e., eye tracking, reading time, number of scrolling, number of clicks obtained in a web document) (Poblete and Baeza-Yates 2008). Both types of feedback contribute to a continuous learning process about customers.

Many companies collect explicit feedback using quantitative methods because of the simplicity in analyzing structured information. For example, questionnaires (i.e., using 5-point Likert scales) help companies analyze predetermined product/service quality attributes (Parasuraman, Zeithaml, and Berry 1988). Despite the importance of these data, evaluating an entire service using predetermined attributes will result in an incomplete understanding of the customer experience (Macdonald et al. 2011; Vargo et al. 2007). Classifying attributes into predefined quality dimensions that are then used to collect structured feedback provides companies with only superficial information about the entire customer experience (Caemmerer and Wilson 2010) and may not capture all the resources and activities involved or the context (Grönroos 2012).

In contrast with these quantitative approaches soliciting structured data, technological advances offer customers new channels and platforms through which they can provide solicited and unsolicited qualitative feedback in a textual and unstructured format (Witell et al. 2011). This form

of feedback includes responses to open-ended questions, e-mails, online reviews, and social media conversations (Witell et al. 2011). Here, the customer takes the lead role, actively defining the process and timing of feedback and the context in which the information is provided. Arguably, this type of feedback is of greater relevance than structured approaches because its expression and content better reflect customer motivation (Belkahla and Triki 2011).

Recognizing that customers play active roles in generating relevant qualitative information could provide more valuable and complete sources of insight to companies (Belkahla and Triki 2011; Wirtz, Tambyah, and Mattila 2010). However, analysis of this information demands significant effort in the time required to generate knowledge from large amounts of qualitative data (Janasik, Honkela, and Bruun 2009). Indeed, feedback from e-mails, customer reviews, short messages, and social media is rapidly growing, pushing organizations to develop more efficient approaches to measure and understand information (Zhan, Loh, and Liu 2010). Text mining methods offer a potential solution for dealing with the sheer volumes of unstructured data (Ur-Rahman and Harding 2011), whether such data are explicit or implicit and solicited or unsolicited.

Text Mining and Customer Feedback

Text mining is the process of analyzing textual information in an attempt to discover structure and implicit meanings "hidden" within texts (Mikroyannidis and Theodoulidis 2006). It is a relatively recent technological development that addresses the information management problem through the use of techniques from data mining, machine learning, natural language processing, information retrieval, and knowledge management (Yu, Jannasch-Pennell, and DiGangi 2011). More specifically, text mining involves processing a collection of documents, or corpus, in which documents are converted into structured data, such that each document is described using a set of features called *concepts* to provide a holistic perspective of textual and nontextual information (Mikroyannidis and Theodoulidis 2006).

Text mining is a technological development with a highly commercial potential (Owens et al. 2009). For example, studies indicate that 80% of company information is contained in text documents (Ur-Rahman and Harding 2011). Studies have also shown the benefits of automating the analysis of large amounts of qualitative customer feedback data related to tourism and financial and manufacturing services and have demonstrated how to effectively manage and convert customers' online reviews to help inform business strategy (Lau, Lee, and Ho 2005; Ludwig et al. 2013).

The approaches described in the literature can be grouped into linguistic and nonlinguistic approaches (Taboada et. al 2011). Linguistic techniques consider the natural language characteristics of the text in the documents (e.g., syntax, grammar), whereas nonlinguistic techniques view documents as a series of characters, words, sentences, paragraphs, and so on (Ur-Rahman and Harding 2011). Nonlinguistic techniques treat each document as a list of terms, counting the number of times specific words appear in a document and calculating their proximity to other related terms in the document or in related documents (Zhong, Li, and Wu 2012).

Linguistics-based text mining often makes use of external resources, such as WordNet, the largest online database of English linguistic terms containing meaning-related words (http://wordnet.princeton.edu/). These resources may pertain to a specific natural language (e.g., dictionary, thesaurus). However, the concepts in a particular document might also refer to a specific subject area, called *domain* (e.g., financial services, biology), in which case it might also be appropriate to use domain-specific resources, such as lexicons, taxonomies, and ontologies. Previous research in this area has shown that linguistics-based text mining models can outperform manual (human) categorization of customer reviews because they are more precise in predicting the star rating associated with the reviews (Ghazvinian 2011).

On this basis, text mining can be further classified as *domain independent* or *domain dependent*. Domain-independent text mining can still involve the use of natural language resources, but their use is independent of any specific body of knowledge, theory, or domain; thus, it could be

argued that it can be applied to all documents of a language. In general, text mining applications are most effective if some level of domain specificity is incorporated into the analysis (Bhuiyan, Xu, and Josang 2009). Thus, in this article we incorporate domain specificity by developing linguistic resources for the domain of customer feedback in car park and transfer services. We develop a framework for capturing information about activities and resources as well as contextual information.

Research on customer feedback and text mining has focused primarily on extracting information related to opinions or sentiments (Goldberg and Zhu 2006; Lin and He 2009). Analyzing the opinion or sentiment embedded in customer feedback can be performed at different levels, such as extracting the overall sentiment of an entire comment, on each sentence of the comment, or in reference to certain aspects or features of the product/service (e.g., price, design, employees) (Feldman 2013). Table 1 summarizes a nonexhaustive list of related research; we do not include research focusing on algorithmic aspects of text mining (Pang and Lee 2008).

(Insert Table 1 about here)

As Table 1 shows, most previous research follows a nonlinguistic text mining approach. Four articles include a mixed approach that uses linguistic techniques such as stemming and parts of speech, with three of the approaches having a linguistic text mining approach. No research addresses the domain we examine in this study. The articles following a linguistics-based approach use a specific set of semantic word patterns that includes sentiment (positive/negative), similar to the approach discussed herein. However, none of the approaches use domain information to guide the definition of semantic features and word patterns.

We summarize the research gap and research aims as follows: Service literature has long emphasized the importance of a perspective and frameworks that represent the interactive nature of

value (co)creation between firm and customer. This perspective has driven researchers to search for more holistic approaches to understand customer feedback, considering not only output evaluations but also the value (co)creation process customers experience. Moreover, after a long tradition of explicit customer feedback analysis based on structured data, companies are shifting toward unstructured forms of feedback that require extensive technological support. As such, text mining models have become the Holy Grail for conducting these types of analyses. However, current models are inherently flawed in terms of potential depth of analysis and accuracy of results. Thus, alternative frameworks are necessary for detailed and accurate assessment of increasing volumes of customer feedback. In the following section, we provide empirical evidence of how a text mining model of customer feedback analysis can be developed. We detail the process of model development and the different stages required to build a linguistics-based text mining model. In contrast with technology-centered approaches, this research is enriched by significant cross-fertilization between service and information systems research.

METHODOLOGY

Case Study

We asked customer insight managers from a group of medium-sized and large U.K. organizations to participate in a study adopting a text mining approach for analyzing customer feedback. All the companies contacted were interested in participating in the study. Six companies in energy, health, recycling, water, telecommunications, and car park and transfer services provided data sets of explicit customer feedback that included unstructured textual data. We evaluated the quality and suitability of all the data sets, along with the characteristics of the particular service sector, for their potential contribution to theoretical and practical discussion.

After reviewing the data from each company, we selected the car park and transfer service at a U.K. airport as the most suitable data set in terms of source, domain/context, average number of words per comment, language, number of comments, and time frame. The comments for recycling,

water, and health were not ideal for model development because of the size of the data sets. The energy data set involved multiple languages and diverse sources, which might have complicated data analysis. Finally, we considered the telecommunications data set inferior to the chosen domain because of the lower average number of words per comment and the excessive variety of the content, which also might have overcomplicated model development.

In our chosen domain, the customer experience consists of key stages that include, but are not limited to, (1) booking and paying in advance, (2) traveling to the airport, (3) locating the car park, (4) paying if not prebooked, (5) entering the car park, (6) finding a space and parking, (7) locating and waiting for a bus transfer, and (8) transferring to the airport, followed by many of the same stages in reverse order on the return journey. This type of service features brief encounters and low levels of interpersonal contact (Mattila and Enz 2002) but also high levels of customer participation (Wreiner et al. 2009) and extended duration. We expected rich customer contexts to emerge for data analysis in terms of these features' impact on how customers experienced the service.

The company solicits explicit customer feedback (including structured and unstructured data) on a daily basis through an online survey sent to customers two days after they use the service. It currently engages in a manual process of analyzing unstructured data collected from answers to an open-ended question included in the survey: "What is the single most important factor you feel we can improve upon to enhance your car park and transfer experience?" The company receives approximately 50,000 responses annually on average and 1000 customer comments weekly. Overall response rates are approximately 14%.

The manual process of analyzing textual customer feedback and responding to the open-ended question takes approximately two weeks. A coder manually categorizes each comment into a specific set of categories related to the service process. These categories represent elements the

company finds important for customer feedback evaluations. However, the main drawbacks of this categorization are that (1) each comment is classified into just one category (despite often including more than one compliment, complaint, or suggestion); (2) positive or negative sentiments are individual categories, with no relationship to a specific element of the service; and (3) the classification of comments by means of manual annotation is not consistent.

The open-ended question focuses on obtaining a single improvement suggestion; however, a review of the answers shows that both multiple improvement factors and compliments and complaints are often embedded in, or appear in parallel with, detailed descriptions of customers' service experiences. This indicates that methods encouraging more active participation from customers can generate more diverse information (Walter, Edvardsson, and Öström 2010).

The Linguistics-Based Text Mining Process

In general, the text mining process refers to a process workflow that consists of user-defined pipelines of analytical tasks that can be either predefined or customized by the user. For our purposes, we modified the Cross Industry Standard Process for Data Mining (CRISP-DM) methodology (Chapman et al. 2000) for a linguistics-based approach using domain specificity. The text mining process adopted the following process:

1. Business and data understanding.

2. Training or model development.

3. Import corpus (set of customer feedback documents gathered from the participant company)

    a. Extract concepts using predefined built-in analyzers and dictionaries; evaluate and, if necessary, extend them. This stage is based on a manual coding process.

    b. Define new concepts, patterns, and text mining models; evaluate and, if necessary, extend them.

4. Testing or model evaluation.

We used IBM SPSS Modeler as a text mining tool to implement two iterations of the text mining model—the first with the purpose of implementing a proposed framework in a text mining model and the second with the objective of giving directions for further improvements of the model. Figure 1 illustrates the overall process.

(Insert Figure 1 about here)

We carried out the first iteration (steps 1–4) on customer feedback data set A (which contained 1092 comments from December 2011). More specifically, we selected a random sample of 100 comments from data set A for the training stage and the entire dataset for the testing stage. The sample was manually annotated by one of the researchers (coder A), who focused on resources and activities as the main components of the value creation process. At the end of this stage, we presented the "sub-" and "main" categories to the company's customer insight manager, who leads a team responsible for managing all the customer feedback, to provide content validity for the proposed model (Yu, Jannasch-Pennell, and DiGangi 2011).

We developed a text mining model for the first iteration from the results of this manual annotation process. The model included developed linguistic patterns based on subcategories (i.e., booking resources of the customer) of concepts (i.e., reference number) generated by coder A. These patterns were assigned to a specific part of the service process (i.e., booking) that distinguished compliments from complaints. We implemented the testing stage throughout the entire data set to generate predictions; this involved an automated classification of comments into compliments and complaints and identification of the resources and activities involved. We used two metrics to evaluate the text mining model predictions: data capture and accuracy (Feldman 2013; Feldman and Sanger 2007). Data capture represents the number of comments for which the model finds one or

more of the developed patterns. From the captured patterns in the data set, data accuracy represents the number of correct predictions according to the model.

Table 2 shows how we applied the main categories to a single comment. For example, for a specific customer comment, we identified the units of information and, for each unit, extracted company resources, customer resources, activities, and sentiments in customer opinions.

(Insert Table 2 about here)

After evaluating the text mining model from the first iteration, to improve the elements we (1) reduced the season bias in the data set, (2) included new coders to validate the framework, and (3) worked to give directions for further improvements. Thus, we carried out a second iteration (steps 1–3) on a different data set (data set B), which contained a random sample of 100 customer weekly comments from winter and summer (mixed set of comments from September and December). We employed sentence-level analysis to extract more insightful information about the customer experience from the comments.

During the training stage, as Figure 1 shows, two independent coders validated the main categories from the first iteration and developed new subcategories. The second iteration adopted a deductive approach to manual annotation, using a template analysis from the previous main concepts (Singh, Hillmer, and Wang 2011). The coders were required to divide each comment into units of information, defined by Singh, Hillmer, and Wang (2011) as phrases or sentences (ideas) in a comment that contain a specific evaluation of the service process. From these units of information, we then developed linguistic patterns for use by the text mining model.

After coders B and C performed the manual annotation process, all coders met to compare the different subcategories and to resolve disagreements; one of the main authors (the judge), whose role was to moderate and generate agreement, chaired the meeting. This procedure is necessary when the

interpretation of textual data can cause disagreement between coders (Fastoso and Whitelock 2010), and its utilization in linguistics-based text mining modeling is beneficial, especially at early stages of model development. The primary issue on which the judge required agreement was the definition of the main categories to be used and the way interactions would be represented in the text mining model. We developed a final set of categories to create new linguistic patterns for analyzing customer feedback. During the second iteration, extended linguistic pattern development, testing, and evaluation helped us analyze the comments sentence by sentence and to apply coder recommendations.

From the second iteration, we classified and mapped concepts to the main categories of the proposed framework, including synonyms. Prior research has used synonyms to resolve the issue of misspelled concepts and concepts having the same meaning (e.g., "signs" and "signage") (Singh, Hillmer, and Wang 2011). Macros, which are reusable linguistic features, also helped simplify the appearance of literals and word strings needing to be extracted (i.e., identification of adverbs, pronouns, and prepositions) (Tsytsarau and Palpanas 2012).

Finally, as part of the model evaluation of the text mining process, we again interviewed the customer insight manager to identify and discuss the evaluation of the resultant text mining model in terms of efficiency, consistency, accuracy, and flexibility. In addition, we asked the customer insight manager to elaborate on the deployment of the text mining model in different service areas and the wider implications for the organization.

RESULTS

We provide insights into how we developed an open learning text mining model with the ability to automate the analysis of customer feedback. The two subsections offer a detailed description of the results of analyzing the customer feedback according to the proposed ARC

framework and the organizational learning outcomes resulting from the deployment of the

linguistics-based text mining model.

First Iteration

The training stage (100 comments analyzed by coder A) generated 600 concepts, 14

subcategories of concepts, and 80 linguistic patterns. The testing stage resulted in the automated

capture of linguistic patterns in 550 comments from the entire data set A (1092 comments). In total,

694 patterns arose from these comments, 55 of which were incorrect predictions, giving an overall

accuracy of 92%, which is high enough to demonstrate the automation level that can be achieved

with text mining (Thelwall et al. 2010). Of the captured comments, the model identified 86%

complaints and 14% compliments.

Table 3 shows the details on model accuracy when extracting compliments and complaints

during the testing stage. The analysis provides evidence of the customer experience across the

different stages of the service process, taking into account the resources and activities involved at each

stage. The analysis indicates which stages of the service received the most customer complaints or

compliments. For example, Table 3 shows that the highest percentage of complaints and compliments

pertained to the use of the facilities to park cars (298). In particular, the analysis classified various

complaints about company resources, such as signage, space, staff, facilities, and other people's

parking, in addition to other customer resources.

(Insert Table 3 about here)

For the customer insight manager the speed of the text mining model proved highly

satisfactory in identifying and mapping elements of the service process with a major impact on

customer compliments and complaints. The results from the model cohered with the company's

quantitative studies but also provided a deeper understanding of customers' suggestions and why

they were (dis)satisfied. For example, customers frequently complained about the price subcategory, with 71% of the booking comments referring to price resources. In most cases, price resources were linked to negative activities, such as (the perceived need to) "reduce" and "increase," and to negative attributes, such as "expensive," "less," and "cheaper." Without the use of linguistic patterns, this feedback would not have had either a positive or a negative meaning because of the absence of emotion descriptors.

Second Iteration

In the second iteration, the three coders made three main recommendations for improving the model. The first recommendation was to include a new main category to capture the customer context of a service experience. The apparent importance of the context corroborates previous research that shows that value (co)creation depends on the context (individual or social) in which it is generated (Grönroos and Voima 2013). Forty-two of the 100 random comments coded from data set B included "personal context," highlighting elements of customers' lives with implications for the service experience (e.g., disabilities, old age), and "situational context," describing uncontrollable external factors that can affect (positively or negatively) customers' experiences (e.g., weather, flight delays, other customers). The second recommendation was to differentiate between the activities performed by the customers and those performed by the company. Distinguishing this category by separating company activities (e.g., informing, opening, reading the card) from customer activities (e.g., entering, parking) is especially useful when developing linguistic patterns in the text mining model. The third recommendation involved distinguishing complaints from suggestions. Many customers provided suggestions such as "a digital display with waiting times," "guidance if possible on bus frequency," and "color boards about parking."

As a result of these improvements in the text mining model, we developed 47 subcategories to provide a clear picture of the parking and transfer service process. In total, we classified and mapped 678 concepts to these subcategories. Figure 2 depicts the model for analyzing customer feedback on

the basis of the sub- and main categories of concepts. The activities in the middle of the figure

represent the standard flow of the service process (we treat the last part of the flow, "feedback," as

part of the service process). The boxes next to the main categories "situational context," "personal

context," and "company and customer resources and activities" contain all the subcategories

developed during the second coding process (47 subcategories).

(Insert Figure 2 about here)

With the proposed approach, we can map the comments to a designated value creation

process. This study adapts the service process shown in Figure 2 to a linguistics-based approach that

generates linguistic patterns for company resources, company activities, customer resources,

customer activities, and sentiment conveyed in opinions (in terms of compliments, complaints, or

suggestions). Overall, the model required 11 macros that support extraction by incorporating

different types of word tags and n-grams, such as the use of word gaps for determining relationships

between word categories (Haddi, Liu, and Shi 2013). The examples in Table 4 explain how we

classified linguistic patterns. In the first comment in Table 4, "Waiting for transport to the airport,"

the pattern (1) automatically analyzed the sentence, extracted the concept "waiting," and classified it

under the <waiting> subcategory; (2) classified the concept "transport" under the <bus resources>

subcategory; and (3) classified the concept "airport" under <airport areas>. "Waiting" fell under the

main category <customer activities>, and the other subcategories fell under the main category

<company resources>. From a linguistic perspective, some literals or word strings were important to

the analysis, while others could be excluded. For example, the preposition "to" was essential during

the analysis to determine whether the customer was going to or returning from the airport. Therefore,

we included the macro <mProp> as part of the pattern construction to extract the two prepositions

from the sentence. Word tokens such as "the" were not important in the pattern output, and we

excluded them from the extraction process. Thus, we used the word gap "@{0,1}" to guide the pattern dealing with the existence of the token "the," without needing to show it in the pattern output. The pattern automatically classified this sentence as a complaint about going to the airport and mapped it to the service process "going to the airport."

(Insert Table 4 about here)

Finally, extracting context from customer comments represented one of the most challenging parts of the process. In the following example, the customer is complaining about not having the option to cancel or amend his booking and about losing money because of a situational context (i.e., a personal loss that resulted in the cancellation of his trip):

A death in my colleague's family on the morning I was due to travel resulted in the trip being cancelled. Having pre-paid, I was informed on your web site that I could not cancel or amend the booking; therefore I lost my money. Not happy about that"

The situational context explains the customer's complaint. The pattern analyzed two sentences, constructing the first sentence "death in my colleague's family on the morning" as *<situational><word gap><mProp><word gap>< mTimeActivities>*. It classified the token "death" as situational and "morning" with the macro *TimeActivities*. The analysis is not concerned with whether the death was the reason for the cancelation, and thus word gap was used. The death was classified under flight issues "contextual," and thus a macro was designed to include contextual flight issues, such as "missed flight," "late for flight," "trip being cancelled," and "flight cancelled." The two sentences were mapped to a situational context category.

For the organizational outcomes, the evaluation of text mining process resulted in lessons learned by the company. Overall, the customer insight manager considered the text mining model useful for analyzing customer sentiments with the standard flow of activities (stages) of the parking

and transfer service. Specifically, the manager's evaluation highlighted organizational outcomes in terms of efficiency, consistency, flexibility, and accuracy.

A follow-up study with the company highlights the value of the ARC model in analyzing customer feedback before and after a process change. The model identified a gap between management and customer perceptions of the impact of a change in the car park name, with implications for future service changes. Customer feedback comments pertaining to the car park's name change increased by 40%; all comments were negative and referred to failures in the service process caused by the name change, such as customers not being able to find allocated spaces.

In general, efficiency is one of the main advantages of a text mining model. For the participant organization, the text mining model provides efficient and faster analysis than the current manual processes. Because companies collect large amounts of textual data from different sources, they need efficient customer feedback systems that deliver automation and service productivity (Rust and Huang 2012). As the customer insight manager noted: "From my point of view, you've developed something that works… you could drag it off to different areas of the business and just be as efficient as possible, …but there's a big benefit to using this compared with doing it manually … especially as the manual method data is so delayed." Manually analyzing information can take several days, resulting in a slow service recovery strategy and the loss of dissatisfied customers (Buttle and Burton 2002; Gruber 2011).

The consistency of the information extracted and the specificity of the analysis provided deliver an additional advantage—namely, the practicality of identifying resources or activities that the company can improve immediately. As the customer insight manager noted: "Tactically, you want to solve the problem straight away… and make sure you improve in a way that affects the majority of people, … not something like price, which can take time, but it might be something like staff, which you could do straight away … and if the customer decides ... an example of what they want improved, I think the customer will be doing your job for you."

The participant organization considered the model flexible and capable of adapting to different contexts. The model can evolve and be enriched over time with new customer terminology on changes in service resources, activities, and customer context. It can also be applied in different services; as the customer insight manager stated: "By using this model, [we could] apply [it] in different service areas in our organization such as lounge, duty free, etc."

In terms of accuracy, the final text mining model demonstrates the high levels of accuracy in the analysis. In turn, this high level of accuracy provides justification for the deployment of such text mining models. As the customer insight manager commented: "By having this accuracy, we could trust the insights from the data and help in decision making."

DISCUSSION

The results demonstrate that collecting and analyzing explicit, unstructured feedback assigns customers more active roles in providing organizations with richer information about their experiences (Witell et al. 2011). Although the open-ended question for data collection focused only on suggestions for a single improvement factor, customers also took the opportunity to provide other types of feedback (e.g., compliments, complaints). The parking and transfer service process comprises a flow of different activities, suggesting that customers will mention more than one improvement factor. This situation is consistent with previous research on the "processes" perspective of the value creation process (Payne, Storbacka, and Frow 2007); multiple factors shape customer experiences (Verhoef et al. 2009). Next, we outline how the ARC framework and the linguistics-based approach facilitated development of a flexible text mining model capable of providing holistic analysis of the customer value creation process contained in customer feedback.

The ARC Framework

We use the value creation process to illustrate customer perceptions of their experiences from a process rather than an output perspective (Payne, Storbacka, and Frow 2007). A customer-centric view of service suggests that this process entails continuous learning about the customer experience

(Heinonen et al. 2010). Adopting this lens, we analyzed the ARC of customer feedback of the participant company. We contend that customer feedback is more than an expression of overall sentiment about the company or the assessment of an output attribute (e.g., tangibility, reliability; Parasuraman, Zeithaml, and Berry 1988); rather, it constitutes a more holistic assessment of an interaction process between resources and activities of the company and the customer that have performed above or below expectations in a certain customer context (Grönroos 2012). Moreover, recognizing the importance of customer context when determining value provides information about elements that guide customer judgments about acceptable or unacceptable experiences (e.g., service systems, social structures) (Edvardsson, Tronvoll, and Gruber 2011; Grönroos 2012). The main contextual elements affecting the customer experience in this case were situational and personal factors. Thus, context can involve activities beyond the direct control of the service provider, and thus the full holistic context of customer experiences should be examined in detail because of its implications for how customers experience value (Lemke, Clark, and Wilson 2011).

Because value creation is a repeating dynamic process in company–customer relationships, service evaluations (feedback) should be considered a key input into maintaining or improving future customer experiences, developing service innovations, and refining service recovery processes (Gruber 2011; Tronvoll 2007). Tronvoll (2007) explains that the cocreation process is iterative and, therefore, that customer feedback can be used to enhance further customer experiences with the organization. For example, for a customer who parks his or her car again in the car park, the first time has implications for the second cocreation episode because it modifies his or her expectations of a further cocreation process (Tronvoll 2007). The proposed ARC framework contributes to developing and enhancing customer relationships and further value creation processes. It does so by allowing firms to modify (if necessary) and leverage resources or activities that customers identify in their previous experiences. This is consistent with Grönroos's (2012) conceptualization of companies as "value facilitators" that support customers in their value creation experience with appropriate

resources and processes. The ARC framework provides a practical architecture that enables companies to design text mining models that facilitate their understanding of the customer experience. This then enables them to improve the efficiency and effectiveness with which they attempt to facilitate customers' value creation experiences.

ARC Modeling through Linguistics-Based Text Mining

Empirical research of text mining modeling using a linguistics-based approach is scarce. The proposed model represents one of the few attempts to provide evidence of the benefits that firms can realize by using such an approach. The current research provides empirical evidence of how to use features of linguistics-based text mining, such as dictionaries and linguistic patterns, to analyze textual customer feedback. We advance linguistics-based text mining by developing a model that not only automates analysis of sentiment conveyed in customer feedback but also focuses on evaluating the value creation components that customers specify as affecting and shaping their experiences. This approach differentiates from similar linguistics-based text mining, such as "aspect-based sentiment analysis" (Feldman 2013), by its customer experience–focused perspective, which goes beyond product features predefined by the organization. We argue that the initial coding stages are crucial to providing not only a text mining modeling framework but also the ability to understand the linguistics of customer feedback in a service domain. In summary, we took the following steps: (1) extract ARC from customer feedback, (2) elaborate and assign linguistic patterns to the service process, and (3) classify them by sentiment. The novelty of the approach lies in the development of a text mining model that captures the customer context (personal and situational), customer activities and resources, company activities and resources, and customer sentiments (compliments, complaints, or suggestions). As a result of the first phase of this procedure, we were able to develop a model that achieved a high level of accuracy in predicting customer compliments and complaints and the resources and activities involved. In the second phase, we provided guidance on how to improve the results by applying the entire ARC framework with extended use of text mining linguistic features.

Application of the ARC framework also facilitated the development of a text mining model that can evolve. That is, it can be enriched over time with new customer terminology on changes in service resources, activities, and customer context. Furthermore, it can be easily adapted and applied to different (service) business domains. Thus, the text mining model is an *open learning model*; it can be enhanced over time by incorporating domain knowledge. The proposed open learning model consists of an initial training process on the specific ARC, followed by a double-loop learning process (Boonstra 2004). Through this process, companies can analyze the results, evaluate them, and provide feedback on how to reevaluate and reframe the extracted service process characteristics and performance metrics. The initial training process involves linguistic mapping, understanding the domain, and developing an active ARC service dictionary. This process can be applied to similar or different service contexts. In this case, we used the ARC framework to understand the domain, providing a structure for the open learning model. We advocate that such an approach is necessary to fully understand the customer experience content embedded in customer feedback.

MANAGERIAL IMPLICATIONS

An important area for mangers is the improvement of the service process in which the text mining model is applied. Use of this model helps close the gaps in the service process from a customer-centric perspective. Concepts such as service blueprinting (Patricio et al. 2011; Shostack 1987) might be updated and improved through text mining. An organization should be able to define a more accurate service blueprint by analyzing customer feedback on specific service encounters. By using the text mining model developed herein, companies can enrich the service blueprint with customer activities and resources, company activities and resources, and aspects of the context from the customer perspective. The customer-centric understanding facilitated by the ARC framework provides organizations with the ability to modify existing service offerings or develop new services, thereby addressing any gaps in their customer-centric service blueprint.

Furthermore, analyzing customer feedback at different periods would help companies understand how the customer-centric service blueprint is perceived, how changes in service offerings affect service encounters, and how activities and resources are affected. For example, using customer feedback, companies could analyze the impact of specific service changes (e.g., the name change of a car park). Timely analysis of this type of feedback would enable organizations to plan ahead when making such service changes, identify specific customers who could be affected, and act accordingly.

Evidence shows that the main question used to gather customer feedback generated not just one factor but multiple improvement factors and even compliments in some cases. Most services comprise multiple value creation opportunities: thus, simply asking customers to comment on "one improvement factor" is limiting. Therefore, we recommend that organizations ask for improvement factors at different stages of their services. In doing so, analysis of the information will be easier and less time will be spent on categorizing customer comments.

The proposed text mining model is increasingly relevant for companies serving Generation Y customers, more than 70 million of whom reside in the United States (Anandarajan et al. 2010) and spend approximately $600 billion a year (Noble, Haytko, and Phillips 2009). Generation Y customers expect fast service and thus are unlikely to fill out traditional comment cards and then wait weeks to receive a reply. Automated text mining could help companies respond quickly to feedback received from these demanding customers. Companies could develop smartphone apps for automated feedback collection, analyze the data automatically, and give feedback to their customers within seconds.

LIMITATIONS AND DIRECTIONS FOR FURTHER RESEARCH

This research has several limitations, which provide directions for further research. First, the model developed for analyzing customer feedback is specific to the situation and the type of service in which the research was deployed (Friman and Edvardsson 2003). However, the text mining process could be easily adapted to other domains or services or to changes in services. Although

additional training might be necessary, in terms of additional coder input, this is similar to what would normally be required to deploy text mining models (Feldman 2013). Second, the proposed model requires work at the training stage to improve data capture and accuracy. Despite achieving a high level of accuracy (92%), data capture was low (just over 50%) in the first iteration.

Further research could investigate how information gathered from a text mining process can be integrated into company information systems (Linoff and Berry 2011), thus complementing other kinds of information being stored by companies (Buttle 2008). For example, improvements in the modeling of individual-level customer lifetime value (CLV) have generated more accurate prediction of customer lapses (Kumar, Ramani, and Bohling 2004) through event history modeling. The combination of text mining data and CLV data might enable firms to make more informed decisions about which potentially lapsing customers they should attempt to retain and might also indicate the type of resources or activities required. This would help companies create rich, dynamic customer-centric models of CLV and customer equity that could provide a deeper understanding of customer behavior, including customer responses to organizational attempts to improve CLV (Rust, Lemon, and Zeithaml 2004).

We also recommend that additional linguistic research be included in further text mining models. The importance of understanding language structures in the development of text patterns could aid in developing better predictive models. This process represents a challenge to text mining researchers because of the complexity of human language and the different methods people use to express themselves. Problems include the possible use of irony to express dissatisfaction (e.g., "The very smart guard didn't let me in") and situations when no words express implicit sentiment (e.g., "It took me 45 minutes to exit") (Balahur et al. 2010; Carvalho, Sarmento, and Silva 2009).

As our framework suggests, customer feedback can be classified in multiple ways—for example, direct/indirect, structured/unstructured, and explicit/implicit. Thus, companies need to learn how to efficiently collect, categorize, and analyze different types of feedback (Poblete and Baeza-

Yates 2008; Witell et al. 2011). We use the ARC framework to analyze an explicit form of unstructured, solicited customer feedback, but this framework can be extended to unsolicited feedback settings, such as social media conversations about products and services. Further research should apply the ARC framework to unsolicited feedback (e.g., online conversations) to offer additional contributions in the area of service productivity (Rust and Huang 2012). Such a real-time, forward-looking measure (Zeithaml et al. 2006) could shed more light on customer experiences and the mapping of the customer journey and develop more intelligent, dynamic customer segmentation and selection. Text mining could also be used to attract future customers through either direct targeting and interaction on social media or indirectly by encouraging positive resource/activity-specific word of mouth within social networks.

Because of information technology improvements, further research is increasingly likely to focus on dynamic evaluations of customer experiences and consumers' resulting engagements with the company, rather than on capturing snapshots of how consumers perceive outcomes. Research could also address the dynamic performance aspects of the model, refining and optimizing it to explore whether even greater accuracy levels can be achieved. Finally, given the flexibility and analytical speed of the ARC framework and the open learning model, further research could evaluate the performance of the proposed model in enhancing understanding of the issues driving sentiment outcomes, across different business domains and different types of service functions. Such improved understanding of the ARC issues influencing value perceptions would facilitate more appropriate organizational responses than those possible through analysis of data gathered through solicited customer feedback collection methods.

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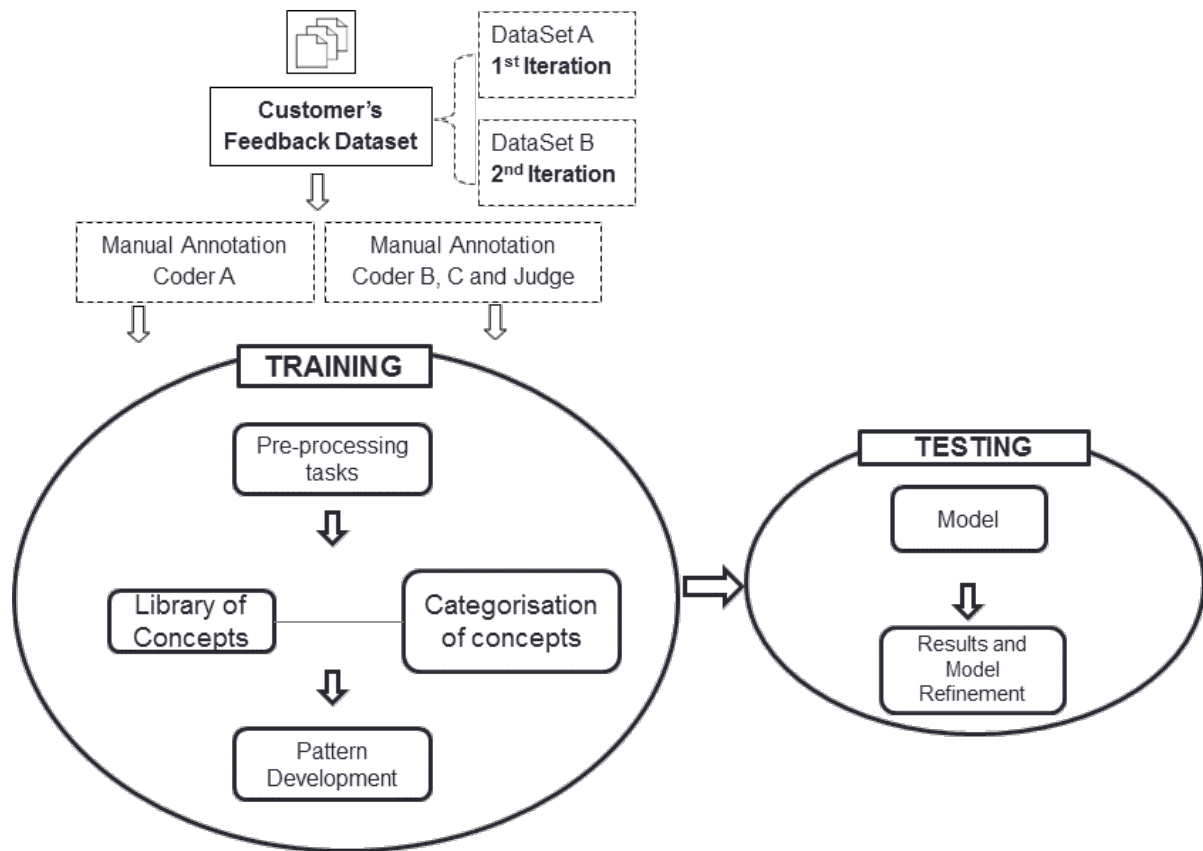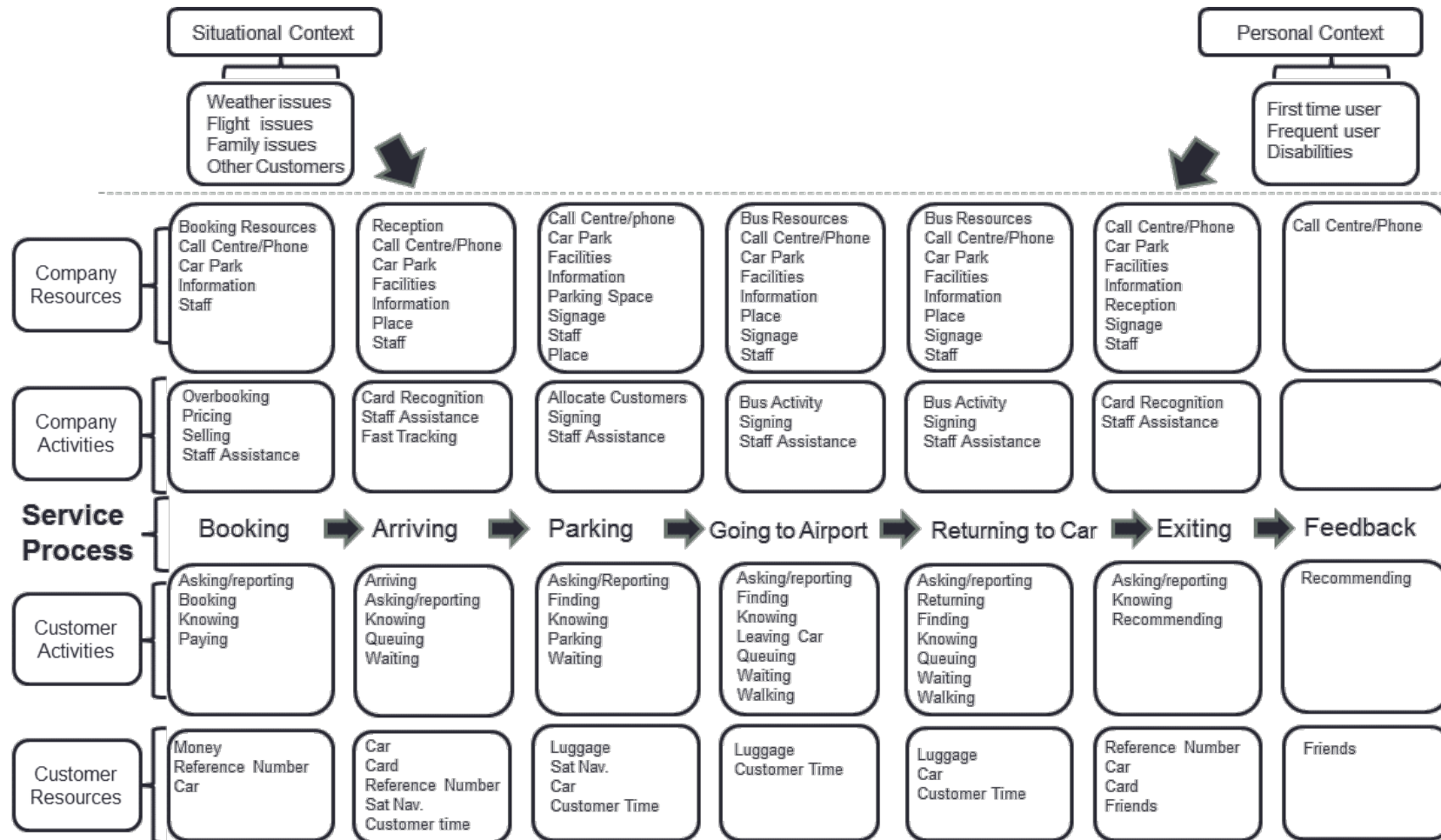
Figure 1. Text mining process.

Figure 2. Parking and transfer service process model from customer feedback comments.

Table1. Review of Text Mining and Customer Feedback Approaches

Articles	Approach	Domain	Feedback Method	Analysis	Techniques
Turney (2002)	Linguistic	Automobiles, banks, movies and travel agent (Epinions)	Active	Classify reviews in "recommended" or "not recommended" categories	Pointwise mutual information; semantic orientation; clustering
Dave and Lawrence (2003)	Mixed	Product reviews (Cnet and Amazon)	Active	Extract positive and negative features from Wordnet and colocation	Support Vector Machine and naive Bayes with smoothing
Hu and Liu (2004a); Hu and Liu (2004b)	Mixed	Product reviews	Active	Extract product features from customer comments, classify as positive or negative	Part-of-speech tagging, frequent features generation, pruning
Gamon et al. (2005)	Nonlinguistic	Automobile reviews	Passive	Extract car make and model and positive and negative sentiment	Clustering, naive Bayes, weighting based on term frequency
Ghazvinian (2011)	Nonlinguistic	Restaurant reviews	Active	Classify reviews and predict sentiment from OpenTable.com, an online service for finding restaurant.	Maximum entropy classification, Sentiment Model
Kobayashi et al. (2006)	Mixed	Automobile reviews	Active	Extract opinion templates in terms of subject, attribute, and value	Classification, anaphora resolution
Kobayashi, Inui, and Matsumoto (2007)	Mixed	Restaurant and cellular reviews	Active	Extract opinion templates in terms of opinion holder, subject, part, attribute, evaluation, condition and support	Classification, aspect-of relationships
Scaffidi et al. (2007)	Linguistic	Product reviews (Amazon)	Active	Extract features and scores each feature based on the review	Part-of-speech, term frequency and patterns, classification
Lehto et al. (2007)	Nonlinguistic	Travel agent reviews (Epinions)	Active	Extract customer service and support, trip schedule change, product experience and firm credibility.	Not described
Coussement and Vandenpoel (2008)	Nonlinguistic	Call center e-mails (newspaper)	Active	Extract key terms that identify complaints and compliments; classify automatically e-mails	Term frequency; Singular Value Decomposition, boosting
Ziegler, Skubacz, and Viermetz (2008)	Nonlinguistic	Siemens website	Passive	Extract key terms and sentiment, create cluster labels and their weights	Clustering, treemap renderings
Zhang et al. (2010)	Linguistic	Product reviews	Active	Extract features such as opinion, part/whole relationship, and "no" patterns	Double propagation method, frequency-based ranking
Zhang, Narayanan, and Choudhary (2010)	Nonlinguistic	Product reviews (Amazon and BrowseNodes)	Active	Extract key terms, frequency, Relative Feature Fraction, importance of feature	Extended page ranking algorithm for each feature
Zhai et al. (2011)	Nonlinguistic	Product reviews	Passive	Extract product features	Naive Bayesian classification, clustering

Table 2. Example of First Categorization of Customer Feedback Concepts

Customer Comment	Unit of Information	Company Resource	Customer Resource	Activity 1	Activity 2	Opinion
Barrier did not recognise my pre-booked credit card - had to press buzzer but person very helpful. Bus going out was fine - after waiting 15mins for bus on return we walked - very poor	Barrier did not recognise my pre-booked credit card	Barrier	credit card	did not recognise	Pre-booked	
	Had to press buzzer but person very helpful	Buzzer/ Person		press		very helpful
	bus going out was fine	bus		going out		fine
	waiting 15mins for bus on return we walked- very poor	bus	15 mins	waiting		very poor

Table 3. Model Accuracy for Compliments and Complaints

Compliments

Service Process	Right Predictions	Wrong predictions	Total	Accuracy
Parking car	82	9	91	90%
-Staff	20	2	22	88%
-Others car park	62	7	69	84%
Bus Service	7	1	8	91%
Total	89	10	99	90%

Complaints

Service Process	Right Predictions	Wrong predictions	Total	Accuracy
Booking	87	3	90	97%
-General	23	1	24	96%
-Price	64	2	66	97%
Arriving Car Park	54	1	55	98%
Parking car	298	38	336	89%
-Space	71	3	74	96%
-Staff	25	4	29	86%
-Facilities	9	0	9	100%
-Directions	111	3	114	97%
-Others car park	65	12	77	84%
-Others Customer resources	17	16	33	52%
Bus Service	111	3	114	97%
Total	550	45	595	92%

Table 4. Pattern Development

Sentence Level Analysis	Library Resources	Macro Development	Pattern Syntax	Service Process
waiting for transport to the airport	Waiting Bus Resources Airport Areas	mProp	<Waiting > <mProp> <Bus Resources> <mProp> @{0,1} <Airport Areas>	Going to airport
poor road signage to the Valet Parking	Negative Opinion Signage Airport areas	mProp	<Negative Opinion> @{0,1} <Signage> <mProp> @{0,1} <airport Areas>	Parking to Car
car parks nearest the terminal can be pre-booked and are good value	Car Park Airport Areas Customer Activity	MSupport mVable	<Car Park> <mSupport> @{0,1} <Airport Areas> <mVable> @{0,1} <Customer Activity>	Booking Service
On Exiting the Car Park we were under the impression we had to place the entry card into the machine	Customer Activity Car Park Customer Activity Customer Resources Reception	mProp	<mProp> <Customer Activity> @{0,1} <Car Park> @{0,8} <Customer Activity> @{0,1} <Customer Resources > <mProp> @{0,1} <Reception>	Exiting Service
On return the lifts were not working	Customer Activity Facilities Negative Opinion	mProp	<mProp> <Customer Activity> @{0,1} <Facilities> @{0,1} <Negative Opinion>	Returning
I would definitely use again and recommend for others	Positive Opinion Customer Resources	mPronouns mVable mProp	<mPronouns> <mVable> @{0,1} <Positive Opinion> @{0,1} <Positive Opinion> <mProp> <Customer Resources>	Feedback