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Customer Feedback Analysis Using Text Mining

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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.

Keywords: Activities, Resources, Context, Customer Feedback, Text Mining, Case Study, Value Co-creation

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I. 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. 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

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.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.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.The deployment of text mining models has clear managerial implications, including the availability of accurate and timely information, for better informed decision making. Customer feedback analysis using text mining has largely focused on developing more accurate models for automatically predicting the sentiment embedded within text.The majority of these studies have emphasized how different text mining methods 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 workload is more. 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 workload, and the atmosphere), sentiment outcomes would offer greater value for decision-making purposes.

II. LITERATURE REVIEW

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 but also can be mapped onto a chain of activities and resources that describes how value is (co)created in a particular context 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 7 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.

III. CONCEPTUAL FRAMEWORK

Service literature has considered the process nature of services, especially the effect of customer–company interactions on customers' evaluations of a service experience. Adequate mapping of these interactions facilitates the identification of encounters, which Shostack defines as "a period of time during which a consumer directly interacts with the service."

In summary, service literature highlights key aspects of the service process that facilitate customers' realization of value. It 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 . This value co creation 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.

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.

IV.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 methodology for a linguistics-based approach using domain specificity.

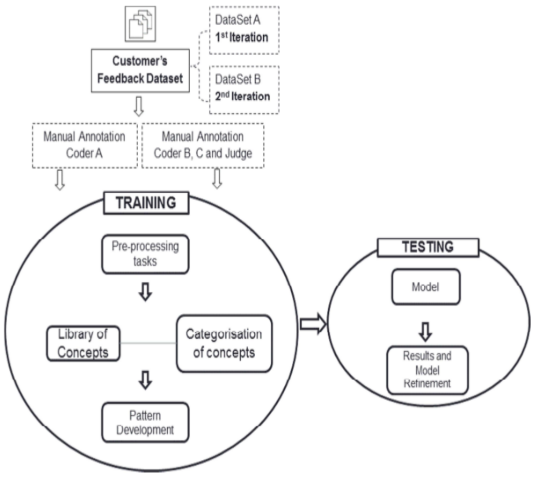
The text mining process adopted the following process:

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.

V. RESULTS AND DISCUSSION

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 19 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.

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.

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 20 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 21 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).

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 subcategory; (2) classified the concept "transport" under the subcategory; and (3) classified the concept "airport" under . "Waiting" fell under the main category , and the other subcategories fell under the main category . 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 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."

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

VI.CONCLUSION

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.

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