Using Text Analysis to Gain Insight into Organizational Change

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Abstract

Businesses often implement changes to improve customer satisfaction, increase revenue or to improve profitability. The best situation occurs when a business can measure the impact of the change before and after such cost-cutting measures. This research analyzes data from a survey of more than 30,000 patients from a Midwestern University Teaching Hospital. We analyze the impact of two very different changes: a move from free parking to paid parking in 2009 and the implementation of new on-line options so that patients can access their medical information. We have first analyzed the quantitative data for an aggregate key business metric and then applied Text Mining and Sentiment Mining on the qualitative data for a deeper insights.

Introduction

we have first analyzed using SAS Enterprise Guide® the quantitative data for an aggregate key business metric and found that average of "recommend the hospital to others" showed a small decrease after free parking was removed and the item, "ease of obtaining test result" showed a significant increase. However, many other changes were occurring in the same time period, so it is difficult to draw conclusive links. To get further insight into customers' evaluations of these changes, we used analyzed over 30,000 comments made by patients using SAS® Text Miner 7.1. In the case of the parking charge, we considered comments made a year before and after the change, while in the Online Portal, we considered comments made following the launch.

In both cases, we first use terms frequency matrix to find out the most used terms related to these changes. We then create a customized synonym list and then produced concept links to get a basic sense of how patients reacted. As a result, we have 707 comments for the Online Portal and 366 for the parking, to do further analysis. We take eighty percent of dataset for building rule-based model and writing sentiment rules. The other twenty percent of dataset is held for testing built rule-based model.

We imported four directories of textual reviews, positive, negative, neutral, and unclassified, to SAS® Sentiment Analysis to build our statistical model. We used the feature of "Import learned feature" to import keywords (terms) to build rule-based model. We then defined the weights of keywords according to a domain free sentiments suggestion website. We have a one-to-four weight scale for sentiment words. We then applied "part-of-speech tagging" separately for each adverb, negative adjective, positive adjective, and noun. Here nouns are referring to target change (portal).

Finally, we used the "held" dataset to test built rule-based model. As a result, overall, the sentiment analysis shows that more positive reviews related to the new service. It indicates same result comparing to its numeric rating.

Material and Methods

Qualitative Analysis:

Parking Service

Comparison of average values for show that there is a small (about 1-point) but statistically significant (at 5% level) decrease from pre-intervention to post-intervention period. While that is bad news for the hospital management, it is not unexpected. The actual differences are rather small, but small differences at the high end of the scale may be managerially important. However, as with all longitudinal studies, these changes in the overall metrics cannot be purely accounted for by the intervention implemented because many environmental components are changing simultaneously.

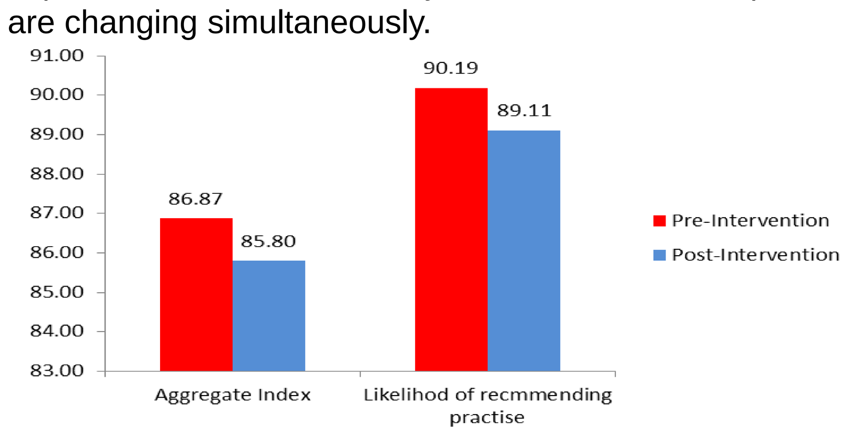


Figure 1.Mean values of Business Metrics

Topic Mining(Parking Service)

The Text Topic node automatically associates the terms and documents according to both discovered and user-defined topics. Each topic is a collection of terms that pertains to a main theme or idea. For this analysis, we have considered quantitative survey data from one year prior and one year post the intervention. For this analysis we have considered quantitative survey data from one year prior and one year post the intervention. For the unstructured data, we have only considered comment from the "bad thing about the clinic section". The goal of the analysis is to detect whether there are changes in the valence of comments related to parking in the textual data after the intervention..

In order to fully understand the valence of the negativity of the comments, the mean values of the overall business metrics associated with the topics of interest i.e., Topic 5 in the pre-intervention data and Topic 1 and 4 in the post-intervention data, are calculated. As can be seen from Figure 2, the averages of both metrics have decreased a lot more (about 3-points) and significantly in the post-intervention.

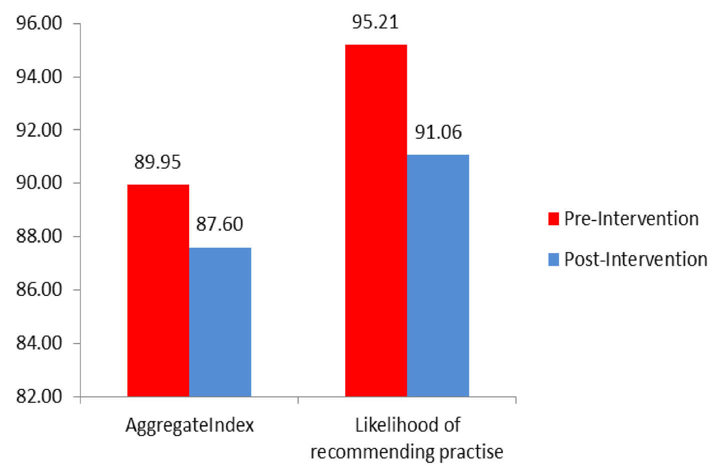


Figure 2. Mean values of Business Metrics associated with the parking related topics.

Online Service

Comparison of average values for show that there is a small (about 1-point) but statistically significant (at 5% level) decrease from pre-intervention to post-intervention period of introducing the Online Service .

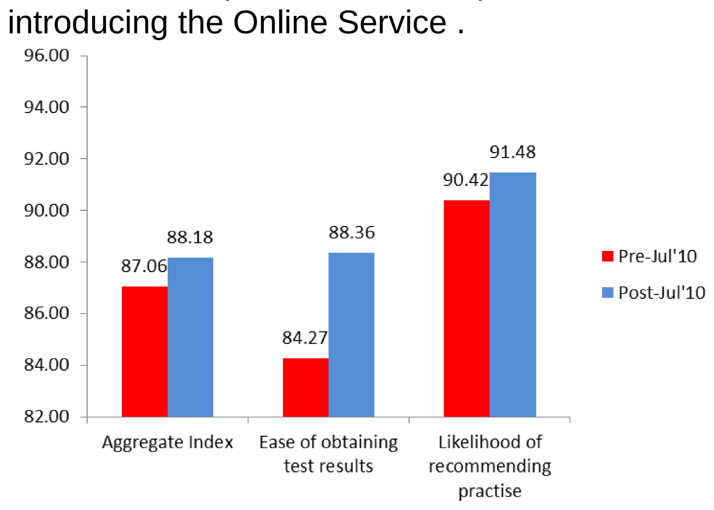


Figure 3. Mean values of Business Metrics before and after Jul'10

While, the comparison of average values between patients who has activated Mychart shows a significant increase (at 5% level) when compared to the patients who has not activated after the introduction of Mychart (Jul'10).

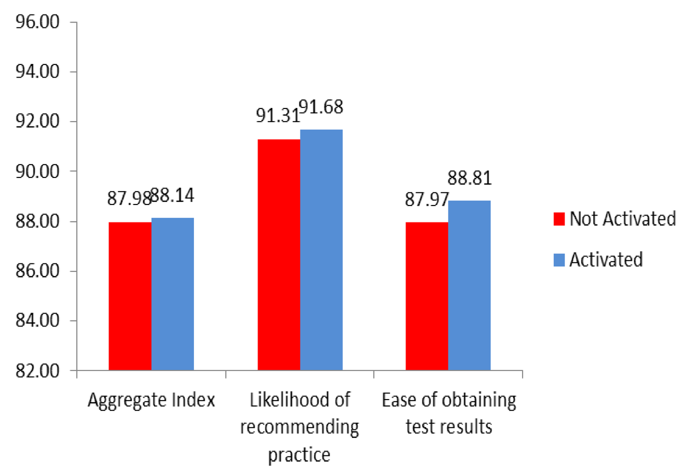


Figure 4. Mean values of Business Metrics of activated and not activated patients

Sentiment Mining (Online Service)

All comments can be associated with the quantitative responses. We use this rating to help us grouping them into positive, negative, and neutral directories. The rating is on a five-level (0, 25, 50, 75, and 100) scale. Rating with "0" and "25" are categorized as negative; rating with "75" and "100" are categorized as positive; rating with "50" is categorized as neutral; and rating with missing value is categorized as unclassified. With help of this rating scale, we are able to classify the textual reviews into four directories. We then started with building Statistical Model in SAS® Sentiment Analysis Studio. Next, we employed the "Import Learned Features" to import keywords (terms). We then decided the score of weights according to a domain free sentiments suggestion website. We defined our sentiment words on a one-to-four scale.

CONCEPT_RULE	(SENT, "_def{ProductFeature}", "_c{_def{NegativeN}}")
PREDICATE_RULE	(SENT, "_def{ProductFeature}","_a{_def{Adverb}}","_b{_def{NegativeN}}")
CONCEPT_RULE	(SENT, "_def{ProductFeature}", "_c{_def{PositiveN}}")
PREDICATE_RULE	(SENT, "_def{ProductFeature}","_a{_def{Adverb}}","_b{_def{PositiveN}}")

Figure 5. Example of rules

In both two types of rules, _c is used for tagging sentiments and _def is used for tagging our target service. "SENT" means the match only happens when both tagged service and sentiment words are in the same sentence. We are doing this because the online service is our only target. "_a" and "_b" are arguments that match when both adverbs and sentiment words are in the same sentence. In "PositiveN" and "NegativeN", the "N" means the weights we defined for sentiment words. For example, "Positive1" means the sentiment words in this entity all have weight of one, and "Negative2" means the sentiment words in this entity all have weight of 2. In the PREDICATE_RULEs, when "adverb" adds to the sentiment words, the weights of will increase by half more weights.

Results

Two-sample T Test

Mean values of business metrics Pre and Post intervention

Variable	Pr>F	Pr>|t|
Aggregate Index	0.0195	<0.001
Likelihood of recommending practice	<0.0007	0.0032

Mean values of Business Metrics associated with the parking related topics

Variable	Pr>F	Pr>|t|
Aggregate Index	0.0053	0.1465
Likelihood of recommending practice	<0.001	0.0123

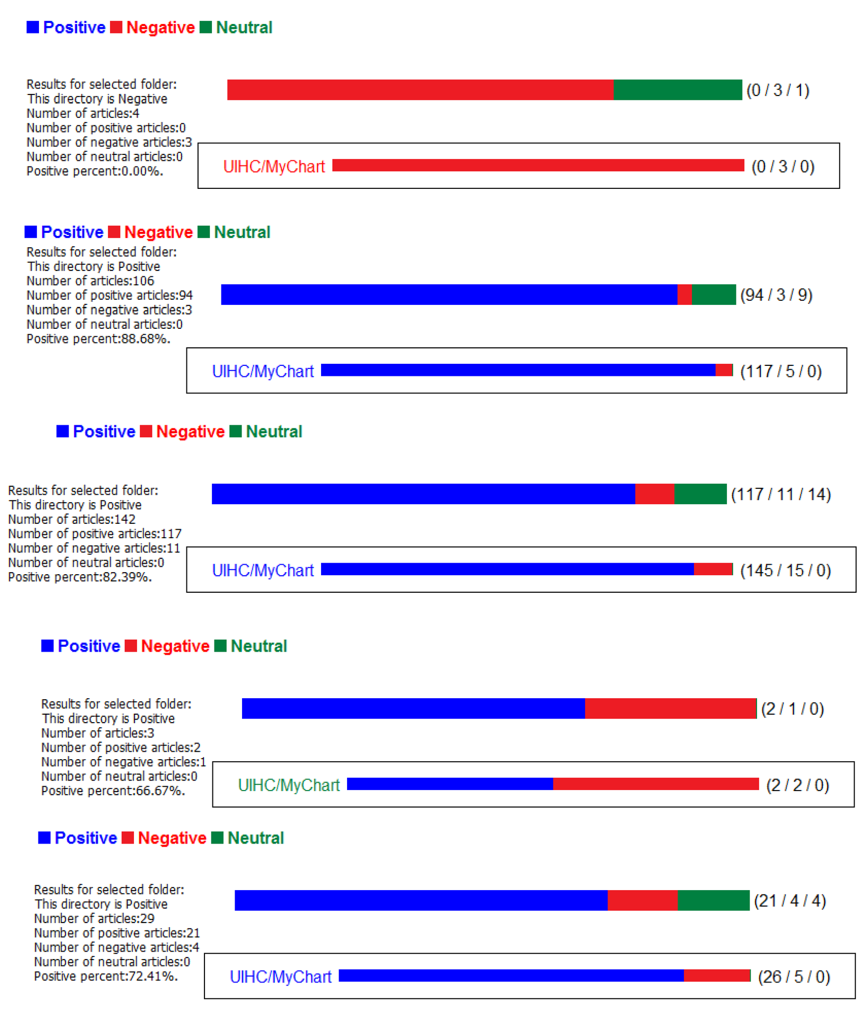
Mean values of Business Metrics before and after Jul'10

Variable	Pr>F	Pr>|t|
Aggregate Index	0.0124	<0.001
Ease of obtaining test results	<0.001	<0.001
Likelihood of recommending practice	<0.001	<0.001

Mean values of Business Metrics of activated and not activated patients

Variable	Pr>F	Pr>|t|
Aggregate Index	<0.001	0.2402
Ease of obtaining test results	0.0007	0.0004
Likelihood of recommending practice	<0.001	0.0479

Rule based model results



Conclusions

Text Mining and Sentiment Mining are good procedures to summarize text and identify the relevant patterns in the comments of any survey. In this research, we demonstrate how deeper insights can be obtained from combining Text Mining and Sentiment Mining results with quantitative data analysis. In particular, we find that the unclear results from the analysis of quantitative data alone improved substantially when Text Mining and Sentiment Mining results were combined with the numeric data analysis. The Text Mining reported in this paper mostly used default options in SAS Text Miner and fine-tuned by incorporating other options such as including the synonyms and using user-defined topics. In future we are planning to extend this research for the other interventions introduced in the hospital management.

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Acknowledgments

The authors would like to thank Dr. Goutam Chakraborty and Dr. Gary Gaeth for their invaluable supervision and support throughout this research, and the Hospital for providing us with the data to carry out the project.

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