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Applying Academic Theory with Text Mining to Offer Business Insight: Illustration of Evaluating Hotel Service Quality

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ABSTRACT

Now is the time for IS scholars to demonstrate the added value of academic theory through its integration with text mining, clearly outline how to implement this for text mining experts outside of the academic field, and move towards establishing this integration as a standard practice. Therefore, in this study we develop a systematic theory-based text-mining framework (TTMF), and illustrate the use and benefits of TTMF by conducting a text-mining project in an actual business case evaluating and improving hotel service quality using a large volume of actual user-generated reviews. A total of 61,304 sentences extracted from actual customer reviews were successfully allocated to SERVQUAL dimensions, and the pragmatic validity of our model was tested by the OLS regression analysis results between the sentiment scores of each SERVQUAL dimension and customer satisfaction (star rates), and showed significant relationships. As a post-hoc analysis, the results of the co-occurrence analysis to define the root causes of positive and negative service quality perceptions and provide action plans to implement improvements were reported.

Keywords: Text Mining, Theory-based Text Mining Framework (TTMF), SERVQUAL, Text Classification, Sentiment Analysis

Ⅰ. Introduction

Using big data to advance service is primary interests among scholars and practioners (Lim et al., 2018). Text mining is one of the most widely applied methodology in big data analysis (Breuker et al., 2016; Shi et al., 2016), and has become an increasingly important analytical tool in both the academic and business communities over the last decade (Abbasi et al., 2016; Berente et al., 2018; Chen et al., 2018). The International Data Corporation (IDC) recently predicted that big data technology and its service market

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is growing at an annual rate of 23.1% (2014 - 2019), projecting that annual spending will reach $48.6 billion in 2019 (Nadkarni and Vesset, 2015). Early applications of text mining in practical fields had involved predominantly data-driven, descriptive understandings of human behavior and perceptions (Rai, 2016). Accordingly, attempts to utilize unstructured text data to determine concrete decisions and prescriptive actions had not fulfilled the high expectation in the field, because the findings had been limited to macro descriptions or majority opinion that is easily detectible from the text (Debortoli et al., 2016). However, over the last few years, text mining has rapidly evolved through technical advancements such as deep learning using convolutional neural networks, becoming a considerably more sophisticated and widespread practice. Along with these technological evolutions, the text-mining field has actively begun to adopt a top-down theory-based approach to offer more accurate, richer, and meaningful findings (Abbasi et al., 2016; Berente et al., 2018).

A host of researchers have acknowledged the merits of integrating a theoretical basis into text mining, and generated a wide range of important findings (Gupta and George, 2016; Rai, 2016). It means more text mining researchers have expanded their aims beyond exploratory data-driven studies to conduct more explanatory, top-down, and theory-based investigations. As such, more researchers have incorporated theory-based text mining into their standard supervised text mining practices, albeit its incorporation has been uneven across the field (e.g., Jabr et al., 2014; Liang et al., 2016; Luo et al., 2017; Moreno and Terwiesch, 2014).

That is, researchers from various academic fields, such as computer science, linguistics, information systems (IS), and hospitality management are conducting text mining using their own traditional methods and skill sets (Debortoli et al., 2016). For example, in most attempts to integrate theoretical frameworks into text mining designs, the theoretical frameworks have been based on the outcomes of quasi-qualitative studies such as pretests, focus groups, or even researchers' subjective and arbitrary assumptions, which are used to identify the initial text-mining dimensions (e.g., Kim et al., 2017).

We believe empirically validated academic theories would offer a better comprehensive understanding and validity of the dimensionality, causality, and parsimony of most business phenomena at the beginning of a top-down text mining procedure. Especially in service fields, as researchers previously addressed, translating theory into practice will provide meaningful practical insights and remedies (Ranaweera and Sigala, 2015).

Therefore, the objectives of this study are twofold. First, we present a standard procedure for theory-based text mining, namely the Theory-based Text Mining Framework (TTMF). The main principle of TTMF is to utilize empirically corroborated theoretical frameworks to motivate research hypotheses at the early stage of text mining research. As a systematic guideline, it provides procedural to-do actions and tactics of theory-based text mining approach. Second, we illustrate the use and benefits of TTMF by conducting a text mining project with TTMF in a hypothetical business case. It is assumed that we need to evaluate the perceived service quality of hotels in a metropolitan city and offer prescriptive actions to improve the service quality. Although this situation is hypothetical, real data is collected and analyzed. Practical implications are provided based on the findings. In addition, findings from a conventional data-driven text mining approach using the same data are compared with the TTMF findings.

This paper is organized in the following manner.

First, a literature review on the evolution and statuses of the most popular text mining methods and their applications are provided. Second, TTMF is introduced, by explaining the process and objectives of each stage. An illustration of a real TTMF implementation is then provided to demonstrate its application, with explanations at each stage of TTMF. As part of the illustration section, a comparison of the findings of TTMF with a data-driven approach is also provided. Finally, TTMF's academic contributions, practical implications, and limitations are discussed.

Ⅱ. Literature Review and Methodological Framework

2.1. Current Status of Text Mining and Academic Research

In general, text mining refers to the process of extracting significant patterns or knowledge from unstructured text documents (Li and Wu, 2010). In the early stages of text analytics, this mainly consisted of qualitative or descriptive research, such as with content analysis or word frequency analysis. However, owing to recent developments in big data analytics, which has successfully been applied to text analytics, various data mining methods such as deep learning have been fruitfully employed in IS fields over the last decade (Abbasi et al., 2016). Representative text analytic techniques can be divided into the following methodological categories: First, collection techniques involving manual or automatic data collection, such as crawling and API (Application Program Interface). Second, pre-processing and structuration involving dimensionality reduction, such as principal component analysis and co-occurrence approaches like Latent Dirichlet Allocation (LDA) or Word2Vec. Third, text-mining techniques developed from data mining, including unsupervised clustering, supervised classification, and regression

<Table 1> Text Mining Techniques

Text Analytics		Definition	Technology / Analytics
Collection	Crawling	Automatic data collection using web crawlier, an internet bot that consistently browses web (Patil and Patil, 2016)	Focused, incremental, distributed crawling
Structuration	Dimensionality Reduction	Estimation of an appropriate number of dimensions, clusters, factors, or predefined categories remains an open issue (Evangelopoulos, 2012)	TF-IDF, PCA, SVD, NMF
	Co-occurrence	A technique used for discovering patterns of simultaneous occurring pairs of items (i.e., words or noun phrases) in order to identify the relationships between ideas within the subject areas presented in the texts (Van Rijsbergen, 1977)	LDA, LSA, pLSA, Word2Vec
Text Mining	Frequency Analysis	Descriptive text analytics based on the number of certain texts (words, n-grams, etc.)	Word cloud, network analysis, trend analysis
	Clustering	Text clustering is an unsupervised learning-based procedure where texts are classified into groups called clusters (Feldman and Sanger, 2007)	Document clustering, topic modeling
	Classification	Text classification is the activity of classifying a text document into one of several pre-defined categories (Sebastiani, 2002)	Categorization, spam detection, sentiment analysis

analysis. A comprehensive taxonomy can be found in <Table 1>.

<Table 2>, as follows, outlines the methodologies, target data, and contexts of some notable text mining studies. As it shows, various text mining approaches (e.g., frequency analysis, co-occurrence analysis, topic modeling, clustering, text classification and sentiment analysis) have been used in both research and practical fields. In the early stages of text mining research, simple text-mining techniques such as frequency analysis or co-occurrence analysis were used to discover descriptive patterns from unstructured data. More advanced techniques such as topic modeling or text clustering were then developed and applied to discover new knowledge from user-generated content. Some of these studies also attempted to test if the performance and accuracy of suggested methods have actually improved (e.g., Lee et al., 2010b; Liu et al., 2005). Moreover, recently, sentiment analysis (e.g., Kim et al., 2014) or hybrid method combining various text analytics (e.g., Singh and Woo, 2019; Wang et al., 2016) have been popular methods to provide researchers and practitioners improved business insights, which specify positive and negative levels of trends and relationships of certain issues.

Despite the increasing volume and impact of text mining research in the academic IS filed, some state-of-the-art text mining methods have been introduced and developed too quickly for researchers to prepare a common systematical and rigorous process, which is especially required for academic research.

From this perspective, we have examined the recently published ones among papers in <Table 2> in terms of that they are "theory-based" or "data-driven". We define "theory-based" research as that apparently having a theoretical basis for at least one stage of the research. On the other hand, data-driven research consists of text analytics with no underlying theories. Our review demonstrates that up until 2013, all studies utilized data-driven approached to discover descriptive patterns from unstructured text data, or developed advanced algorithms and proved their effectiveness over existing approaches. From 2013, we find studies that some attempts to integrate theory in generating a conceptual framework or research model or developing hypotheses (e.g., Dong et al., 2018; Li et al., 2015; Luo et al., 2017; Mai et al., 2018; Singh et al., 2014; Wang et al., 2013). There appears to be an apparent increase in the amount of theory-based text mining research. This increase would indicate that the integration of theory into text mining techniques is indeed a new trend in the academic IS field.

<Table 2> Examples of Previous Studies Using Text Mining

Source	Data	Research Objectives	Context	Methodology (algorithm)					
				FA	AC	TM	CCC	SA	Others
Nasukawa and Nagano, 2001	Academic Journal, VOC	Knowledge discovery	Medical	✓	✓	✓			
Uramoto et al., 2004	Documents	Knowledge discovery	Medical	✓	✓		✓		
Liu et al., 2005	Academic Journal	Algorithm comparisons	Medical		✓		✓		
Jiao et al., 2007	Documents	Knowledge discovery	Medical						Decision tree
Tseng et al., 2007	Documents	Trend report	Technology			✓	✓		

<Table 2> Examples of Previous Studies Using Text Mining(Cont.)

Source	Data	Research Objectives	Context	Methodology (algorithm)					
				FA	AC	TM	CCC	SA	Others
Lo, 2008	VOC	Knowledge discovery	E-commerce				√		
Chang et al., 2009	VOC	Knowledge discovery	CRM						Decision tree
Kim and Ahn, 2010	Customer Data	Testing algorithm performance	Information Stystems				√		
Lee et al., 2010a	Academic Journal	Trend Report	Biometrics			√			Profiling
Lee et al., 2010b	UGC (Reviews)	Testing algorithm performance	E-commerce			√			
Li and Wu, 2010	UGC (Community)	Monitoring & Prediction	Sport				√	√	
Liu et al., 2010	Database (Journal)	Trend Report	Bibliometric				√		
Lu et al., 2010	UGC (Community)	Knowledge discovery	Security		√				
Suh et al., 2010	UGC (Petitions)	Prediction	E-government			√			
Cho et al., 2011	UGC (Community)	Testing algorithm performance	Information Systems				√		
Hong and Park, 2011	Company Data (S&P 500)	Testing algorithm performance	Finance & Information Systems				√		
Park and Lee, 2011	UGC (Reviews)	Proposing Framework (Methodology)	Marketing		√				Decision tree
Baek et al., 2012	UGC (consumer reviews)	Causality testing	E-commerce				√	√	Regression
Chau and Xu, 2012	UGC (Blog)	Proposing Framework (Methodology)	Social Networks						
Thorleuchter and Van Den Poel, 2012	Web Page	Knowledge discovery	E-commerce				√		Logistic regression
Duan et al., 2013	UGC (Consumer reviews)	Knowledge discovery	Hospitality				√	√	Regression
He, 2013	VOC (Online chat messages)	Knowledge discovery	E-learning					√	
Jakopović and Preradović, 2013	UGC(Social media)	Service evaluation	Hospitality					√	
Wang et al., 2013	Report, News	Causality testing	Information Security			√			Regression
Kang and Park, 2014	UGC (Consumer reviews)	Proposing Framework (Methodology)	Mobile service					√	Math modeling

<Table 2> Examples of Previous Studies Using Text Mining(Cont.)

Source	Data	Research Objectives	Context	Methodology (algorithm)					
				FA	AC	TM	CCC	SA	Others
Kim et al., 2014	UGC(Social media)	Knowledge discovery and testing causality	Finance & Information Systems					✓	Regression
Singh et al., 2014	UGC (Blog)	Knowledge discovery	Marketing			✓			Math modeling
Yee Liau and Pei Tan, 2014	UGC (Consumer reviews)	Diagnosis (Service evaluation)	Hospitality				✓	✓	
Godnov and Redek, 2016	UGC (Traveler reviews)	Knowledge Discovery (Review Summary)	Tourism			✓			
Li et al., 2016	UGC(Social Media)	Proposing Algorithm	E-commerce				✓	✓	
Rossetti et al., 2016	UGC (Traveler reviews)	Proposing Model (Methodology)	Tourism			✓			
Shi et al., 2016	Web Page	Proposing Framework (Methodology)	Marketing			✓			Correlation analysis, Logistic Regression
Wang et al., 2016	Product Data (App store) & UGC (Review)	Proposing Model & Causality testing	E-Commerce					✓	Regression
Zhang et al., 2016	UGC(Brand pages)	Proposing Framework (Methodology)	Marketing					✓	Sentiment analysis
Calheiros et al., 2017	UGC (Traveler reviews	Knowledge discovery (Review summary)	Hospitality			✓		✓	
Luo et al., 2017	UGC (Expert Blog)	Knowledge discovery	Marketing					✓	Sentiment classification
Kim et al., 2017	UGC (Traveler reviews	Knowledge discovery (Review summary)	Hospitality			✓			
Dong et al., 2018	UGC(Social Media)	Proposing Framework (Methodology)	Finance & Information Systems				✓		Text classification
Mai et al., 2018	UGC(Social Media)	Knowledge discovery and testing causality	Finance & Information Systems				✓	✓	Sentiment analysis
Zhou et al., 2018	UGC(Consumer Reviews)	Propose Algorithm	Maketing				✓		Dimensionality Reduction, Co-occurrence
Singh and Woo, 2019	UGC(Consumer Reviews)	Model development, testing causality, and prediction	Information Systems				✓		Logit regaression

Note: FA-Frequency Analysis; AC-Association & Co-occurrence analysis; TM-Topic Modeling; CCC- Clustering & Classifier & Categorizing; SA-Sentiment Analysis; VOC-Voice of Customers; UGC-User-Generated Content)

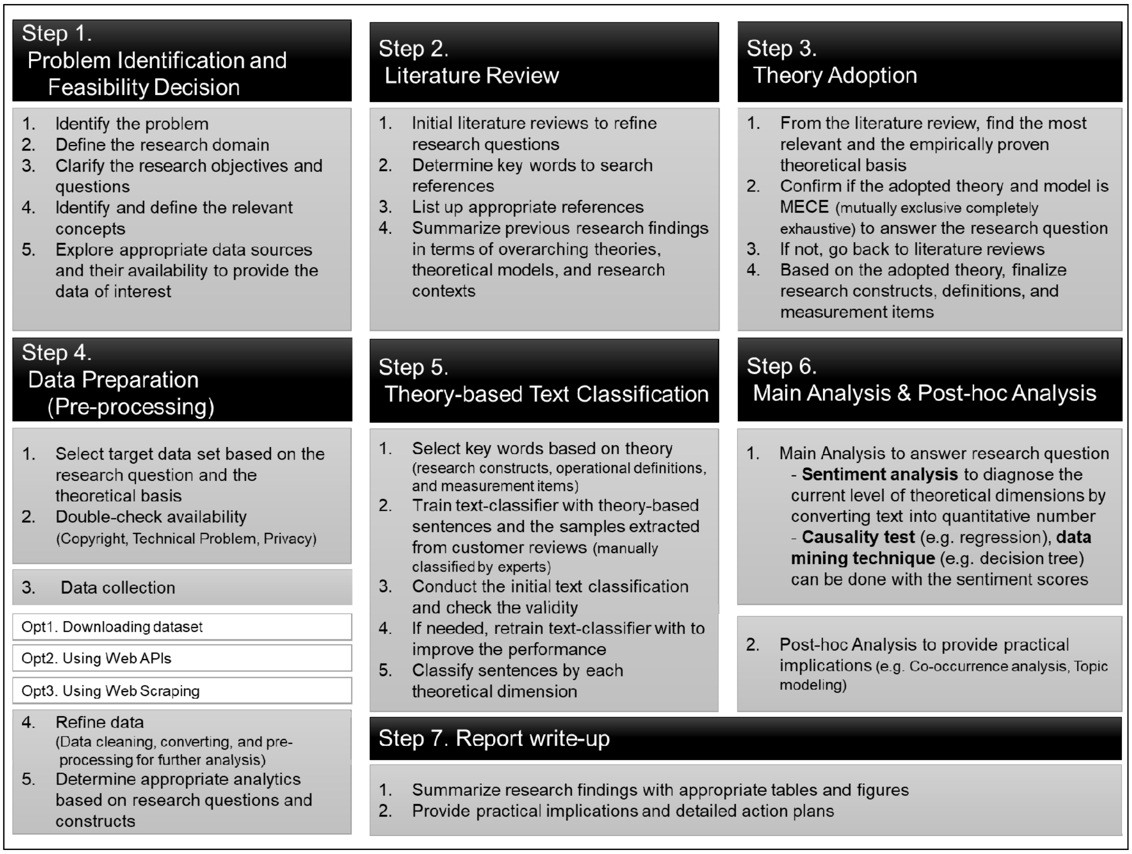
2.2. Theory-based Text Mining Framework (TTMF)

Considering the existing text miming research and its trend, we believe theory-based text mining framework is necessary in following reasons: First, the importance of theory-based text mining has been recognized, and its utilization has been increasing in recent years. Second, the uses and rationale for theoretical bases in theory-based approaches have been varied in terms of their sources and rigor. Third, regardless of whether an approach is theory-based or data-driven, more various text analytic techniques have recently been developed and utilized. Finally, and most importantly, while there have been a few examples providing standard methods of conducting a data-driven data mining process, such as the CRISP-DM analytics process (Chapman et al., 2000), there has been very little research effort towards offering a standard method of conducting theory-based text mining processes, offering step-by-step guidance or a general implementation methodology.

Theory plays a prominent role in academic research. An effective theory consists of a system of ideas that includes concepts, constructs, and relationships to explain why certain events or acts occur (Corley et al., 2011; Sutton and Staw, 1995; Weber, 2003). The central goal of a theory is to develop a conceptual model composed of constructs to answer questions about a problem or phenomenon (Van de Ven, 2007). We argue that the benefits of academic theory-based text mining research can be maximized when we adopt an empirically validated theoretical basis at the early stage of text mining to provide practical business insights. We believe that such an adopted theoretical base can significantly reduce the uncertainty, avoid potential data bias, and provide solid stepping-stones throughout the text mining process. Furthermore, it can help to fully understand the mutually exclusive and comprehensively exhausted dimensions of the phenomenon of interest. In other words, the "synergies between big data and theory" can be achieved by generating, elaborating, and testing a theory along with text mining as a data collection and analytic method (Berente et al., 2018; Rai, 2016).

As a systematic guideline, we introduce TTMF, which provides procedural to-do actions and tactics. It is grounded in typical research processes, incorporating previous research efforts in the theory-oriented text-mining field. <Figure 1> summarizes how TTMF proceeds at each stage. The procedures of TTMF are similar to those of a generic theory-validating research process. One of the major differences occur in the data collection stage. Unlike traditional data collection methods such as surveys, experiments, or simulations, text mining methods are employed to collect unstructured big data from the secondary data sources. While the detailed explanations for each step below apply to the context of a business case, any service management and business context can be applied without much adjustment.

When conducting text mining research to solve business-related problems, TTMF offers systematic guidelines. In Step 1, business opportunities or threats result in management problems, which must be either resolved or improved upon. Such real-world issues can motivate text-mining research. The step following the problem identification is to define the specific research scope of the study. At this point, the business problems must be transformed into a clearly defined and researchable question. Clear research questions facilitate the identification of relevant concepts (e.g., research constructs). Finally, appropriate data sources should be explored at this stage to define the concepts of interest. If data sources are unavailable, then other



<Figure 1> TTMF Process

data collection technologies methods should be considered. In summary, the objectives in Step 1 are as follows: (1) Refine service management questions into researchable questions, and (2) define the feasibility of utilizing large quantities of text data.

In Step 2, an extensive and systematic literature review should be carried out to prepare for the next level (theory adoption). Effective high quality literature reviews create a firm foundation for advancing knowledge and provide focused knowledge on certain concepts that are pertinent to the research study (Webster and Watson, 2002). This process provides an overview, synthesis, and assessment of previous research, challenges existing knowledge, and indicates promising research questions (Boell and Cecez-Kecmanovic, 2015).

In Step 3, the most relevant and empirically proven theoretical basis should be adopted for further analysis. Various theories and theoretical models should be evaluated for their relevance to the research context and questions. Furthermore, it should be noted that strong theories must be sufficiently validated by empirical evidence. The next step is to choose the most predominant theoretical framework that is relevant to the research. Upon choosing a theoretical framework, one can identify and adopt the corresponding constructs and their operational definitions for research purposes. Research constructs, definitions, and measurement items provide guidelines for determining the sample sites and target data in Step 4, and the classification criteria in Step 5.

In Step 4, the data collection and pre-processing processes are normally employed. Target data is selected, collected, and refined to maximize data validity, while obeying company policies and protecting customer privacy. There are three popular approaches to collecting data. The first method consists of "downloading a dataset" from a target website. If authority to access a website or a bulletin board is granted, then it is easy to download datasets using a simple program. The second method is "using APIs" to download data (Bizer et al., 2007), and the third method is "using web-scrapers." Researchers can code web-scrapers themselves, as well as downloading commercial web scraping programs or using open-source web scrapers.

Efficiency in data collection and pre-processing, which is critical in text mining research, can be vastly improved through TTMF, because the boundary of the target data becomes considerably clearer and the pre-processing becomes much simpler. Here, it is imperative to consider the source of the data (e.g., documents, websites, or social media). Appropriate target data (e.g., posts, reviews, or questions and answers) should be carefully determined based on research questions and the selected theory, rather than only focusing on easy-to-access data, in order to avoid the streetlight effect, which intensifies the side effects of data-driven approaches.

Step 5 is the most important and critical step in the TTMF process. Unlike traditional data-driven text mining clustering methods (e.g., topic modeling), the texts (sentences) are classified based on the hypothesized dimensions derived from the adopted theory or model. This step is quite similar to a confirmatory factor analysis. Text classifiers are initially trained using keywords and sentences based on operational definitions and measurement items from research articles about chosen theoretical basis. In this process, training set (sentences) are carefully reviewed and manually allocated the proper dimension by domain experts to enhance classifier accuracy. Trained text classifiers automatically allocate texts with designated theoretical dimensions, and the text classifier is evaluated in terms of its accuracy and/or performance. At this stage, we assume that theoretical dimensions capturing all the related concepts behind the phenomena exist.

Unless the initial results can satisfy the thresholds for accuracy and performance, the classifier should be trained again with additional sample sentences to improve the results. To test validity of the classifier, the test set (validation set) must be separated from whole data set. Once a satisfactory outcome is reached, we can proceed to the next step.

In Step 6, the main analysis is conducted based on the results of the theory-based text classification (e.g., Li and Wu, 2010). This is composed of a main text analysis and post-hoc analysis. Similar to the collection of data through questionnaires in survey studies, the main analysis of TTMF mostly consists of a sentiment analysis (e.g., Meire et al., 2016; Winkler et al., 2016), which can convert text data into quantitative data representing the degrees of positivity and negativity of certain sentences. Another possible main analysis is a regression analysis such as linear regression or ordinal logistic regression (e.g., Cao et al., 2011; Gao et al., 2017). As in behavioral studies, we can test the nomological validity, dimensionality and/or causality between independent variables and dependent variables adopted from a theory.

With the result of the main analysis in hand, a post-hoc analysis such as a co-occurrence or network analysis can be conducted to obtain more fruitful and practical implications. After Step 5 (text classification), the TTMF sample can be divided into several sub-datasets based on the theoretical dimensions (i.e., datasets for construct A, B, C, etc.), whereas traditional text-mining techniques are generally conducted using a single dataset. Therefore, in TTMF prescriptive action plans can be generated by each dimension in a more specific and detailed manner through a post-hoc analyses. For instance, extremely negative comments can be filtered out from datasets of a certain dimension through a TTMF-based sentiment analysis. Here, the most predominantly mentioned word groups implying the root causes of customer's negative feelings can be identified by conducting a co-occurrence analysis such as a post-hoc analysis.

In Step 7, the final stage of TTMF, a comprehensive report is written to address the findings of the study based on the theoretical basis. First, the overall text-mining findings should be clearly summarized. Then, the report should present the implications of the findings and offer prescriptive suggestions based on the implications.

Ⅲ. Illustration: Evaluating the Service Quality of Hotels in Seoul

3.1. TTMF Implementation

This example intends to illustrate the practical steps, interpret the findings, and demonstrate the extra benefits of TTMF over existing text-mining methods. For our illustration, we consider a hypothetical situation in which the Tourism Bureau of Seoul faces certain service quality problems observed in most hotels in Seoul, Korea. To cope with this potentially critical threat to the tourism business in Seoul, we, a consulting team, was hypothetically assigned by the Bureau to investigate the problems and find a way to improve the service quality level of hotels in Seoul. While the illustration is based on an imaginary situation, real data was collected from a famous travel information sharing website, and text mining was actually implemented according to the proposed TTMF steps. In the following illustration, we provide a detailed description and discuss the implications from the research findings. In addition, the findings of the TTMF-based approach are compared with those of a general data-driven, bottom-up text mining approach.

TTMF Step 1. Problem Identification

First, the research questions provided to us by the Bureau were "What are the core service quality issues of hotel services in Seoul, and how can we improve them?" Our mission was to identify weaknesses in major hotel service management and formulate an action plan for the Bureau to provide guidelines and managerial support to hotels located in Seoul. Upon finalizing the contract, the research domain was limited to lodgings classified as "hotels." Other lodgings, such as motels, Airbnb, guesthouses, and others, were excluded.

Related concepts were identified and defined based on our research questions. We focused on the concept of "service quality," defined as customers' assessments concerning the delivered service in comparison with their expectations (Cronin and Taylor, 1992; Gorla, 2011; Hemmington et al., 2018). Service quality is crucial to most service companies, because it comprises a major factor in determining various outcomes, such as customer satisfaction, loyalty, word-of-mouth, complaints, service abandonment, and ultimately company profits (Zeithaml et al., 1996).

The following procedure in this step is to check the feasibility of applying the text-mining technique. That is, to confirm whether data is available. We explored the possible data sources that could identify the level of service quality perceived by customers, and discovered several sites that allowed us to access customer reviews.

TTMF Step 2. Literature Review

In Step 2, extensive literature focusing on customer perceptions and service quality in various service settings such as hotels, restaurants, hospitals, and banks was reviewed to determine the most appropriate and rigorous theoretical basis. As a result of this initial search, we found that "service quality" is an appropriate keyword for searching references. Then, we focused on a list of leading marketing and IS journals, with "service quality" as a search keyword. Empirical studies, literature review studies, and meta-analyses were the main targets of our literature review.

Through this process, we identified a series of research papers containing key information on how to develop or test research models and measures for service quality that were applicable to our study. We carefully and systematically reviewed the selected articles and summarized the previous research findings in terms of overarching service theories, theoretical models, and research contexts.

TTMF Step 3. Theory Adoption

We decided to utilize the SERVQUAL model (Parasuraman et al., 1988) as our theoretical basis, because this is one of the most appropriate theoretical models for evaluating the service quality level in hotels and illustrating the best fit between our research questions and the results of the literature review. The SERVQUAL model was developed by Parasuraman, Zeithaml, and Berry (PZB) (1988); they presented a 22-item scale consisting of five service quality dimensions, namely tangibles, reliability, responsiveness, assurance, and empathy. The five dimensions of SERVQUAL allow us to cover all the various aspects of a hotel's service quality. PZB's SERVQUAL model has been predominantly recognized as both a parsimonious and comprehensive theory, evaluating physical, face-to-face, and online service quality, and has been empirically validated

<Table 3> Operational Definitions of SERVQUAL Constructs

Dimension	Definition and Keywords(adopted from Parasuraman et al., 1988)
Tangibles	Appearance of physical facilities, equipment, personnel, and communication materials (up-to-date equipment, neat personnel, interior concept, cleanness, visually appealing facilities, material)
Reliability	Ability to perform the promised service dependably and accurately (service on time, problem solving, delivery of services at promised time)
Responsiveness	Willingness to help (internal) customers and provide prompt service (prompt service, staff shift where needed, willingness to help customers, responsiveness to customer's requests)
Assurance	Knowledge and courtesy of employees and their ability to convey trust and confidence (knowledgeable staff, trained & experienced employees, making customers feel safe in their transactions)
Empathy	Caring, individualized attention the employees provide to each other (anticipate customer needs, sympathetic employees, dealing with customers in a caring fashion, friendliness, kindness)

in various service management settings (Gorla, 2011; Kettinger and Lee, 1994). Especially, to evaluate hotel customers' perceptions of service quality, many previous studies have utilized this theoretical model (e.g., Hsieh et al., 2008; Keith and Simmers, 2013; Yilmaz, 2009). Therefore, we deemed SERVQUAL to be the most appropriate theoretical model for addressing our research objectives. The definitions of the five dimensions of the SERVQUAL model are presented in <Table 3>.

TTMF Step 4. Data Preparation

In this step, target data was defined and collected from the possible data sources identified in Step 1. We decided to utilize a popular travel information-sharing website as our data source, because it is a one-stop website offering hotel information, reservation services, and customer reviews simultaneously. Furthermore, it is a popular global website used by customers worldwide, which allows for unbiased data acquisition. It possesses longitudinal and extensive customer reviews describing service evaluations by actual customers. In this hypothetical project for the Tourism Bureau of Seoul, we individually programmed a web-scraper to achieve more comprehensive and efficient data collection. Using the scraper, we collected 22,085 reviews generated by customers who have stayed in "hotels" located in "Seoul" from a target site during the period of June 2004 to October 2015. Owing to the unstructured nature of user-generated reviews, we refined the raw datasets to suitable formats for text mining, and divided the 22,085 reviews into 212,385 sentences for further analysis.

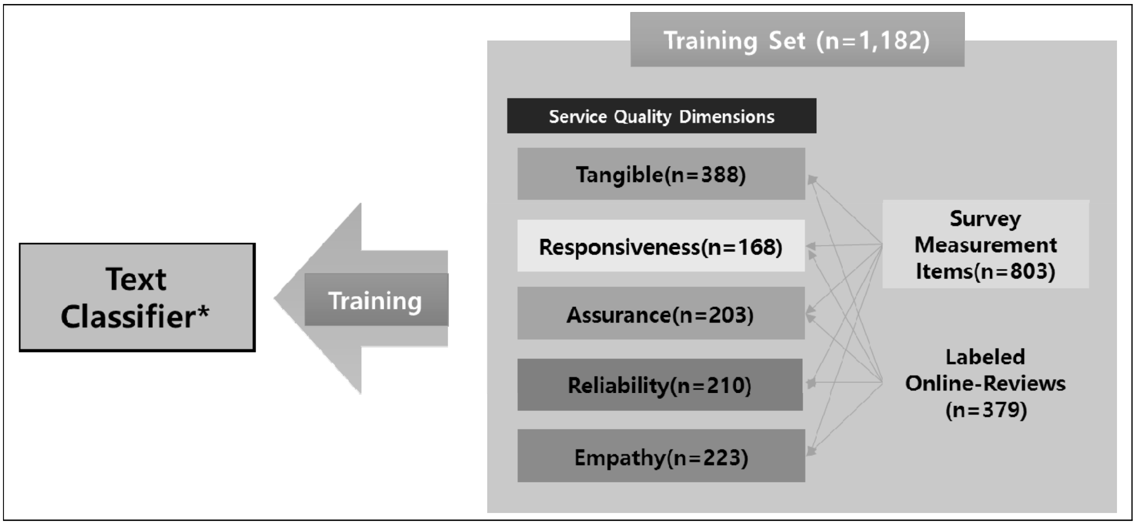
At this stage, we also determined suitable text-mining techniques considering our research questions, theoretical model, and constructs. Our first research challenge was to identify the current problems of hotel services in Seoul. To address this problem, we decided to conduct a text classification analysis based on the dimensionalities of SERVQUAL, followed by a sentiment analysis to generate sentiment scores for the five SERVQUAL dimensions. The next analysis, a regression analysis, was chosen to verify the causal relationship between the SERVQUAL dimensions and customer satisfaction in line with the theory. To answer the second question of "How can we improve the problems in service quality?", we decided to perform a co-occurrence analysis as a post-hoc analysis, which is a type of cluster analysis for revealing groups of words frequently shown together in a sentence. This analysis should produce specific insights into why customers feel positively or negatively about the service.

TTMF Step 5. Text Classification

Based on the proposed TTMF method, we employed a text classifier to divide the sentences of reviews into SERVQUAL's five dimensions. Text classification (categorization) aims to automatically sort the target sentences using predefined labels (Tan, 2006). When training the text classifier to categorize sentences based on each dimension of the SERVQUAL model, it is vital that researchers input a carefully prepared training set into the text classifier to ensure the text classification accuracy.

As a training set, we utilized survey measurement items extracted from about 40 academic research papers using SERVQUAL or SERVPERF model[1)]

1) Cronin Jr & Taylor (1992) proposed the SERVPERF model, which applied perception-only scores, unlike the SERVQUAL model, which uses perception-minus-expectation difference scores. However, in this study we included both because we are not interested in whether it used a gap score or a perception-only one.



<Figure 2> Training Text Classifier Based on Research Constructs

<Table 4> Testing Accuracies of Trained Models

Ranking	Algorithm	Accuracy of Trained Classification Model(Matched / Mismatched / Total Sentences)
1	SVM	0.8295(146/30/176)
2	SLDA	0.7954(140/36/176)
3	Boosting	0.7897(139/37/176)
4	MNET	0.6590(116/60/176)
5	TREE	0.6534(115/61/176)

(n = 803). In order to enhance the validity of the classification, we then trained the classifier using sample sentences (n = 379) extracted from 3,000 review sentences, which were allocated to each dimension by three experts in the information systems and hospitality management fields. We only used the results agreed upon by all three coders. After excluding the sentences used for training, the text classification was conducted on the entire remaining data using RTextTool (R 3.2.2). This process is visually summarized in <Figure 2>.

The validity and performance of the trained text classification model must be verified in terms of the classification accuracy. The accuracies of several classification algorithms were tested and compared with the test set (n = 176 sentences) that was extracted from 600 actual review sentences (Junker et al., 1999). As shown in <Table 4>, the SVM[2] -based model exhibited the highest accuracy (0.8295) among the five text classification algorithms. Therefore, we adopted the SVM algorithm for further text classification.

2) The support vector machine (SVM) method has proven its classification accuracy (Cortes & Vapnik, 1995; Tong & Koller, 2001). The SVM probability is the probability that the classified reviews belong to each dimension based on the algorithm. In general, an SVM Probability above 0.7 is regarded as desirable, although there is not an exact threshold to measure the classification performance.

<Table 5> Results of Text Classification

Dimensions	Original Result		Enhanced Result SVM Probability (above 0.7)	
	# of Sentences	SVM Probability (Mean)	# of Sentences	SVM Probability (Mean)
Tangible	141,722(66.7%)	0.626	48,639(79.4%)	0.853
Reliability	24,293(11.4%)	0.500	3,004(4.9%)	0.783
Responsiveness	8,296(3.9%)	0.517	1,441(2.34%)	0.819
Assurance	16,301(7.7%)	0.511	2,431(3.96%)	0.830
Empathy	21,773(10.3%)	0.579	5,789(9.4%)	0.833
Total	212,385(100%)	0.547	61,304(100%)	0.824

<Table 6> Sample Sentences of Each Dimension

Dimensions	Sample Sentences	SVM Probability
Tangible	The room was very cozy with a big bed and a Cleopatra chair on the side	0.911
	The room appearance, furnishing, cleanness and facilities were very good	0.986
Reliability	The staff at the reception didn't know how to solve the problems and didn't seem very concerned with client service	0.796
	Check in is very efficient, and the multi-lingual staff referred to me by name at all times when at the front desk	0.730
Responsiveness	Our requests were precisly attended, and the housekeeping is the most efficient housekeeping service i ever seen in a hotel	0.844
	Special mention for their team who is super prompt and always willing to help	0.872
Assurance	Staffs speak very good English and were all very efficient	0.905
	Hotel staff don't understand English at all, rude, impolite, discourteous and uncivilized	0.857
Empathy	The staff on duty at the front desk be very helpful and give we precise direction to where we want to go	0.839
	Housekeeping staff for my stay at level 11 is also friendly and helpful	0.898

Based on the selected classification algorithm and validated classification models, 212,385 sentences, excluding the training and test sets, were allocated into the five dimensions (See <Table 5>). The results of the text classifier imply that hotel customers normally mentioned their experiences in tangible aspects (66.7%), and average the SVM probability of text classification was 0.547. In this study, to enhance accuracy of classification we only selected the sentences for which the SVM probability was over 0.7. As a result of this more rigorous requirement for classification, 61,304 sentences were included in the main analysis, and the average SVM probability of the sentences increased to 0.824.

Sample sentences resulting from the text classification are presented in <Table 6>.

TTMF Step 6. Main Analysis

Sentiment Analysis: In Step 4, a sentiment analysis was used to diagnose the level of customers' perceived service quality by converting unstructured text data into meaningful numbers. Sentiment analysis (opinion mining) identifies sentiment, affectation, subjectivity, and other emotional states in online text (Chen et al., 2012; Kim et al., 2014; Montoyo et al., 2012). In the present study, out of several possibilities we employed the Stanford sentiment analysis algorithm (Socher et al., 2013). This algorithm presents five sentiment classes (scales), from very negative to very positive (1 to 5). <Table 7> illustrates the number of sentences allocated in each dimension, the mean values of the sentiment scores, and sample sentences for each SERVQUAL dimension corresponding to their sentiment classes.

As seen above, the mean value for the assurance dimension (3.21) is the highest, followed by the empathy dimension (3.04), while the service quality of the reliability dimension (2.74) is the lowest. We can assume from these results that staff's professional knowledge (assurance) and kindness (empathy) in hotels in Seoul is at a desirable level. However, the level of service provided is relatively low in terms of punctuality (reliability) and prompt problem solving (responsiveness).

Regression Analysis : Using the generated sentiment scores, an ordinary least squares (OLS) regression analysis was conducted to test the pragmatic validity of our research model, representing the causal

<Table 7> Results of Sentiment Analysis

Dimension	Freq. (%)	Mean Values (SD)	Sentiment Level	Sample Sentences	SVM Prob.
Tangibles	48,639 (79.4%)	2.89 (0.86)	5	As mentioned in prior reviews, this hotel is very clean and is well situated	0.864
			4	Small rooms but with clean and crisp bathrooms and free internet	0.996
			3	BW hotel is an average hotel, with small dark rooms, modestly equipped and furnished	0.955
			2	Rooms are basically clean but they are really old, giving them a slightly look	0.933
			1	Stayed here during winter months and still find the room hot as the centralised heater is turned on - it is suffocating as the rooms do not have openable windows	0.929
Reliability	3,004 (4.9%)	2.74 (0.84)	5	I've stayed here several times on business trips, and each time has been a great experience	0.874
			4	Hopefully, the hotel's quality and service provided will keep up with higher occupancy rates and as time passes on	0.853
			3	BREAKFAST: good quality, low variety, but it takes a lot of time to refill	0.914
			2	May be it is good for long stay, but as a business hotel for short stays, I do experience some little problem in my recent stay	0.810
			1	I stayed 3 times in the past year (office is right next door) and have consistently seen a service deterioration which is no longer acceptable. Now moving to another property which has a reputation of true first class service	0.888

<Table 7> Results of Sentiment Analysis(Cont.)

Dimension	Freq. (%)	Mean Values (SD)	Sentiment Level	Sample Sentences	SVM Prob.
Responsive-ness	1,441 (2.3%)	2.86 (0.87)	5	Service at the club lounge was excellent, with staff being very professional and always willing to help	0.956
			4	The service is good and the receptionists are really willing to help	0.924
			3	I had requested an early checking on my booking and he double checked and was able to present keys to a room	0.962
			2	This kind of front desk who is misrepresenting facts or not willing to help customers will undermine customer experience, the image and reputation of the hotel	0.893
			1	When I request for the clean up after I come back, they told me to wait until tomorrow and nothing can help	0.955
Assurance	2,431 (3.9%)	3.21 (0.87)	5	Nice and simple hotel with good hospitality (staff can speak English and chinese for those we require) and excellent location for shopping	0.970
			4	The staff is excellent and all have a reasonable command of English	0.890
			3	The front staff sort of speaks English but not the rest of the staff	0.948
			2	The hotel personnel spoke English poorly, and they often did understand my English	0.897
			1	Hotel staff don't understand English at all, rude, impolite, discourteous and uncivilized	0.857
Empathy	5,789 (9.4%)	3.04 (0.91)	5	Hotel is So convenient, Super friendly and helpful staffs	0.914
			4	Pleasant hotel, it was clean and staff were very friendly ,thank you to alex the concierge who was the most helpful by giving us the right directions, service at the restaurant was good	0.878
			3	The rooms were nothing special, but were clean and functional and the staff were friendly and helpful	0.954
			2	One last thing, i had a very bad bad experience with a front desk person he called MR YS Bang in Nine Tree hotel	0.900
			1	When my friend and I asked for a direction to a restaurant, a lady at the lobby said, I don't know	0.883

relationships between the five SERVQUAL dimensions as independent variables, and the customer satisfaction on a five-point star scale rated by actual hotel customers as a dependent variable. The number of stars rated by customers was used as a surrogate for customer satisfaction concerning the overall service in various service contexts, including hotel services (e.g., Cao et al., 2011; Duan et al., 2016).

We selected OLS regression for testing the causality because it is the most general and popular analysis method for this stage of text mining (Debortoli et al., 2016). <Tables 8> and <Tables 9> summarize the descriptive statistics and regression results, respectively. <Table 8> shows that the service quality related to physical aspects (tangibles) occupies almost 80 % of the total classified sentences, and exhibits a relatively low level. Lower levels of service quality are observed in the reliability and responsiveness dimensions as shown in the findings of sentiment analysis. The regression analysis indicates that all five dimensions of SERVQUAL significantly affect customer satisfaction, showing the acceptable pragmatic validity of our model.

Post-hoc Analysis (Co-occurrence Analysis) : In most previous text mining studies employing sentiment analyses, only the overall sentiment scales have been reported. Furthermore, those studies did not attempt to understand why customer emotions are positive or negative. To reveal the root causes of positive and negative reviews from the sentiment analysis and suggest suitable counter measures for the hotels and Bureau, we employed a co-occurrence analysis as a post-hoc analysis. This additional analysis can provide justifications for the detailed prescriptions for improving the service levels.

A co-occurrence analysis is a type of co-word analysis (Small, 1973), and provides an important biblio-

<Table 8> Descriptive Statistics of TTMF Construct

	Tangible	Reliability	Responsiveness	Assurance	Empathy	Overall	Star Rates
Mean	2.891	2.738	2.857	3.213	3.035	2.947	4.095
SD	0.861	0.838	0.869	0.871	0.913	0.871	0.945
Min	1	1	1	1	1	-	1
Max	5	5	5	5	5	-	5
N	48,639	3,004	1,441	2,431	5,789	61,304	61,304
%	79.3%	4.9%	2.4%	4.0%	9.4%	100%	100%

<Table 9> OLS Regression Results of TTMF Model

Independent Variable	Coefficient	SE	*t*-value	*p*-value
Tangible	$.1987^{***}$	.0044	45.21	0.000
Reliability	$.1942^{***}$	.0068	26.40	0.000
Responsiveness	$.2234^{***}$	.0092	24.30	0.000
Assurance	$.2098^{***}$	.0074	30.82	0.000
Empathy	$.2321^{***}$	.0055	42.03	0.000
Number of Observations (N)	61.304			
R-square	0.0369			
RMSE	0.9271			
Prob > F	0.0000			
F(5, 61298)	469.64			

Note: 1. Dependent Variable: Star Rates evaluated by hotel customers (5-scale)
2. $^{***}p < 0.001$

metric method of mapping the relationships between concepts, ideas, and problems (Callon et al., 1983). Researchers in various fields have adopted co-occurrence analyses to find cognitive constructs of topics from text data (e.g., Liu et al., 2011; Wang et al., 2015; Yan et al., 2015).

<Table 10> Results of Co-Occurrence Analysis

Tangible Dimension					
Positive Reviews			Negative Reviews		
Words		Frequency	Words		Frequency
Room (7,593)	Clean	1227	Room (10,134)	Small	1227
	Bed	670		Bathroom	545
	Bathroom	477		Little	331
	Wi-Fi	193		Just	309
	Equipment	193		Wi-Fi	349
	Amenity	215		Water	199
Assurance Dimension					
Positive Reviews			Negative Reviews		
Words		Frequency	Words		Frequency
Staff (917)	English	718	Staff (418)	English	291
	Speak	578		Communicate	23
	Good + Excellent	427		Reception	20
	Professional	84		Language	14
Responsiveness Dimension					
Positive Reviews			Negative Reviews		
Words		Frequency	Words		Frequency
Service (236)	Help	38	Service (208)	Request	27
	Staff	67		Check	22
	Request	21		Time	13
	Willing	13		Check-in	10
	Fast + Quick	14		Concierge	11
Reliability Dimension					
Positive Reviews			Negative Reviews		
Words		Frequency	Words		Frequency
Time (415)	Great	97	Time (840)	Problem	40
	Excellent	18		Service	32
Good (255)	Service	75		Breakfast	63
	Front + Reception	18	Problem (412)	Room	71
	Concierge	9		Desk + Reception	45
Empathy Dimension					
Positive Reviews			Negative Reviews		
Words		Frequency	Words		Frequency
Staff (1,169)	Friendly	816	Staff (495)	Need	86
	Helpful	637		Hour	12
	Attentive	199		Provide	18
	Front-desk	96		Find	18
	Kind	60		Make	36
	Warm	47		Desk	59

We divided our dataset into two groups (negative and positive sentences) based on SERVQUAL's five dimensions. The sentences with sentiment scores of 1 and 2 (very negative and negative) were categorized into a "negative dataset," which may imply service failure situations or negative experiences. On the other hand, sentences that were labeled with sentiment scores of 4 or 5 (positive or very positive) formed a "positive dataset," representing favorable service encounters. Following this, a co-occurrence analysis was conducted on each group using the Text Mining (TM) package in R (version 0.6-2), based on R.3.2.2., and the results are summarized in <Table 10>.

It can be seen that room (n = 7,593) was the most frequently mentioned word in both positive and negative sentiment groups of the tangible dimension. "Room" appeared most frequently with the words clean (n = 1,127), bed (n = 670), bathroom (n = 477), and size (n = 533) in positive dimensions. Moreover, as the number of smartphone users has been increasing, Wi-Fi (n = 193+349) was frequently considered in both sentiment groups, although the number of negative evaluations concerning Wi-Fi was higher. On the other hand, in the negative aspects of the tangible dimension, the words small (n = 1,227) and bathroom (n = 545) frequently appeared.

In the assurance dimension, the words staff (n = 917+418) and English (n = 718+291) were the most frequent keywords in both positive and negative reviews. This shows that staff language skills represent one of the important determinants of customer satisfaction. In addition, frequent problems were detected at the reception (desk) (n = 19+20), which is one of the representative face-to-face service encounters.

Similarly, in the responsiveness dimension the keyword service (n = 236+208) was the most frequently occurring, and was observed together with words in both the positive (e.g., staff, willing, fast/quick) and negative (e.g., time, check-in, concierge) groups. In the reliability dimension, the word time (n = 415+840) appeared to be the most frequent word. Finally, in the empathy dimension, the most common keyword was staff (n = 1,169+495). Customers felt empathy from the staff when they were friendly (n = 816), attentive (n = 199), kind (n = 60), and warm (n = 47).

TTMF Step 7. Report Write-up

As the final step of the illustration, our research findings were summarized and reported to the Bureau. We not only reported the results and findings, but also interpreted them to generate useful implications and detailed action plans. Major findings, implications, and the prescriptive actions are summarized as follows.

First, the result of the text classification was reported. A total of 61,304 sentences extracted from actual customer reviews were successfully allocated to SERVQUAL dimensions. Furthermore, the SVM probability representing the validity and performance of our theory-based text classification and the programmed algorithm was satisfactory (<Table 6>). Second, the average sentiment scores of each SERVQUAL dimension were reported along with sample sentences and the SVM probability (<Table 7>). Third, the pragmatic validity of our model was tested by the OLS regression analysis results between the each SERVQUAL dimension and customer satisfaction (star rates) (<Table 8> and <Table 9>). Finally, the results of the co-occurrence analysis to define the root causes of positive and negative service quality perceptions and provide action plans to implement improvements were reported as shown in

<Table 10>. Overall, our findings identify reliability as the most dissatisfactory service dimension in terms of the sentiment score. According to our analysis, although the tangibles dimension was clearly a predominant factor, we identified reliability to be define a subtle but important aspect of the perceived service quality, which requires improvement as a top priority.

Based on the post-hoc analysis with which provided practical and highly detailed insights into the reasons why customers are satisfied or dissatisfied, our findings indicate a few practical prescriptions that hotels can enhance their strengths and improve on their weaknesses based on these results. For example, the Bureau could consider frequent word groups in the positive reviews of the tangible dimension when designing leaflets, websites, or SNS to attract potential visitors to Seoul. WIFI, cleanliness, and the sizes of rooms should be the top priority concerns in the hotel service. The results from the reliability indicates the frequent dissatisfied comments concerning timely and punctual service delivery, breakfast, and the reception desk. Therefore, hotels could prioritize improvements to these service qualities. Furthermore, in order to improve on issues and minimize complaints and negative reviews, the Bureau could offer language-training programs for hotel employees, as identified from the assurance dimension.

3.2. Comparative Findings between TTMF and a Data-driven Approach

To illustrate the difference between TTMF and a data-driven approach, the same set of 212,385 sentences was subjected to one of the typical data-driven text mining options, namely topic modeling. We have included 59,871 sentences composed of more than 100 characters that can result in stable topic modeling outcomes in further analyses. While the number of dimensions can be flexibly set in topic modeling for the optimal result (Chen et al., 2018; Kotu and Deshpande, 2014; Wang and Xu, 2018), we set the number of clusters to five topics, in order to be consistent with the number of SERVQUAL dimensions, because this leads to a direct comparison between the two methods. As shown in <Table 11>, five dimensions and related keywords concerning location, room quality, facility/service, transportation, and staff performance were generated. Further analyses were performed in the same way of TTMF approach, comprising a sentiment analysis followed by OLS regression using the acquired sentiment scores. The results are summarized in <Table 12> and <Table 13>.

Although the results of the regression analysis, including the sizes of the R-squared values and the fact that all hypothesized paths are significant, are similar to those of TTMF, the findings of the topic modeling from the data-driven approach exhibit dramatically different dimensionalities from those of the TTMF approach. The four dimensions but staff performance dimension were all related to the tangible or physical aspects of hotels only. That is, the data-driven topic modeling without the TTMF process resulted in a potentially biased emphasis on the tangible dimension of service quality and physical aspects of hotels, because the clustering process for topics is initially based on the most frequent words. Thus, this outcome would provide a myopic view of the data, because it neglects other important feedback, and we cannot evaluate all five important dimensions of service quality owing to this limitation of existing data-driven text mining methods. Other important dimensions of service quality, such as empathy or responsiveness, did not emerge as important dimensions, although they are an integral part of customer perception.

<Table 11> Results of Topic Modeling (T = 5)

Topic Modeling (# of Topics=5)		
Topic #	Dimension	Major Keywords
1	Location	Station, Shop, Restaurant, Around, Street, Close, Subway
2	Room Quality	Room, Floor, Clean, Small, Bathroom, Comfort, View
3	Facility/Service	Breakfast, Service, Korean, Price, Lounge, Offer, Coffee
4	Transportation	Airport, Bus, Taxi, Way, Arrive, Find, Stop (Bus or Taxi)
5	Staff Performance	Staff, Help, Check (in), Front (desk), English, Ask

<Table 12> Descriptive Statistics of Topic Modeling

	T1 (Location)	T2 (Room Quality)	T3 (Facility/Service)	T4 (Transportation)	T5 (Staff Performance)	Overall	Star Ratings
Mean	2.650	2.567	2.793	2.392	2.603	2.601	4.071
SD	0.852	0.841	0.946	0.688	0.843	0.834	0.995
Min	1	1	1	1	1	-	1
Max	5	5	5	5	5	-	5
N	13,974	14,225	12,069	8,922	10,681	59,871	59,871
%	23.3%	23.8%	20.2%	14.9%	17.8%	100%	100%

<Table 13> OLS Regression Results of Data-driven Approach

Independent Varible	Coefficients	SE	*t*-value	*p*-value
Topic1 (Location)	$.2327^{***}$	.0054	43.46	0.000
Topic2 (Room Quality)	$.1717^{***}$	.0055	31.26	0.000
Topic3 (Facility/Service)	$.2052^{***}$	.0051	39.78	0.000
Topic4 (Transportation)	$.1777^{***}$	.0065	27.24	0.000
Topic5 (Staff's Performance)	$.1409^{***}$	.0130	24.74	0.000
Number of Observations (N)	59,871			
R-square	0.0359			
RMSE	0.9772			
Prob > F	0.0000			
F(5, 59865)	445.24			

Note: 1. Dependent Variable: Star ratings evaluated by hotel customers (5-point scale)
2. $^{***}p < 0.001$

Another clear difference in the dimensionality lies in topics concerning location (Topic1) and transportation (Topic 2), which are not directly associated with hotels' internal and genuine service quality. Of course, convenience in location and transportation is a highly important consideration for customers in selecting a hotel. However, these are irrelevant issues when considering our original question, "What are the core issues of hotel services in Seoul, and how can we improve them?" This major difference in dimensionality means that there is no need to perform any further comparative psychological validity or reliability tests in this comparison. That is, the two approaches are based on very different content, ruling out a comparison of the validity. This difference in dimensionality alone demonstrated some important merits of TTMF over the data-driven approach.

Ⅳ. Conclusion

4.1. Research Findings

In this research, a standard procedure for theory-based text mining, TTMF was introduced, by explaining the process and objectives of each stage. An illustration of TTMF implementation, using 22,085 reviews regarding hotel services, was then provided to demonstrate its applicability and effectiveness. A total of 61,304 sentences extracted from actual customer reviews were successfully allocated to SERVQUAL dimensions. The pragmatic validity of our model was tested by the OLS regression analysis results between the sentiment scores of each SERVQUAL dimension and customer satisfaction (star rates), and showed significant relationships. As a post-hoc analysis, the results of the co-occurrence analysis to define the root causes of positive and negative service quality perceptions and provide action plans to implement improvements were reported. Additonally, findings from a conventional data-driven text mining approach using the same data are also compared with the TTMF findings.

4.2. Theoretical Contribution

Existing service theories can act as an appropriate framework for interpreting big data on new service environments. Theoretically, the unique contribution of our research lies in this aspect.

First, most previous text-mining research has been conducted in the computer science or computer engineering fields, focusing mainly on technical aspects such as algorithm improvement, the adoption of deep learning techniques, and the efficiency of crawling engines. This study contributes to the field by presenting an interdisciplinary approach, which merges theory with current text-mining techniques. This approach enhances our ability to evaluate the nuances of human factors, and challenges text-mining researchers to extend traditional approaches to encompass the fundamental goal of understanding the complexities of human behavior and perception especially in service fields.

Second, applications of theories in various service contexts using TTMF would add the value, and invite a renewed evaluation of the relevancy and validity of the existing academic theory. Revisiting and applying these established theories can lead to new, interesting, and contextualized research questions in the service research tradition.

Finally, beyond the empirical validation of the existing models TTMF can also be employed as a new multi-method research tool to explore and construct a causal research model using qualitative and unstructured text data. Quantitative data (e.g., sentiment scores) transformed from qualitative text data would provide a novel method of identifying hidden patterns from a vast amount of data. This could potentially lead to a mixture of exploratory and explanatory research methodologies, which could enhance the capacities of service and hospitality research.

4.3. Practical Implications

First, the TTMF approach allows all the available data to be analyzed in detail by capturing the subtle and intangible aspects of data, owing to the use of a more effective guided keywords list derived from the underlying theory. As revealed in our illustration, an existing text-mining method, the bottom-up approach deriving important dimensions from the data, is too dependent on the tangible and physical attributes of the data to adequately describe complicated latent phenomena such as customer perceptions (i.e., customer satisfaction or service quality). It is shown in <Table 10> that topic modeling effectively measures tangibles (e.g., room quality, facilities, and location/transportation) and partial aspects such as staff performance (assurance), but is lacking in its ability to measure other dimensions of service quality. This means that the results of data-driven text mining methods without TTMF overlook minor but important aspects of customer reviews, and thus cannot provide a full and comprehensive report of customers' perceptions. Based on the findings of the comprehensive, mission-oriented findings in our illustration, The Bureau can set the priority of service improvement efforts based on the finding and also supervise hotels ranked with the lowest service quality scores. Specific guidelines can be provided in correspondence to dimensions that exhibit a low service quality. For example, foreign language education programs or other vocational training may be offered to staff members at hotels that receive low sentiment scores in the assurance dimension.

Second, TTMF can provide a more mission-oriented approach. It derives clearly defined sub-dimensions and their causal relationships, focusing on the original objective of the analysis. In our illustration of the data-driven approach, a couple of dimensions were not directly associated with the internal service quality itself, rather with the overall satisfaction or hotel preference. This is because the data-driven approach cannot effectively filter or focus on the topic of our interest, namely service quality. By integrating academic theory into the business world, TTMF allows us to identify more precisely focused dimensions and the causality of interest, which helps to determine the root causes of certain phenomena and prioritize these in terms of their importance.

Third, in practice the outcomes of TTMF can be fully exploited to regularly monitor consumer perceptions concerning products or services over an extended time period using a predefined computer program. Notifications can be set up to report any significant failures on specific dimensions or the overall performance. Keyword selections can also be updated through longitudinal data collections using a machine learning process. For example, if Wi-Fi suddenly began to emerge as a prominent factor in negative comments in the tangible dimension, then the Bureau or hotels could immediately resolve this problem by improving the quality of wireless communication, and then follow up with periodic analyses of customer reviews concerning Wi-Fi.

Finally, as there are many rigorously validated service theories available, TTMF can be conveniently extended to almost any service-related questions, not only those pertaining to consumer behavior, but also to internal service dilemmas and opportunities. Hybrid text-mining methods consecutively conducting the main and post-hoc analyses, as well as combining text mining and traditional research methods such as qualitative content analysis (Niu and Fan, 2018) importance-performance analysis(IPA) (Hemmington et al., 2018) with valid service theories, allow managers to effectively answer challenging questions.

4.4. Limitation of the Study and Further Directions

First, dataset of this study were limited on hotel reviews and a single, typical case of the data-driven text mining. In order to confirm the clear difference between the theory-based TTMF and data-driven approaches, analyzing various contexts of data, mission, and text-mining tactics are needed by the future research.

Second, as an initial research focused on theory-based text mining, TTMF, in this study, only describe the action plans for very primitive research setting; that is, we focused only a single construct with multiple sub-dimensions. When more complicated research model with more variables is proposed to be analyzed, the more diverse analysis methods in the Step 5 and 6 of TTMF should be considered.

As an initial systematic approach to integrate academic theory into text mining tactics, this research proved TTMF's effectiveness as a more mission-oriented approach. Hybrid text-mining methods regularly conducting the main and post-hoc analyses, as well as combining text mining and traditional research methods with valid academic theories, allow managers to effectively answer challenging business-related questions.

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