Structural Equation Modeling with Sentiment Information and Hierarchical Topic Modeling

Takurou Ogawa
Department of Sustainable System Sciences
Graduate School of Humanities and Sustainable Systems
Osaka Prefecture University
Japan
e-mail: saa01052@edu.osakafu-u.ac.jp

Ryosuke Saga
Department of Sustainable System Sciences
Graduate School of Humanities and Sustainable Systems
Osaka Prefecture University
Japan
e-mail: saga@cs.osakafu-u.ac.jp

***Abstract*—Service evaluation depends on various factors, such as assurance, responsiveness, and tangibles. Given that emotional satisfaction affects service satisfaction, analyzing both the evaluation and sentiments is important in improving service. Previous studies have identified the evaluation factor and determined the degree of influence on the resulting evaluation. However, there is little effective analysis that reflects the influence of such a factor on sentiment. In this study, we use hierarchal Latent Dirichlet Allocation and structural equation modeling (SEM) to express the causality relationships of service evaluation visually and quantitatively. Sentiment obtained quantitatively by using sentiment analysis is newly applied to SEM to obtain knowledge reflecting the influence of sentiment. As a result of the experiment, we can identify the causality of service and determine the influence of the evaluation factor and sentiment quantitatively. Furthermore, we conduct an experiment that compares a causal model with and without sentiment information and improve the model interpretability.**

Keywords-sentiment analysis; service analysis; structural equation modeling; hierarchical Latent Dirichlet Allocation; causal analysis

I. INTRODUCTION

In recent years, the service industry has grown rapidly such that in developed countries, there are so many markets that account for 60% to 70% of a country's gross domestic product (GDP). In the United States where GDP is the highest, the service industry's GDP is $ 15.52 trillion, accounting for 80% of the total GDP [1][2]. In addition, with the spread of smartphones, apps for various services (e.g., Twitter, navigation), the introduction of recommended hotels, and the rise of electronic services (e.g., Internet shopping) are rapidly increasing. With this background, the importance of services has grown in recent years. Service improvement is important as services are produced and consumed at the same time compared with products that are released and finished. Thus, analyzing the evaluation of the service in order to improve such service is important.

Service evaluation depends on various factors, such as assurance, responsiveness, and tangibles. For example, SERVQUAL evaluates the quality of service [3] with five-dimensional indicators, and Airport Service Quality [4] defines airport evaluation factors. As there are many factors in the evaluation of services, it is necessary to find out the evaluation factors to analyze the evaluation.

Generally, analyzing services is difficult because these have special features that ordinary products do not have like Intangible, Heterogeneous, Inseparable, and Perishable. However, there are several clues to analyze the services from the data (e.g., questionnaire). Especially, user review is useful because the review describes user experience of and perceived from the services. It is possible to analyze the quality of service and the evaluation of service. Meanwhile, emotional satisfaction is also regarded as an important and attractive factor in service satisfaction. That is, customers experience different positive and negative sentiments related to service, and these sentiments influence service satisfaction [5]. Of course, these factors influence service evaluation and the sentiments related to the service are implied in the user review; however, there is no study to identify and analyze evaluation factors together with sentiment information.

This paper describes the method by which to perform causality analysis from text data, such as user review. In order to treat causal analysis, we use the topic-based approaches by applying a topic model to the review. In addition, the sentiments for evaluation factors in the text are quantitatively determined using sentiment analysis method to understand emotional satisfaction. By applying topic and sentiment information to structural equation modeling (SEM), we analyze the influence of each factor quantitatively.

The first contribution of this paper is that it obtains the knowledge reflecting sentiment information from the user review by using sentiment analysis. Second, it understands the influence on the sentiment of the evaluation factor based on the idea that sentiments are essential for service evaluation factor analysis. By using SEM with path diagram, we can also analyze and understand the causality relationships among topics and their sentiments associated with topics that are visually and quantitatively express.

This paper is structured as follows. Section II refers to the existing related research, Section III explains the core method of the analysis process, and Section IV describes analysis experiments using actual data. Finally, Section V discusses future work and Section VI concludes this study.

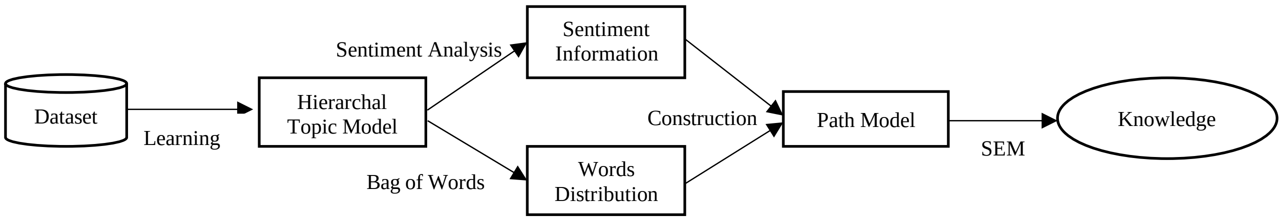

Figure 1. Analysis process

II. LITERATURE REVIEW

In related research for service analysis, SERVQUAL [3] measures the quality of service by measuring the gap between advance expectation and subsequent experience using five indicators prepared in advance. SURVPERF [6] measures the quality of service based on the subsequent experience alone. Related researches include a study that further increased the dimension from these five dimensions [7] and another that changed the dimension to measure the quality of electronic service [8]. There are many evaluation indicators, but it is difficult to measure all services by one standard because there are many types of services and their characteristics largely differ.

Meanwhile, related works on SEM include a study that has found relationships between customer loyalty and service quality [9] and another that has proposed a model to infer the purchase factor of the game by combining hierarchal Latent Dirichlet Allocation (hLDA) and SEM [10]. A previous work used SERVQUAL and SEM to examine the effects of the former [11]. A study increased dimensions of the SERVQUAL and analyzed it through SEM [7]. Another study identified the factors that affect customer satisfaction and the dimensions of service quality and their ranking in the context of fast food restaurants [12]. A previous study used the main aspects of pedestrian level of service (PLOS) [13], namely, safety, security, mobility and infrastructure, and comfort and convenience, to provide a comfortable and safe walking environment. PLOS is a measurement tool for evaluating the degree of pedestrian accommodation on roadways. This study also used SEM to provide the essential information for interpreting the aspects of the walking environment that influence PLOS [14]. Another research analyzed the influence of e-commerce services, which are the core dimension of e-service quality, on internet banking adoption and brand loyalty of banks [15]. These works, however, do not consider the sentiment contained in the text.

Meanwhile, emotional satisfaction is largely believed to affect service satisfaction [5]. In relation to this, sentimental analysis is useful in comprehending and handling the sentiment information. A study utilizes sentiment analysis and Latent Dirichlet Allocation (LDA) to evaluate the quality of airport services [16], while another determines the user's evaluation for each attribute by combining Airport Council International-defined airport service quality attributes and sentiment analysis [17]. In these studies, sentiment is considered one of the important factors in sales of services; thus it is essential to consider sentiment. However, no study has proposed structural equation modeling that considers the sentiment contained in text.

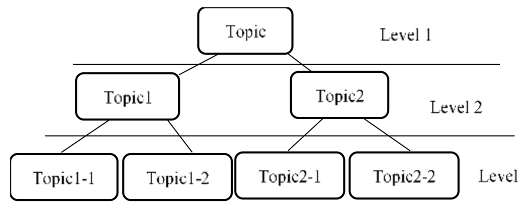

Figure 2. Hierarchal structure of topics

Therefore, the current paper proposes the model for SEM with sentiment information. By using this model, we can acquire knowledge including sentiment information visually.

III. METHODOLOGY

In this paper, the analysis is performed according to the process of Figure 1. First, topics are extracted by learning a topic model. Next, we find the sentiment and topic distribution for that topic. Finally, a model is constructed based on these data and this is then analyzed by SEM so that can gain knowledge.

A. Topic Model

The topic model is a method that tries to clarify the structure of a document group by inferring words contained in the topic based on the premise that the document group has a specific topic. In a topic model, a document is a collection of words probabilistically generated by the topic to which it belongs.

Topic models include different methods, such as latent semantic analysis (LSA) [18], LDA [19] and hLDA [20]. The LDA assumes a multi-topic model in which the document is based on mixed topics. LDA has a 1:*n* relationship between documents and topics, not 1:1 like LSA. LDA is considered to be a more natural model in documents, such as review texts that are written in one document about various aspects [19].

HLDA is an extended method of LDA and is a hierarchal model as shown in Figure 2. It has the property of automatically constructing relationships among hierarchical topics. As a learning result, a hierarchical model constructed hierarchically and a keyword group constituting each topic are generated together with their generation probabilities. The specific content of the topic can be inferred from the keyword groups of a topic. In this study, hLDA is used because it is a natural document model and the relationships between topics are defined automatically.

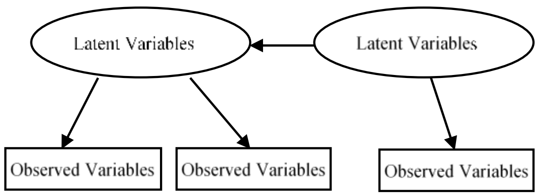

Figure 3. Path model of SEM

B. Sentiment Analysis

Sentiment analysis literally refers to the analysis of sentiments. By using sentiment analysis, such as posted comments, one can determine whether consumers have negative or positive sentiments and the strength of such sentiments. Sentiment analysis can be performed on a per-document or per-sentence basis.

To embed sentiment to SEM explained later, we have to recognize sentiments on each topic for each review. In this study, we regard the average of sentiment values ranging between -1(negative) and 1(positive) as document sentiments by calculating Equation (1) as

$$E_{im} = \frac{1}{|T_i(S_m)|} \sum_{s \in T_i(S_m)} E(s), \quad (1)$$

where E_{im} is the sentiment about the topic T_i of the review R_m; S_m is a set of sentences in R_m and $|\,|$ is the element number of a set; $T_i(S_m)$ represents the sentence set of S_m, including the topic I; and the function E recognizes the sentiment of a sentence. If there is no sentence related to a topic, the result of Equation (1) is 0 (neural) and regards this sentiment about the topic as neutral. The longer the review, the more likely it is to include other topics. Therefore, it is possible to extract sentiments related to topics more accurately by focusing only on sentences containing topics in reviews.

Here, valence aware dictionary for sentiment reasoning (VADER) [21] is used as function E in the equation. This method is particularly accurate for sentiment analysis in social media. There are several studies that used VADER. One study analyzed the correlation of positive and negative user reviews of mobile apps before and after app update, respectively, by using VADER because VADER has the high precision in the social media field [22]. In VADER, the value of sentiment is represented by -1 to 1 (the closer to -1 the more negative and the closer to 1 the more positive the sentiment). Therefore, the E_{im} outputs the value between -1 and 1.

C. Strucuture Equation Modeling (SEM)

SEM [23] is a method characterized by the use of factor analysis and regression analysis. Factor analysis is the idea that observed variables are based on some hidden factor, and the influence of the factor is to be determined by “correlation” (variance / covariance). Regression analysis is a technique for finding the relationship between a variable to be predicted (target variable) and a variable (explanatory variable, independent variable) that describes the target variable. In other words, SEM can be considered as a factor regression analysis.

The SEM can express causal relationships between variables visually and quantitatively by using a path model, as shown in Figure 3. A path model consists of three elements: latent variables, observed variables, and paths. Latent variables are factors that cannot be observed in actual. Observation variables can actually be observed and are essential for estimating a latent variable. In the path model, latent variables are represented by ellipses and observation variables are represented by rectangles. The causal relationship between such items is represented by the path of the arrow, and the degree of influence is represented by the path coefficient.

D. Construct Path Model and Find Knowledge

Topics that cannot be observed directly are considered as latent variables serving as correspondence between SEM and topic model. The keywords that make up the topic, the sentiment for the topics, and the rating values of each review are the observation variables. From the idea of the topic model that words are generated by topics, each topic is regarded as a factor and the paths from the topics are drawn to the keywords to which the topics are related. Moreover, the paths between topics are drawn from the upper topics to the lower ones based on the idea of the hierarchical structure of the hLDA topics.

Next, we explain the process of incorporating sentiment information into the path model. Sentiment information influences the intention of a model. Thus, we have to carefully determine how to incorporate sentiment information. Generally, sentiments for service are generated as perceived experience (after the service) or the expectation (before using the service). Therefore, the model is expressed by drawing a path to sentiment information from each topic. When we draw a path from the topic to sentiment information, the causal relationship between the sentiment and the topic becomes clear. Moreover, rating evaluation is considered to be generated from the top-level topic that includes all elements. Therefore, by drawing the path from the top-level topic to the rating evaluation, the model can represent the causal relationship with the rating.

Furthermore, by comparing the values of path coefficients from the higher topics to the lower topics, it is possible to find an important factor for the rating. By paying attention to the path coefficient from the lowest topic to the keyword, we can find the degree of influence of more detailed factors. The path coefficients from each topic to sentiment are large and the causal relationship with sentiment could be expressed. By comparing the path coefficient from each topic to sentiment, topics with a larger causal relationship with sentiment can be found.

However, the path model of SEM is usually prone to model identification failure, especially if there are too many latent variables. Conversely, if the number of latent variables is less, the amount of information in the model may be too small for interpretation. As the topic is a latent variable in the path model, the number of topics must also be adjusted. We also need to remove unreliable paths and observation variables with relatively small influence.

IV. Experiments

The purpose of this experiment is to confirm the feasibility of proposed approaches described in Section III. Furthermore, we consider the experimental results.

A. Dataset, Parameters, and Processing

In this analysis, the data must have text data and numerical evaluation data, and it is ideal to have as many review data as possible in order to apply the topic model. In addition, in order to characterize statistical data based on the concept of Bag of Words, the text of one review data must include many words. In this experiment, we employ user-reviews of the datasets published online by Kaggle and Github: the hotel[1], airport[2], app[3] for shops and electronic services[4] for purchasing clothes. Airport, app and electronic services reviews are collected by web scraping. Hotel reviews are provided by Datafiniti's Business Database. Each review has review text with a rating between 1 and 5 or 1 and 10. We also regard a review text as a document. In this method, we have to ensure that the topics and the appearance frequency of the feature words described are included in each document. In addition, we examined reviews of each dataset and understood that a review that passes for a document have about 30 words. Therefore, only documents stated with more than 30 words are used. The app analyzes information from randomly extracted data. The number of reviews after these pre-processing is shown in Table I. In this experiment, sentiments on topics in the lowest level are determined for the construction of a path model. Moreover, T_i in (1) indicates a topic of the lowest level (i.e., topic in third level). Whether a sentence includes or does not include a topic is determined based on whether or not a keyword constituting the topic is included.

As criteria to evaluate the result, we use goodness of fit index (GFI), adjusted GFI (AGFI), root means square error of approximation (RMSEA), and Bayes information criterion (BIC) were used [24][25]. As equations for GFI, AGFI, RMSEA, BIC,

$$GFI = \frac{tr((\Sigma(\hat{\theta})^{-1}(S - \Sigma(\hat{\theta})))^2)}{tr((\Sigma(\hat{\theta})^{-1} - S)^2)}, \tag{2}$$

where $\Sigma(\hat{\theta})$ is the estimated value of covariance matrix and S is value of the actual sample covariance matrix. $tr((A)^2)$ expresses $tr(AA')$,

$$AGFI = 1 - \frac{n(n+1)}{2df}(1 - GFI), \tag{3}$$

where n is the number of observed variables and DF is degrees of freedom,

$$RMSEA = \sqrt{\frac{\max[\frac{\chi^2 - DF}{N-1}, 0]}{DF}}, \tag{4}$$

where N is the number of samples,

$$BIC = \chi^2 - DF\log(N). \tag{5}$$

And as an equation to calculate degrees of freedom,

$$DF = \frac{1}{2}n(n+1) - p, \tag{6}$$

where p is the number of variables in equation. Equation (2) expresses how well the total variance in the saturation model that includes paths between all possible variables can be explained by the estimation model that is the analysis result of this experiment. A value between 0 and 1 is taken and the closer a value is to 1, the better the model becomes. A value of 0.9 or higher is desirable. GFI is unconditionally improved in fitness as model degrees of freedom decreases. Equation (3) corrects the shortcomings of GFI and penalizes models with many parameters and high complexity. The same value as GFI is taken, and the closer it is to 1 the better the resulting model. If the model is not complex, GFI and AGFI will be close values. Equation (4) is an index that expresses the difference between the model distribution and the true distribution. The fit is good with a value of 0.05 or less, and the fit is bad with 0.1 or more. Equation (5) estimates the posterior probability based on chi-square value when the model is selected. This is used to evaluate the balance between model suitability and the amount of information and is used in carrying out relative evaluation. It is better for the value to be smaller.

In this experiment, we used several packages and libraries: Mallet package [26] for hLDA, Python's nltk package with VADER method [27] for sentiment analysis, and SEM package of R [28] for SEM analysis.

1. https://www.kaggle.com/datafiniti/hotel-reviews#Datafiniti_Hotel_Reviews.csv
2. https://github.com/quankiquanki/skytrax-reviews-dataset/tree/master/data
3. https://www.kaggle.com/usernam3/shopify-app-store#reviews.csv
4. https://www.kaggle.com/nicapotato/womens-ecommerce-clothing-reviews#

TABLE I. Data and result

Dataset Name	# of Reviews	GFI	AGFI	RMSEA	BIC
Hotel[1]	8104	0.9025	0.8881	0.05525	9188
Airport[2]	13444	0.9152	0.9005	0.05266	12950
App[3]	5442	0.8979	0.8835	0.05960	6848
e-Commerce[4]	19354	0.9213	0.9060	0.05446	19272

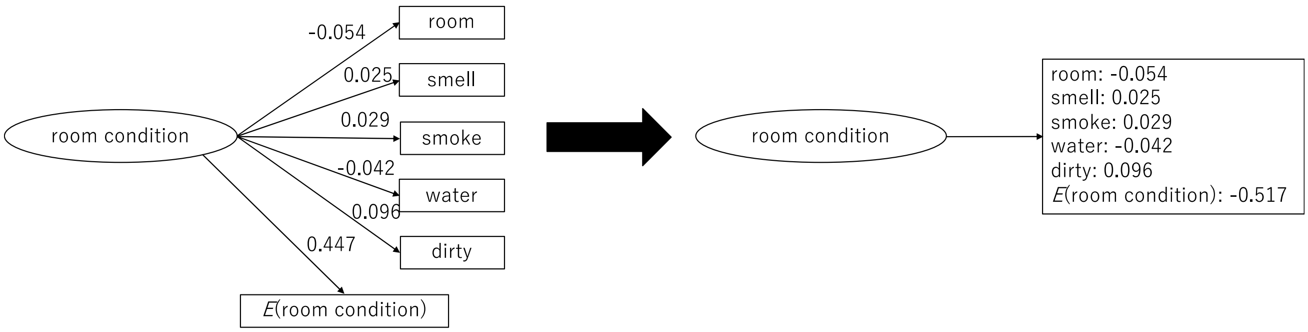

Figure 4. Expression of a path from the latent to the observed variable

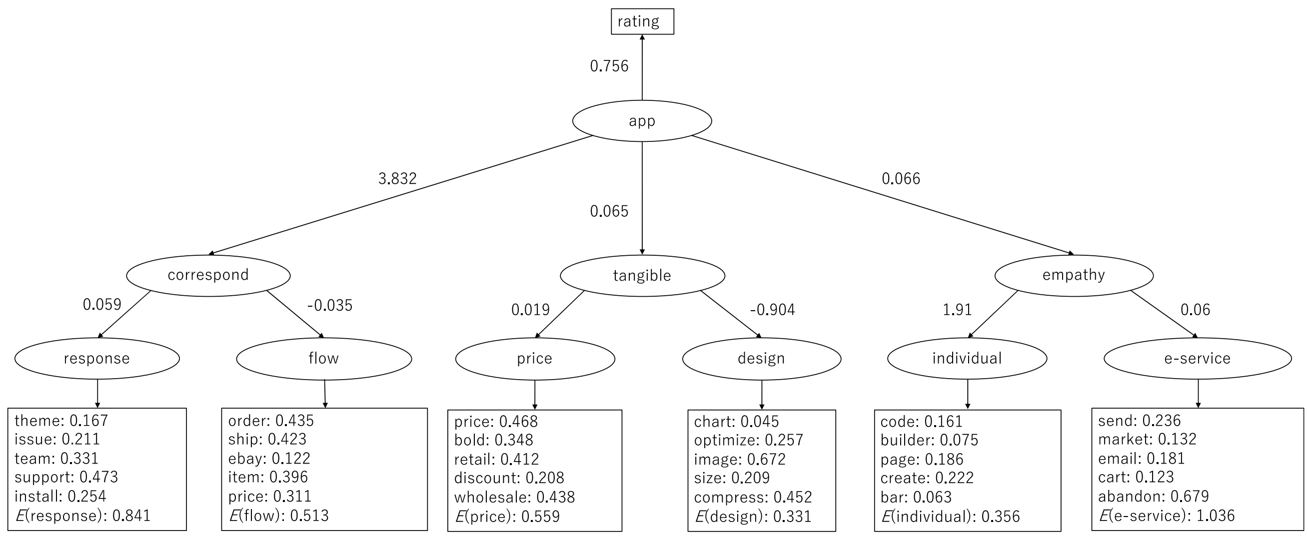

Figure 5. Analysis result of the app dataset

B. *Result*

Table I shows the calculation results of the evaluation indexes for each data and analyzed models. From Table I, we could find that hotel, airport, and e-commerce models have a GFI of over 0.9 and AGFI maintains high levels. Moreover, none of the models have an of less than 0.05, but it is much closer to 0.5, compared to the model whose fit is bad with 0.1 or more.

It can be said that all of models fit well to the dataset and the constructed models are reliable from the viewpoint of these indices.

As an example, let us show the result of the app dataset in Figure 5. The causal relationship among the keywords that comprise a topic is similar to the depiction in Figure 4. The words at the bottom of the model are those that make up the identified topics from the text data of the review using the topic extraction with hLDA. Here, the topics (latent variables) are estimated by authors from the words that make up each topic. For example, “response” is estimated because it has a large causal relationship with “support” and is considered to be a topic related to responses to actions, such as “install,” “team,” and “issue.” We were able to create a path model based on the hierarchical structure of a text data document group revealed by hLDA. Further, causal relationships can be analyzed by paying attention to arrow and values calculated by SEM between topics or between topics and words or sentiment information at the bottom of the model.

We focus on the “correspond” area with a large path coefficient from the top topic. The “response” is also considered to be an important factor for evaluation because when comparing the two topics under “correspond,” the path from “correspond” to “response” has a larger path coefficient. Here, the path between the latent variable “response” and the value of the sentiment “E(response)” has a large coefficient, implying that “response” has a strong relationship with the sentiment strongly. Therefore, it can be considered that the sentiment of “response” also leads to evaluation.

In the same way, when we check the other paths to sentiments, we could find the relationships with and influences to evaluation. From the figure, “response,” “flow,” “price,” and “e-service” have an effect of sentiments (the paths over 0.5) and the “design” and “individual” did not. We are not certain whether the results agree or not, but this specific one indicates which topics lead to emotional satisfaction. In this way, it is possible to improve the service

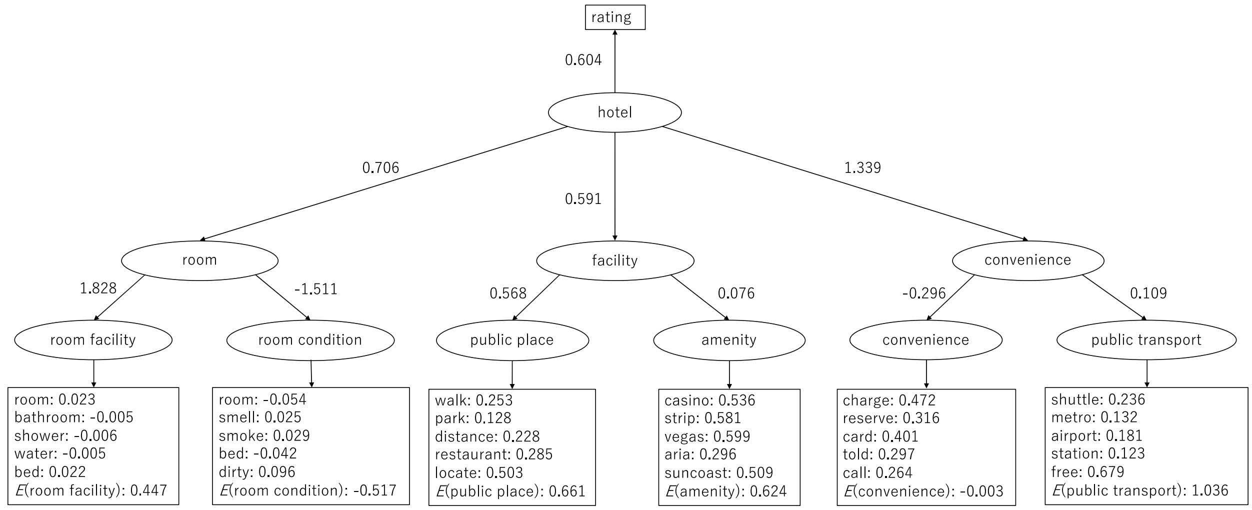

Figure 6. Analysis result of the hotel dataset

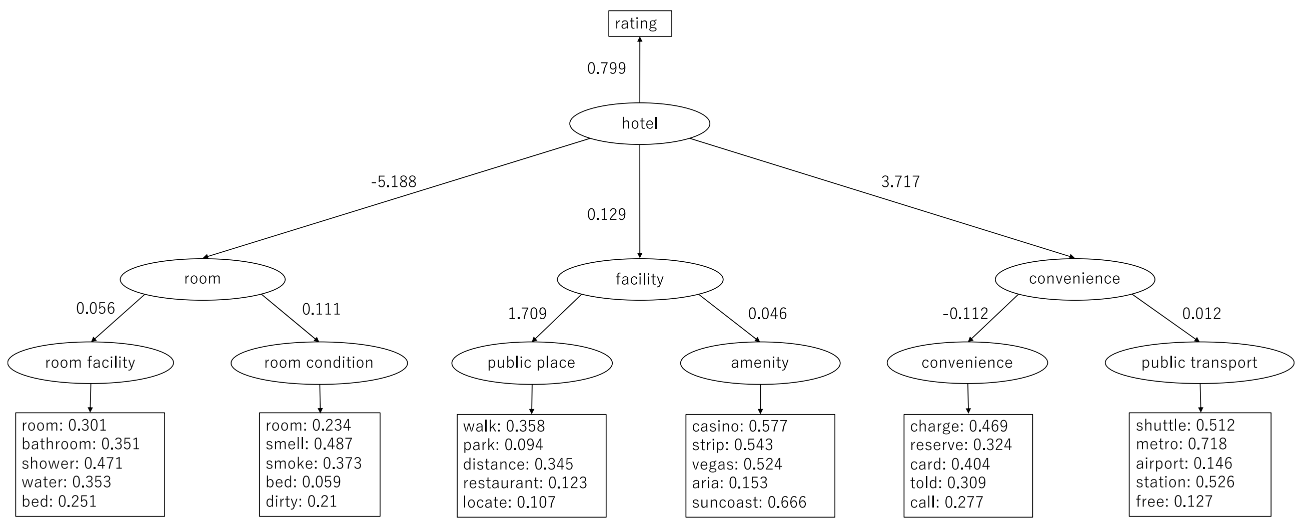

Figure 7. Analysis result of the hotel dataset that deletes sentiment information from Figure 6

by quantitatively understanding the specific service factors that influence to the sentiments and evaluation.

Figure 6 presents another example of analysis. For instance, "room facility" is estimated by different room features namely, "bathroom," "shower," and "bed" and "room condition" is evaluated using "smell," "smoke," and "dirty." The hotel structure can be reviewed by examining the results of the analysis of hotel data. Hotels are evaluated using "room," "facility," and "convenience." By focusing on low hierarchy, the details of the evaluation factors, such as "room condition" and "public transport," can be analyzed. Moreover, the factor that influences sentiment can be comprehensively understood. We focus on the "convenience" area with a large path coefficient because this topic exerts large influence on the evaluation (rating). "Convenience" that has "charge" and "card" has a small effect on sentiment, whereas "public transport" that has "shuttle" and "metro" exerts a large effect. Therefore, "public transport" leads to emotional satisfaction, whereas "convenience" does not.

We then compare the analysis results with and without sentiment information. Figure 7 illustrates the analysis result of the hotel dataset that does not consider sentiment information. We compare Figures 6 and 7. The topic "convenience" composed of "charge" and "reserve" shares a weak relationship with sentiment information. Therefore, even if the sentiment information is deleted, no large difference is observed in the path coefficient between the topic and the words that constitute the topic.

Subsequently, we analyze the topic "public transport," which is strongly related to sentiment information. If sentiment information is not considered, the largest path coefficient is observed in the path to "metro;" otherwise, the path to "free" possesses the largest coefficient This phenomenon occurs because the path coefficient from the path to the words that have strong relationships with sentiment information increases, that is, if "free" has a strong

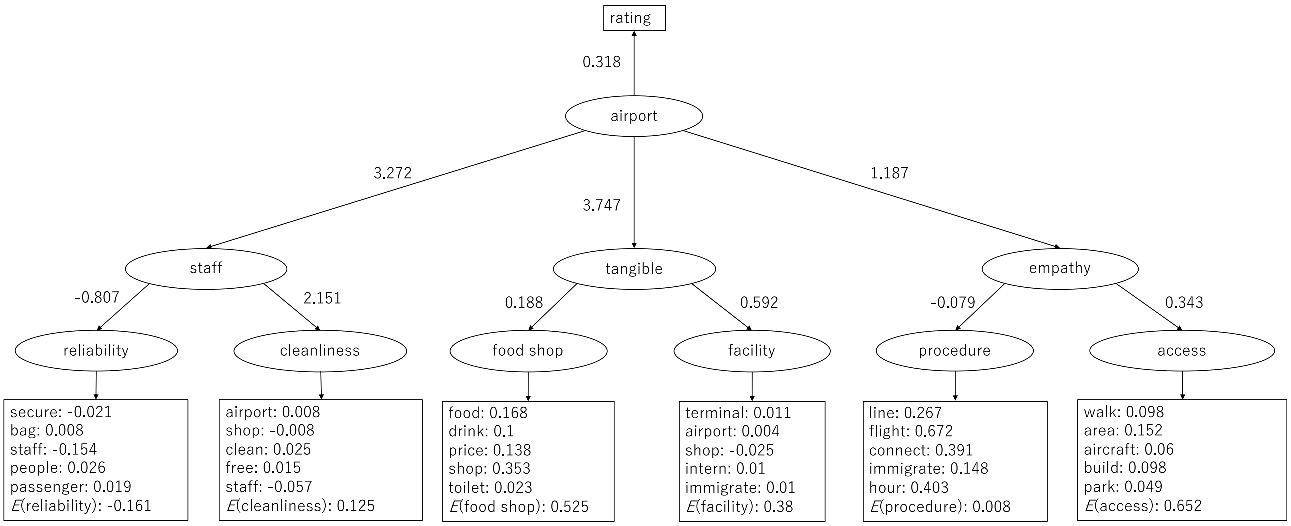

Figure 8. Analysis result of airport dataset

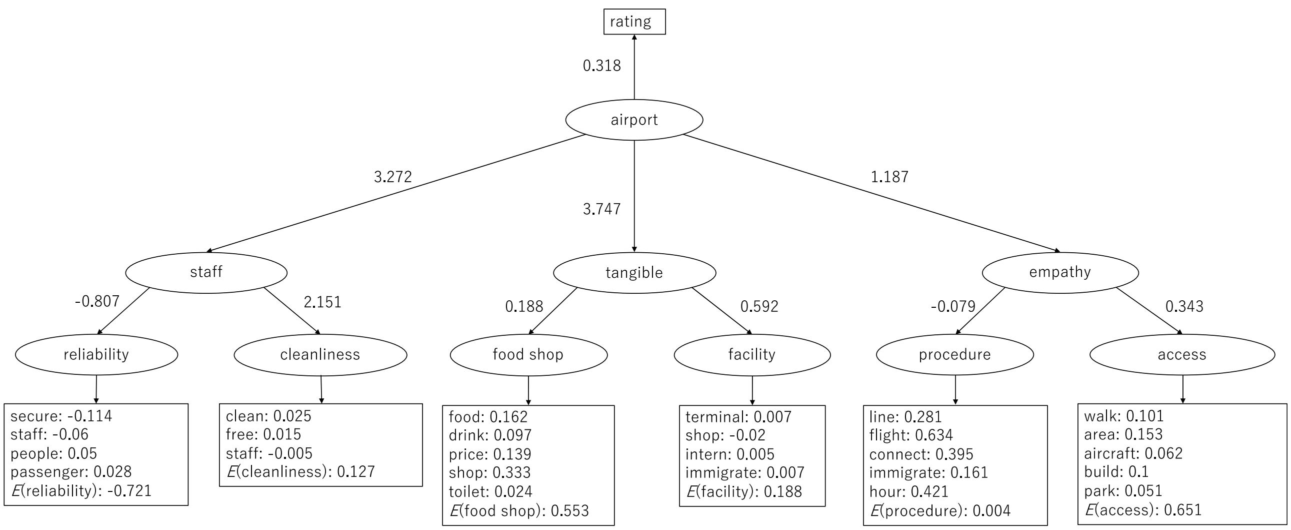

Figure 9. Analysis result of airport dataset that deleted several paths from Figure 8

relationship with sentiment information, then this word is the important factor in the causal model of hotels that considers sentiment information.

In the topic “room facility” in Figure 7, all path coefficients have positive values. However, in the same topic in Figure 6 , which considers sentiment information, paths with negative values, such as those to “smell” and “smoke,” appear. This phenomenon can be ascribed to the negative relationship of these words with the sentiment information of

TABLE II. EVALUATION INDICES OF AIRPORT DATASET

Figure Name	GFI	AGFI	RMSEA	BIC
Figure 7	0.9152	0.9005	0.05266	12950
Figure 8	0.9210	0.9007	0.05275	11358
Figure 9	0.9275	0.9134	0.05287	9885

the topic “room condition.” For instance, the sentiment values in documents that contain these words tend to be negative, whereas those in documents that do not have these words are positive. Therefore, adding sentiment information to the topic leads to the clarification of the negative factor.

In summary, a causal model that considers sentiment information can be constructed.

This study aims to improve the interpretability of the causality model. Figure 8 shows the result of the airport dataset. The figure displays several paths that have small path coefficients. A causality model with enhanced interpretability can be constructed by deleting these paths because the two variables connected by a small path coefficient have almost no causal relationship. Figure 9 displays the result after deleting the paths in Figure 8 that have small path coefficients (path coefficient < 0.01), except those with sentiment information. Figure 10 shows the result after deleting the paths in Figure 9 that have small path

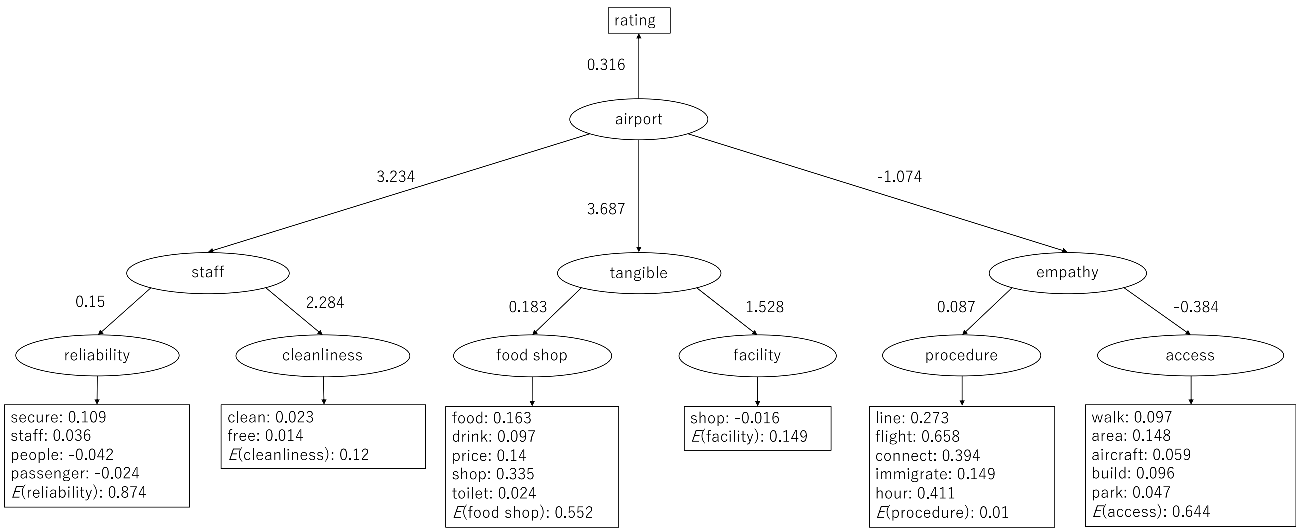

Figure 10. Analysis result of airport dataset that deleted several paths from Figure 9

coefficients (path coefficient < 0.01), except those with sentiment information.

Table II summarizes the calculation results of the evaluation indices for Figures 7, 8, and 9. GFI and AGFI increase as the paths that have small path coefficients are deleted, whereas RMSEA decreases because of the change in the number of observed variables. The results suggest that all figures fit well to the dataset, and the constructed models are reliable from the viewpoint of these indices.

An easy-to-interpret causality model of the airport dataset can be constructed from Figure 10 because the paths that have small causal relationships are deleted. In other words, the amount information decreases, but we can construct a simple model and focus only on the important elements.

V. DISCUSSION AND FUTURE WORK

From the experiment, we found that sentiment information is useful for analyzing services, but we have to consider improving sentiment expression. For example, we extracted sentiment information of topics based on (1), but this equation does not consider the length of the sentence. Nevertheless, it enables us to accurately determine the sentiment on the topic by considering the weight based on the sentence length. For example, longer sentences are more likely to include other topics. Therefore, it may be possible to extract sentiments related topics more accurately by reducing the impact of such sentences on sentiments of specific topics. Secondly, when two or more topics are included in one sentence, even if it is used in a contrasting sentence, such as "(Text about TOPIC A) but (Text about TOPIC B)," the same sentiment value is calculated for the topic. If there is a conjunction (e.g., "but"), a more accurate sentiment analysis can be performed by further processing, such as dividing. Thirdly, several factors such as "smells" in Figure 4 are considered negative but it would be positive for several people. Therefore, it is possible to express this situation by dividing reviewer into a group that thinks the factor is negative and a group that thinks factor is positive and expressing it to path model. Finally, in this paper, the accuracy improvement and knowledge are obtained by constructing path models under different assumptions during the construction of the path model.

Furthermore, we consider the hierarchical topic structure to construct the path model. In this study, we use hLDA to extract such structure. Several methods can be used to extract the hierarchical topic structure. Zhu et al. proposed an extraction method [29] that combines a biterm topic model (BTM) [30] and Bayesian rose trees (BRTs) [31]. The present study extracts the topics by using BTM and constructs a hierarchical structure by utilizing BRTs. Moreover, this study adopts simBRT to account topic similarity. Viegas et al. proposed CluHTM [32], which is a novel non-probabilistic hierarchical topic modeling strategy based on non-negative matrix factorization and CluWords [33]. This method ensures topic coherence and reasonable topic hierarchies and uses the utilization as an original cross-level stability analysis metric to define the number of topics and the shape of the hierarchical structure. The abovementioned methods can be used to accurately estimate the document structure.

A topic is defined as a bag of words without explicit semantics. In this study, the contents of the topics are estimated using the words that compose them. However, the topic model loses objectivity. To address this issue, we can use topic labeling. Several methods can be used to add semantic labels to the topic model. Nalasco et al. proposed an automatic labeling technique by using a new candidate selection algorithm and three scoring methods [34]. Bhatia et al. proposed a neural embedding approach that involves automatic topic labeling by using Wikipedia article titles [35]. Mao et al. proposed an automatic labeling technique for hierarchical topic structures [36].

VI. CONCLUSION

In this paper, we analyzed the causal relationships in service by using SEM and sentiment information. We constructed the path model by using hLDA and sentiment analysis between topics and sentiments. The findings of the experiment using the user reviews of airports, hotels, shopping apps, and electronic services show the feasibility of our proposed model. We summarize the following findings from the experiments:

- We obtained knowledge by analyzing service while considering sentiments.
- We determined the impact on the rating of each topic.
- We obtained the causal relationship between each topic and sentiment quantitatively and provided clues for further analyses.

Service analysis that considers sentiment information is conducted by this study. We found that sentiment information has the relationship with service evaluation.

We also performed service analysis considering sentiment and obtained knowledge reflecting sentiment information from the user reviews. The consideration of sentiment information is essential for service analysis, and the creation of path models with sentiment information is considered effective in extracting information that helps increase service satisfaction. It is suggested that the analysis process in this paper may provide useful knowledge for service analysis and service improvement. On the one hand, this can be used by service providers in improving services and creating new services. Service providers can quantitatively find factors that have major impacts on the evaluation of services and customer sentiments. On the other hand, it can be used by service users to efficiently grasp the outline of services that are not formed. Although we analyzed the indefinite service in the experiments, it can be applied to other things like tangible products. The potential applicability is high because analysis is performed from the text.

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