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Article

Asymmetric Effect of Airline Customer Opinions for Service Quality Attributes: Text Mining Approach

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Abstract: The purpose of this study is to identify airline asymmetric attributes that affect customer satisfaction based on the three-factor theory and to build an Asymmetric Impact-Sentiment Analysis (AISA) for resource allocation prioritization. We identified food and beverage service as a basic factor; inflight service as a one-dimensional factor; and seat comfort, ground service, and airline seat class as attractive factors. AISA analysis results showed that food and beverage services should be prevented from falling into customer dissatisfaction through Urgent Action (cell II), and in-flight services should be improved continuously to increase satisfaction (cell IV). Low-priority improvement is required for seat comfort, which is an attractive factor (cell VI), and strong maintenance is required for ground service and airline seat class as strength factors (cell V). The first contribution, the asymmetric relationship between customer opinions for service attributes and satisfaction, was verified. Second, this paper extended the IPA to the text mining-based asymmetric AISA.

Keywords: three-factor theory; service quality; text mining; Asymmetric Impact-Sentiment Analysis; Sentiment Analysis



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1. Introduction

COVID-19 is causing serious hardship on the global economy, with major impacts around the world. When the World Health Organization (WHO) declared a pandemic, the aviation industry was in great trouble. The global aviation industry is making various efforts to overcome COVID-19. With these efforts, demand from air customers is expected to recover faster than expected (Tseng, 2020), but in the era of high oil prices, the aviation industry entered a more difficult period. In order to overcome such difficult times wisely, it has become more important than anything else to provide satisfaction to returning customers. In an increasingly competitive environment, the importance of evaluating and managing customer satisfaction is increasing (Thelwall et al., 2013). In other words, it is important to identify important factors that determine satisfaction and loyalty. In addition, in order to obtain a high level of satisfaction, it is important to accurately reflect the company's limited resources on quality attributes.

Most traditional studies exploring the relationship between overall customer satisfaction (OCS) and quality attributes assume that these relationships are symmetric and linear. However, in recent years, many studies have shown that the impact of attributes on customer satisfaction is asymmetric (Abenoza et al., 2019; Albayrak, 2019; Blei & Lafferty, 2009; Jin et al., 2019; Oliver, 1999). These studies are based on the Kano model, which introduces the classification of product or service attributes by identifying their potential to

create satisfaction and dissatisfaction (Kano et al., 1984). The asymmetric effect on satisfaction means that the negative performance of the attribute can have a greater impact on customer satisfaction than the positive performance. Conversely, the positive performance of an attribute may have a greater impact on customer satisfaction than the negative performance. That is, one unit of negative performance on an attribute may have a greater impact on overall satisfaction than a corresponding unit of positive performance. This asymmetry studies are based on Herzberg's motivation-hygiene theory (Herzberg, 1976), Oliver's expectancy disconfirmation theory (Mikulić & Prebežac, 2012), Kano's three-factor theory (Kano et al., 1984), and Kahneman and Tversky's prospect theory (Kahneman & Tversky, 1979).

The majority of previous research on this topic has relied on the Kano model (Kano et al., 1984) and the modified Penalty-Reward Contrast Analysis (PRCA) model (Albayrak & Caber, 2013). The Kano model is a satisfaction and dissatisfaction survey method. From the customer's perspective, it is complicated, and it is difficult to measure the significance or performance of quality attributes. The PRCA method, on the other hand, modified the Kano model's survey method to measure customer satisfaction on a five- or seven-point scale. Due to the continued reliance on the customer's cognitive ability, it is time-consuming and expensive. Due to the recent development of big data analytics, text mining-based research on the asymmetry of quality attributes has emerged (Bi et al., 2020; Y. Chen et al., 2022; Ding et al., 2020; Hu et al., 2020; Oliver, 1976; Yang & Han, 2013). Previous text mining-based studies have demonstrated asymmetry by extracting quantitative data of quality attributes from online reviews. However, it is difficult to locate asymmetry studies involving unstructured data on quality attributes. Consequently, this study employs topic modeling and sentiment analysis among text mining techniques to identify quality attributes and sentiment and recommends overall customer satisfaction and Asymmetric Attribute-Sentiment Analysis (AISA) techniques. In addition, the AISA-proposed use of online airline reviews is implemented, and detailed improvement strategies, including investment priority for quality attributes, are presented.

J. Kim and Lee (2023) employed topic modeling to extract hotel selection attributes, while M. Kim and Kim (2024) utilized machine learning-based sentiment analysis on online reviews. These recent studies indicate that research using topic modeling and sentiment analysis has been actively conducted.

The purpose of this study is to develop an Asymmetric Impact-Sentiment Matrix (AISM). Previous studies on asymmetry (Albayrak, 2019; Hu et al., 2020) have predominantly utilized PenaltyReward Contrast Analysis (PRCA), which has been widely adopted by many researchers. Furthermore, Bi et al. (2020) employed Asymmetric Impact Penalty Analysis (AIPA) as an asymmetry analysis method for hotel attributes, identifying hotel service characteristics and using the findings as a resource allocation strategy. These studies primarily relied on surveys to calculate PRCA and to identify asymmetric relationships based on the results.

However, this study integrates traditional PRCA with Sentiment Analysis to derive asymmetric relationships for service attributes and propose resource allocation strategies for those attributes.

2. Literature Reviews and Theoretical Basis

2.1. 3 Factor Theory

The majority of quality characteristics have a positive effect on customer satisfaction overall (Anderson & Mittal, 2000). When examining the relationship between quality attributes and customer satisfaction, the hospitality and tourism literature has primarily focused on linear or symmetric effects (Kuo et al., 2012). According to Elkhani et al. (2014), the high service quality attributes of an airline result in overall service satisfaction,

which ultimately fosters customer loyalty. While these linearly symmetric effects are still essential for understanding the relationship between attributes and satisfaction, ignoring the asymmetric effects of quality attributes on satisfaction may obscure insights into quality attributes that are particularly sensitive to satisfaction or dissatisfaction. For example, passengers may not be satisfied because they take the pleasant cabin temperature attribute for granted. Nonetheless, passengers are extremely dissatisfied when the air conditioning fails to function during the flight. In other words, some attributes may be more sensitive to dissatisfaction than to satisfaction, while others may generate more satisfaction than dissatisfaction. In light of the fact that satisfaction and dissatisfaction respond differently to various types of attributes (Anderson & Mittal, 2000; Mikulić & Prebežac, 2011; Mittal et al., 1998; Ramanathan & Ramanathan, 2011), the asymmetric effect of quality attributes on satisfaction should be interpreted as different effects of quality attributes on satisfaction and dissatisfaction.

The asymmetrical effect of quality attributes on satisfaction is exemplified when service providers invest in improving certain attributes but do not see commensurate satisfaction gains. In contrast, their asymmetry can be demonstrated when other attributes produce greater customer satisfaction with the same expenditure. According to Herzberg's two-factor theory (Herzberg et al., 1959), there is an asymmetric relationship between these characteristics and satisfaction. According to this theory, attributes are categorized as motivators and hygiene factors, and the accomplishment of motivators, such as challenging work, increases job satisfaction. In contrast, hygiene factors such as job security do not increase job satisfaction if they are provided appropriately, but their absence can lead to job dissatisfaction. Since then, marketing literature has expanded this two-factor theory into a three-factor theory consisting of a basic (dissatisfaction) factor, a one-dimensional factor (performance factor), and an attractiveness (satisfaction) factor to clarify the asymmetric effect of attributes on customer satisfaction (Anderson & Mittal, 2000; Bi et al., 2019; Hu et al., 2020; Kano et al., 1984; Mikulić & Prebežac, 2012; Oliver, 1999; Ramanathan & Ramanathan, 2011).

Kano et al. (1984) derived this three-factor theory from the five-factor quality theory with customer expectations and satisfaction as axes. Since quality attributes affect satisfaction differently, the Kano model (Kano et al., 1984) classifies them as "attractive", "must-have", "one-dimensional", "indifferent", and "reverse factors". Attractive factors are value-added characteristics that passengers do not ordinarily anticipate (Kano et al., 1984). Passengers are satisfied and impressed, for instance, when these features are provided. These features are unanticipated, so passengers are neither disappointed nor dissatisfied when they are not provided. Thus, attractive factors are considered a positive asymmetric characteristic. In contrast to attractive factors, passengers take must-have factors for granted (Kano et al., 1984). Passengers are more likely to be dissatisfied if the previously mentioned services are unavailable or do not meet their expectations. However, because passengers take these attributes for granted, they are unlikely to be satisfied even if these attributes meet expectations. Therefore, the must-be factor is a negative asymmetry characteristic. Next, one-dimensional attributes are categorized as symmetric (Kano et al., 1984). If these characteristics are not provided, the passenger is dissatisfied; if they are, the passenger is content. The three-factor refers to the four factors in the Kano model excluding the reverse and indifferent factors. These factors are expressed as shown in Figure 1.

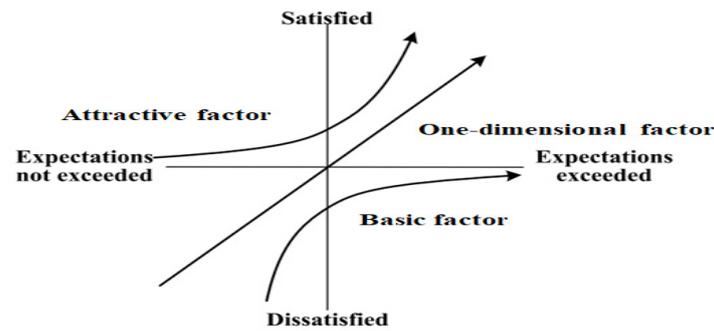


Figure 1. Three-factor theory.

2.2. Penalty–Reward Contrast Analysis (PRCA)

The most important component of the three-factor theory is the classification of asymmetrical attributes. Until recently, this method was presented as an easy-to-use method beginning with the Kano model (see Figure 2). Due to its complex structure and inapplicability to customer satisfaction data on a typical five-point or seven-point scale, researchers began to criticize the Kano model (Busacca & Padula, 2005). The Critical Incident Technique, the Importance Grid, and the Penalty–Reward Contrast Analysis (PRCA) were developed by subsequent researchers on the basis of the Kano model to classify quality attributes according to their asymmetric effects on customer satisfaction. (See Figure 2). PRCA is the most preferred and trusted method among researchers to identify the asymmetric effects of quality attributes (Abenoza et al., 2019; Albayrak, 2019; Busacca & Padula, 2005; Hu et al., 2020; Ju et al., 2019; M. Kim & Kim, 2024; Leem et al., 2021; Mikulić & Prebežac, 2008).

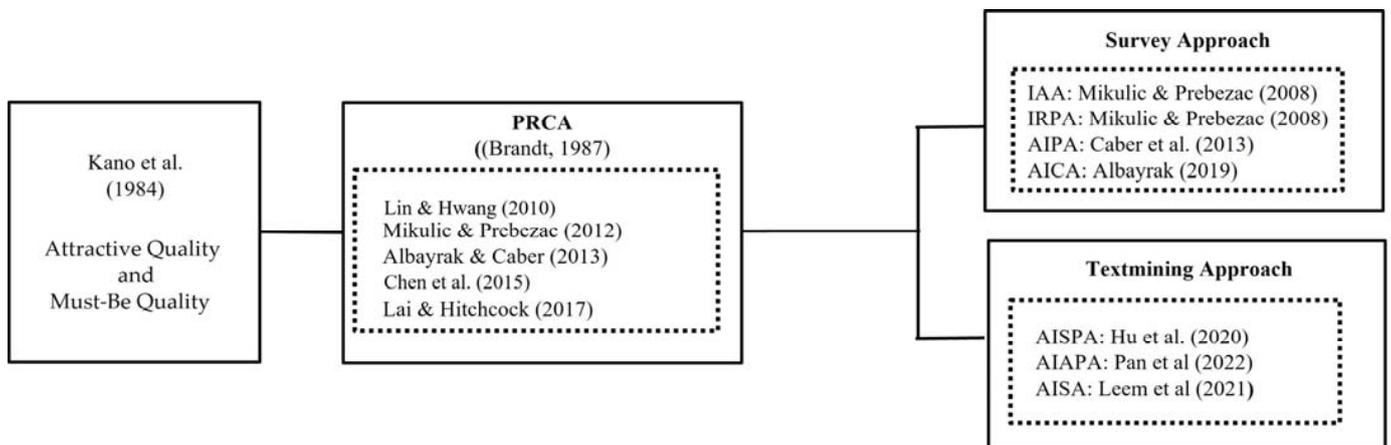


Figure 2. Literature on the three-factor theory adapted from (Kano et al., 1984; Brandt, 1987; Lin & Hwang, 2010; Mikulić & Prebežac, 2012; Albayrak & Caber, 2013; L. C. Chen et al., 2015; Lai & Hitchcock, 2017; Mikulić & Prebežac, 2008; Caber et al., 2013; Albayrak, 2019; Hu et al., 2020; Pan et al., 2022; Leem et al., 2021).

Visualization for classifying asymmetric quality attributes starts with Importance–Performance Analysis (IPA), and as shown in Figure 2, various methods are suggested. IPA divides attributes into four quadrants, and each quadrant presents improvement strategies (Bi et al., 2019; Jang et al., 2009). This method is still widely employed by researchers, but it does not account for the asymmetry of attributes. To counteract this, Mikulić and Prebežac (Mikulić & Prebežac, 2008) transformed IPA into IAA or IRPA based on the range or ratio of the asymmetry impact by the penalty index and the reward index. Later on, Albayrak and Caber (2013) proposed AIPA on the basis of an Asymmetric Impact and Performance Matrix. These methods utilize Kano’s survey method or the seven-point or five-point scale survey method developed by the PRCA.

Hu et al. (2020) proposed a three-dimensional Asymmetric Impact-Sentiment-Performance analysis (AISPA) by integrating Sentiment Analysis into AIPA and applied it to the analysis of the asymmetric relationship between hotel attribute performance and customer satisfaction. This method has the disadvantageous requirement of visualizing AISPA in three dimensions. Pan et al. (2022) proposed Asymmetric Impact-Attention-Performance Analysis (AIAPA) to address this shortcoming. They evaluated the attribute's performance in terms of consumer satisfaction based on the sentiment score of the attribute and measured the consumer's interest in the attribute based on the frequency with which the attribute was mentioned. However, this method still encounters difficulties when executing complex procedures. This study proposes an Asymmetric Impact-Sentiment Analysis (AISA) method using Netminer 4.0, a specialized text mining tool, by simplifying the AISPA and AIAPA methods, and intends to apply it to airlinequality.com data.

2.3. Asymmetry of Airline Quality Attributes

Numerous studies have been conducted on the service quality attributes of airlines, and numerous structural equation model-based studies have been conducted on the relationship between quality attributes and satisfaction (Bogicevic et al., 2017). However, there are far fewer studies on the asymmetric attributes of quality attributes in the aviation industry compared to the hospitality and tourism industries. Consequently, this session examines the literature on the survey approach and text mining approach in the aviation industry and illustrates the differences between this study and the literature. Studies based on questionnaires include Yang and Han (2013), Cha (2018), Tahanisaz and Shokuhyar (2020), and Albuquerque et al. (2022) on the asymmetry of quality attributes of airlines. Using the Kano model survey method, Yang and Han (2013) categorized 29 items related to airline service quality into attractive factors, must-have factors, one-dimensional factors, indifferent factors, and reverse factors. Using a survey, Cha (2018) demonstrated the asymmetry between service quality attributes and overall customer satisfaction for low-cost airlines. In addition, he categorized quality attributes as desirable, must-have, and one-dimensional based on the ratio of their standard coefficients. Using the Kano model, Tahanisaz and Shokuhyar (2020) presented the Importance-Satisfaction Analysis (ISA) method and categorized air service quality attributes. Albuquerque et al. (2022) applied the SERVQUAL dimension of the airline to the KANO model in order to determine customer satisfaction and dissatisfaction in relation to asymmetric attributes. The previous studies reviewed are based on the KANO model and consist of two questionnaires regarding satisfaction and dissatisfaction; therefore, the questionnaire is lengthy and complex.

Recent studies (Bogicevic et al., 2017; Eum & Leem, 2022; Lee et al., 2017; Park et al., 2020) have examined the asymmetric effect of attributes on satisfaction and dissatisfaction by extracting airline online review data. Bogicevic et al. (2017) derived service, staff, cabin seat comfort, and entertainment as positive or negative attributes based on 901 online reviews of passengers.

Park et al. (2020) extracted passenger online reviews of 20 US airlines from Tripadvisor and developed a negative variance model and a positive variance model by the airline's overall rating (satisfaction) and individual ratings. The presence or absence of differences between the two models indicated asymmetry. According to their findings, the factors of satisfaction (attractive factors) included cleanliness, food and beverage, and in-flight entertainment, whereas the factors of dissatisfaction (must-have factors) included customer service, check-in, and boarding.

Using quantitative customer evaluation data provided by skytrack.com, Lee et al. (2017) illustrated the asymmetry of airline service quality attributes. Eum and Leem (2022) compared the asymmetries of Korean and Chinese airlines. The majority of studies on

airline quality attribute asymmetry based on online reviews extracted quantitative data and categorized asymmetry attributes.

However, it is difficult to locate studies on passengers' opinions or the implicit sentimental characteristics of online reviews. This study, therefore, proposes a method to extract airline service quality attributes from qualitative text data of airline online reviews, classify asymmetry according to the three-factor theory, and prioritize resource allocation using the proposed AISA.

This study differs from others in that it derives quality attributes using Netminer 4.0, a text mining tool, and provides an AISA method through Sentiment Analysis.

3. Research Methodology

This study aims to extract airline service quality attributes from customer reviews, define the effect of asymmetry of customer opinions for quality attributes on customer satisfaction based on Kano's three-factor theory, and propose an Asymmetric-Sentiment Analysis (AISA) method employing sentiment scores of reviews. In addition, this study provides a strategic utilization plan for airline resources by extracting and applying actual online reviews of airlines to AISA. This study consisted of three stages, as shown in Figure 3. The first stage entailed deriving airline service attributes and acquiring sentiment scores for each attribute. First, airline service quality attributes were derived by preprocessing and topic modeling of review text extracted from an online review website (airlinequality.com). Text preprocessing included tokenization, stop word removal, and POS tagging, among other procedures. After preprocessing, Latent Dirichlet Allocation (LDA)-based topic modeling was used to determine the primary quality attributes. Along with the document–topic matrix and the topic–term matrix, the association probability was computed at this point. The final step of stage 1 was to obtain sentiment scores for each topic using supervised machine learning and Sentiment Analysis.

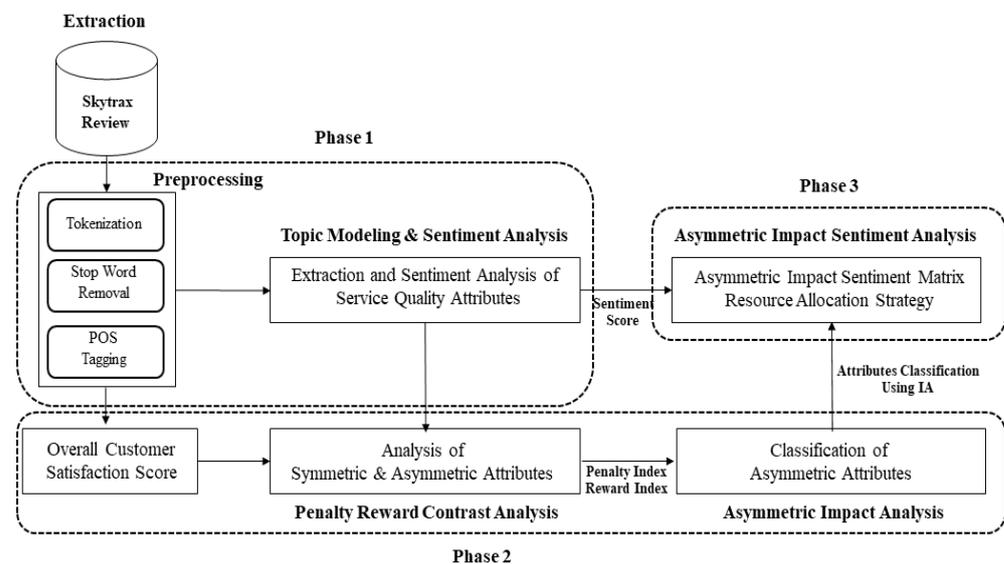


Figure 3. Research procedure.

Stage 2 involved categorizing symmetric and asymmetric service quality attributes. This can be classified using Penalty–Reward Contrast Analysis (PRCA) with the overall customer satisfaction score (OCS) extracted together as a dependent variable and the sentiment score for each attribute obtained in stage 1 as an independent variable. There are currently a number of methods for classifying the asymmetry of attributes; however, this study was divided into three factors (attractive factor, basic factor, and one-dimensional factor) based on

the IA value of Impact Asymmetry Analysis (IAA) presented by [Albayrak and Caber \(2015\)](#) and [Mikulić and Prebežac \(2008\)](#). IAA is an enhanced version of Importance-Performance Analysis (IPA). Establishing the Asymmetric Impact Sentiment Matrix (AISM) to prioritize strategic resource allocation was stage 3. A matrix was constructed with the asymmetry of service quality attributes as the vertical axis and the sentiment score as the horizontal axis, and the investment priority for resources for each cell's quality attributes is presented.

3.1. Phase 1: Service Quality Attribute Extraction and Sentiment Analysis

3.1.1. Data Extraction and Preprocessing

The R 4.4.2 software was used to extract 36,983 online reviews of 32 airlines with more than 100 reviews provided by [airlinequality.com](#) as of 30 April 2021 (see [Figure 4](#)). The extracted data include the airline's name, the text of customer reviews, the overall customer satisfaction score, and specific quality attributes. Additionally, the customer nationality and date of review writing were extracted. Using Netminer 4.0, in the data preprocessing phase, we implemented a systematic approach beginning with the conversion of all textual data to lowercase format and the removal of special characters, numerical values, and URLs, followed by tokenization. Subsequently, we eliminated stop words (e.g., "is", "the", "at", "which") and other low-semantic-value terms, along with redundant lexical items. Through POS tagging procedures, we selectively extracted essential grammatical categories including nouns, adjectives, and verbs.

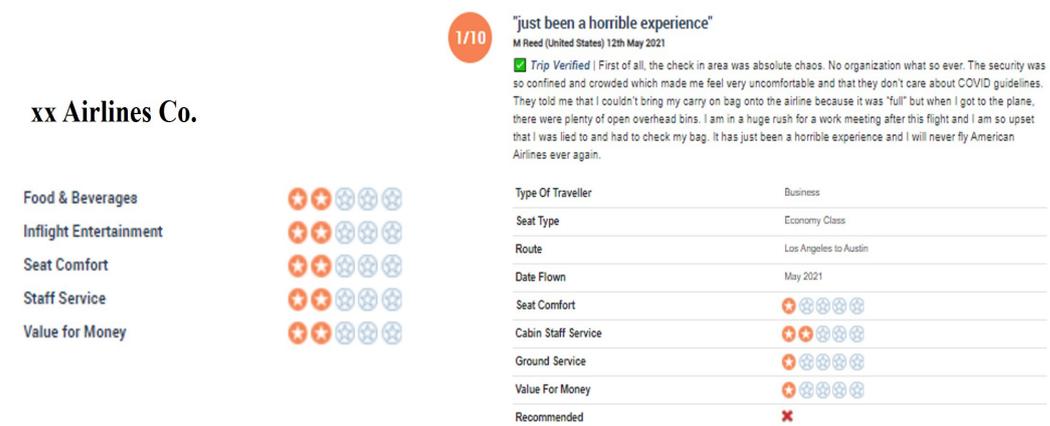


Figure 4. Data extracted from [airlinequality.com](#).

Furthermore, we applied minimum threshold filtering for both word frequency and document length, while also conducting spam detection and character refinement procedures to ensure data quality for subsequent analytical processes. Furthermore, out of the total 36,983 samples, 12,000 were utilized as training data for the Sentiment Analysis.

3.1.2. Topic Modeling and Sentiment Analysis

After completing the preceding preprocessing steps, we derived service quality attributes via topic modeling and conducted Sentiment Analysis on each attribute. LDA, which is currently the most popular technique for topic modeling and is supported by Netminer 4.0, was the method used. This LDA method employs a probability distribution model to identify potentially significant topics in documents ([Blei & Lafferty, 2009](#); [Blei et al., 2003](#)). The LDA method assumes that a set of words is grouped into a particular topic and extracts a high-probability set of words by calculating the probability that the corresponding word is grouped in that topic ([Blei & Lafferty, 2009](#)). LDA focuses on co-occurring words in documents and uses the word distribution of latent topics to automatically identify them ([Blei & Lafferty, 2009](#); [Blei et al., 2003](#)). The visualization of extracted topics is based

on probabilistic word–topic matrices and document–topic matrices (Blei & Lafferty, 2009; Chaney & Blei, 2012). After extracting themes from online reviews, we gave them names and used them as service quality characteristics. Following the extraction of service quality attributes through topic modeling, Sentiment Analysis was performed on each topic.

Sentiment Analysis focuses on the automatic extraction of favorable or unfavorable opinions from text data (Lai & Hitchcock, 2017). Since texts frequently contain a mixture of positive and negative emotions, it is useful to determine the polarity of a text and the intensity of that polarity (Lai & Hitchcock, 2017; Streukens & de Ruyter, 2004). Support Vector Machine (SVM), Naive Bayes, and Matrix Factorization are the Sentiment Analysis algorithms most frequently used to classify text into positive and negative categories (Hu et al., 2020; Lai & Hitchcock, 2017; Oliver, 1976). This study uses Naive Bayes-based supervised machine learning to classify document sentiment as positive, negative, or neutral and assigns +1 to positive sentiment, −1 to negative sentiment, and 0 to neutral sentiment to derive sentiment scores for each attribute. This sentiment score is used to construct an Asymmetric-Sentiment Matrix (AISM).

3.2. Phase 2: Asymmetric Classification of Service Quality Attributes

The penalty index and reward index for the calculation of IA are derived from a PRCA analysis between service quality attributes extracted by topic modeling and customer satisfaction. Brandt (1987) first proposed PRCA to identify value-adding attributes that increase customer satisfaction. Since then, numerous researchers have utilized PRCA to examine the asymmetric impacts of product or service attributes on customer satisfaction (Fuchs & Weiermair, 2004; Matzler & Renzl, 2007; Matzler & Sauerwein, 2002). The principle of PRCA is to use a dummy variable-based regression analysis, as depicted in Equation (1), to determine the effect of attributes on customer satisfaction at low (penalty) and high (reward) sentiment score of product or service quality attributes:

$$\text{OCS} = \beta_0 + \sum_{i=1}^n (\beta_{pi}d_{pi} + \beta_{ri}d_{ri}) + \epsilon \quad (1)$$

where n is the total number of attributes, β_0 is a constant, β_{pi} is the OCS increment for the penalty of attribute i , and β_{ri} is the OCS increment for the reward. d_{pi} denotes a dummy variable of attribute i using 1 in the penalty case of attribute i and 0 in all other cases, and d_{ri} denotes a dummy variable of attribute i using 1 in the reward case of attribute i and 0 in all other cases.

The following describes the method for obtaining the IA index value for each attribute through PRCA and classifying attributes based on this index (Albayrak & Caber, 2013; Bi et al., 2020; Caber et al., 2013; Matzler & Sauerwein, 2002; Mikulić & Prebežac, 2008). First, the low-performance and high-performance level definitions separated the sentiment scores into quartiles, defining the lowest quartile as ‘low performance’ and the highest quartile as ‘high performance’ (Füller et al., 2006; Leem et al., 2021). Then, two sets of dummy variables for the attributes were introduced, with ‘low performance’ being coded as (0,1), ‘high performance’ as (1,0), and ‘medium performance’ as (0,0). In the PRCA model, high performance and low performance are subsequently referred to as the reward index and penalty index, respectively. Second, a multiple regression analysis of Equation (1), with the penalty and reward indices as independent variables and customer satisfaction as the dependent variable, was conducted. Reward and penalty indices are calculated using non-standardized regression coefficients derived from regression analysis results (Mikulić & Prebežac, 2008). Third, based on the IA value of Equation (2), it is categorized as either a fundamental factor, a one-dimensional factor, or an attractive factor. IA compares the satisfaction-generating potential and dissatisfaction-generating potential of an attribute (Matzler & Sauerwein, 2002; Mikulić et al., 2016; Mikulić & Prebežac, 2008). The exponential

value of IA ranges from -1 to 1 , simplifying exponential comparisons. Consequently, this study categorized the asymmetry attribute using the IA value. IA can be calculated using the coefficients of these penalty and reward dummy variables (Albayrak & Caber, 2013; Matzler & Sauerwein, 2002).

$$IA_i = \frac{|\beta_{ri}| - |\beta_{pi}|}{|\beta_{ri}| + |\beta_{pi}|} \tag{2}$$

The meaning of IA, which has a value between -1 and 1 , is as follows. $IA = -1$ indicates that the attribute has only dissatisfaction potential and no satisfaction potential when the reward coefficient is zero. $IA = 0$ is reached when the reward coefficient and penalty coefficient are equal, indicating that the attribute has the same capacity to cause dissatisfaction and satisfaction. $IA = 1$ occurs when the penalty coefficient is equal to zero, indicating that the attribute can only cause satisfaction and cannot cause dissatisfaction. If the IA value is between -1 and -0.1 , it is categorized as a basic factor, between -0.1 and 0.1 as a one-dimensional factor, and between 0.1 and 1 as an attractive factor (Albayrak, 2019; Albayrak & Caber, 2015; Matzler & Sauerwein, 2002; Mikulić & Prebežac, 2008). The fundamental factor is likely to result in customer dissatisfaction if it falls short of expectations but is unlikely to result in customer satisfaction even if it exceeds expectations. A unidimensional factor has the same capacity to cause customer dissatisfaction and satisfaction as do high and low customer expectations. The attractive factor is more likely to result in customer satisfaction if expectations are exceeded but less likely to result in customer dissatisfaction if expectations are not met (Kano et al., 1984; Pandey et al., 2022; Thipwong et al., 2020; Tseng, 2020).

3.3. Phase 3: Asymmetric Impact Sentiment Analysis (AISA)

Asymmetric Impact Sentiment Analysis (AISA) analyzes the asymmetric impact between airline service quality attributes and customer sentiment. For example, it examines the influence of specific service characteristics or attributes on customer sentiment in an asymmetric manner, rather than viewing them symmetrically. In other words, it considers both the positive and negative aspects of customer emotions regarding airline service attributes.

AISA creates a matrix (AISM) with the sentiment score for each service quality attribute obtained in steps 1 and 2 as the horizontal axis and the asymmetric classification for each attribute as the vertical axis (see Figure 5) and presents a strategy for resource allocation. AISM is a concept that extends AIPA to a text mining-based method.

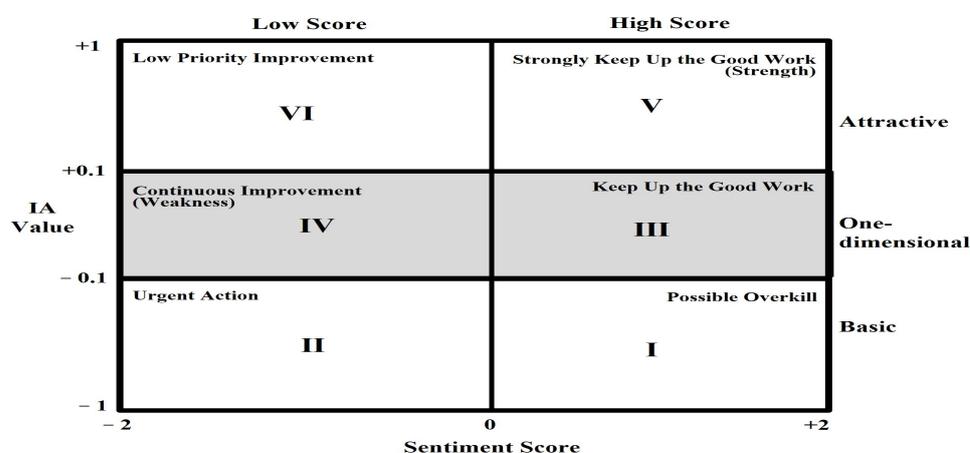


Figure 5. AISA Matrix.

Based on prior research beginning with IPA, the strategy and significance of each cell were described (Albayrak, 2019; Bi et al., 2019; Hu et al., 2020; J. Kim & Lee, 2023; Tontini et al., 2017).

Cell VI is the ‘Low Priority Improvement’ area, comprising attributes with low performance in attractive factors. These attributes, while having a high likelihood of causing dissatisfaction, are less likely to provoke negative emotions. Companies should allocate resources to monitor and improve these attributes as necessary. Since they are unlikely to result in dissatisfaction even if expectations are not met, these attributes can be enhanced gradually, depending on available resources.

Cell V, known as ‘Strongly Keep Up the Good Work’, consists of attributes with high performance in attractive factors. These characteristics are likely to enhance customer satisfaction and can serve as a competitive advantage. With high positive sentiment arousal, these attributes have the potential to delight customers beyond satisfaction. If resources permit, continuous improvement of these attributes is recommended for competitive positioning strategies.

Cell IV is referred to as the ‘Continuous Improvement’ area and consists of attributes with low performance in one-dimensional factors. Failure to meet customer expectations in this domain often results in dissatisfaction. These symmetrical attributes are weaknesses that require immediate improvement. After addressing attributes in the ‘Urgent Action’ cell, managers should allocate resources to improve the performance of attributes in this area.

Cell II comprises attributes with low performance as a basic factor called ‘Urgent Action’. Attributes in this area are highly likely to lead to dissatisfaction if they fail to meet customer expectations. Since this cell has a negative sentiment arousal score of 0 or less, it represents asymmetric attributes that necessitate immediate priority in resource allocation. Even if a company excels in attraction factors, inadequate performance on these attributes may render efforts ineffective.

Finally, Cell I consists of attributes with high performance as a basic factor called ‘Possible Overkill’. Since these attributes are basic requirements for a product or service, even if an attribute has a performance score higher than the minimum performance, it is unlikely to lead to customer satisfaction. These are prerequisite natural characteristics. Therefore, attributes in this cell are likely to be overinvested, and managers should redirect their resources to other attributes instead.

4. Results and Discussion

4.1. Topic Modeling and Sentiment Analysis

Using Netminer 4.0, a specialized text mining tool, we extracted topics based on nouns in which words co-occurred in text for text data collected from airlinequality.com, an airline review website. The likelihood of the topic for each document and the likelihood of the word for each topic were then determined.

In order to apply the LDA topic model, the parameters were set according to the method proposed in Blei and Lafferty (2009) and Park et al. (2020). The Dirichlet prior parameter α for document–topic distribution, which typically uses small values such as $50/K$ (where K is the number of topics) or 0.1, was set to 0.1 in this study. The Dirichlet prior parameter β for topic–word distribution, which typically uses small values such as 0.01 or 0.001, was set to 0.01 in this study. On this basis, we extracted the document–topic matrix and the term–topic matrix, as shown in Tables 1 and 2, respectively. On the basis of the extracted topics and review texts, we named the topics according to the quality attributes of airline service. Topic 1 is titled “Ground service”, Topic 2 is “Airline seat class”, Topic 3 is “In-flight service”, Topic 4 is “Seat comfort”, and Topic 5 is “Food and beverage service”.

Table 1. Document–topic matrix and probability.

| Document No. | Topic 1 | Topic 2 | Topic 3 | Topic 4 | Topic 5 |
|--------------|---------|---------|---------|---------|---------|
| Doc1863 | 0.797 | 0.067 | 0.054 | 0.047 | 0.034 |
| Doc3023 | 0.778 | 0.074 | 0.061 | 0.048 | 0.039 |
| Doc1132 | 0.777 | 0.084 | 0.059 | 0.05 | 0.031 |
| Doc 329 | 0.776 | 0.073 | 0.07 | 0.049 | 0.032 |
| Doc2793 | 0.773 | 0.072 | 0.063 | 0.057 | 0.035 |

Table 2. Topic–term matrix and probability.

| Topic No. | Term-Order | | | | |
|-----------|------------|----------|------------|---------|---------------|
| | 1st | 2nd | 3rd | 4th | 5th |
| Topic1 | hours | boarding | time | airport | crew |
| Topic2 | airline | customer | ticket | back | economy |
| Topic3 | service | staff | experience | return | trip |
| Topic4 | seats | class | business | leg | better |
| Topic5 | good | food | great | meal | entertainment |

The sentiment score for each topic was then calculated using the Sentiment Analysis of each document and the probability value for each document–topic. Here, 1000 learning data were constructed and learned for the Sentiment Analysis, and then the entire document was classified according to its sentiment. Three marketing-trained experts with experience analyzing online reviews constructed and validated the learning data structure. The validity of the Sentiment Analysis was verified using a confusion matrix. In the validation results, precision represents the ratio of actual positives among predicted positives, indicating the predictive accuracy. This study achieved a precision value of 0.809. Recall, which represents the ratio of correctly predicted positives among actual positives, measures the model’s sensitivity. Our study obtained a recall value of 0.812. Accuracy, which indicates the ratio of correct predictions among all predictions, was 0.812. Finally, the F-score, which provides a balanced evaluation of the model’s overall performance, was 0.81. The metrics demonstrated remarkably high values across all indicators, validating the robustness of our analytical approach (see Table 3). All documents resulted in positive (57.8%), negative (40.2%), and neutral (2.0%) results from the Sentiment Analysis of online airline customer reviews. The Sentiment Analysis for each topic (attribute) yielded the following results: 1586.57 for topic 1 (ground service), 947.57 for topic 2 (airline seat class), 634.46 for topic 3 (in-flight service), 499.50 for topic 4 (seat comfort), and 346.48 for topic 5 (food and beverage service). In this study, the sentiment score for each topic is expressed as a numeric value between -2 and 2 and utilized in the AISA (see Figure 6).

Table 3. Confusion matrix.

| | | Actual | |
|-----------|----------|----------|----------|
| | | Positive | Negative |
| Predicted | Positive | 445 (TP) | 103 (FN) |
| | Negative | 105 (FP) | 420 (TN) |

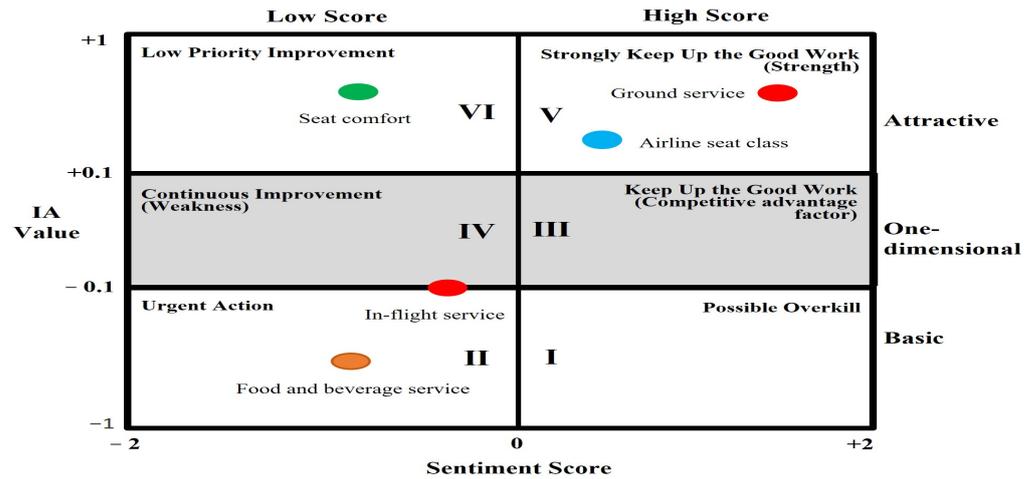


Figure 6. Asymmetric Impact-Sentiment Analysis Matrix.

4.2. Penalty–Reward Contrast Analysis and Attribute Classification

To confirm the asymmetrical effect of quality attributes, we conducted a PRCA analysis between five service quality attributes extracted via topic modeling and customer satisfaction. For the PRCA analysis, we encoded five service quality attributes into 10 dummy variables and conducted multiple regression analysis according to Equation (1). Table 4 displays the non-standardized values of the independent variables, the penalty and reward coefficients, as the penalty and reward indices as a result of multiple regression analysis. Using penalty and reward indexes for the five service quality attributes, we then computed the IA values. The calculated IA values were as follows: 0.5 for ground service, 0.4 for airline seat class, -0.1 for in-flight service, 0.6 for seat comfort, and -0.5 for food and beverage service. Following the recommendations of Albayrak and Caber (2015) and Mikulić and Prebežac (2008), we set the attribute as a basic factor when the IA was between -1 and -0.1 , a one-dimensional factor when the IA was between -0.1 and 0.1 , and an attractive factor when the IA was between 0.1 and 1 . We identified basic factors such as food and beverage service, one-dimensional factors such as in-flight service, and attractive factors such as ground service, airline seat class, and seat comfort using this criterion.

Table 4. PRCA results, sentiment score, and asymmetric category.

| Attribute | Penalty Index | Reward Index | IA Value | Sentiment Score | Asymmetric Category |
|---------------------------|---------------|--------------|----------|-----------------|---------------------|
| Ground service | 0.256 | 0.817 | 0.5 | 1.59 | Attractive |
| Airline seat class | 0.267 | 0.598 | 0.4 | 0.31 | Attractive |
| In-flight service | -0.081 | 0.061 | -0.1 | -0.32 | One-dimensional |
| Seat comfort | -0.207 | -0.832 | 0.6 | -0.67 | Attractive |
| Food and beverage service | -3.504 | -1.045 | -0.5 | -0.9 | Basic |

4.3. Asymmetric Impact-Sentiment Analysis

Figure 6 shows an Asymmetric-Sentiment Matrix (AISM) in which the IA value is the vertical axis and the standardized sentiment score is the horizontal axis. According to each AISM cell in Figure 6, the priority of resource allocation can be established. Priority should be given to attributes with low sentiment scores (Lu & Stepchenkova, 2012; Mikulić et al., 2016; Ramanathan & Ramanathan, 2011; Tontini et al., 2017, 2019) when determining the attributes to be improved in service quality. Food and beverage service in cell II is a primary factor that can lead to customer dissatisfaction if expectations are not met, and as such, it must be addressed immediately. Cell IV’s one-dimensional factor, in-flight service,

is an attribute that can result in customer dissatisfaction if it falls short of expectations. This characteristic can be a company's weakness, so performance should be enhanced through investment. Cell V's attractive factors, ground service and airline seat class, are attributes that can lead to customer satisfaction if they meet their expectations. This characteristic can be a company's strength and thus a point of differentiation. Cell VI is a low-performance attractive factor, and seat comfort is unlikely to cause dissatisfaction even if it does not meet passenger expectations. Therefore, if resources permit, it is necessary to have a plan to increase performance through investment. Therefore, it is necessary to invest in food and beverage service, in-flight service, and seat comfort in that order to improve services.

5. Conclusions, Limitations, and Future Works

5.1. Conclusions

This study employed topic modeling and Sentiment Analysis to determine the asymmetric relationship between customer opinions regarding quality attributes and customer satisfaction. To achieve this, airline service quality attributes were extracted through topic modeling, sentiment scores for each topic were derived through Sentiment Analysis, and Asymmetric Impact-Sentiment Analysis (AISA) was derived by comparing this to the IA value, which was determined through PRCA analysis.

We identified food and beverage service as a fundamental factor; in-flight service as a one-dimensional factor; and seat comfort, ground service, and seat class as attractive factors. The sentiment scores were as follows: 1.59 for ground service, 0.31 for airline seat class, -0.32 for in-flight service, -0.67 for seat comfort, and 0.90 for food and beverage service. Urgent Action should be taken to prevent food and beverage services from falling into customer dissatisfaction (cell II), and in-flight services should be continuously enhanced to increase customer satisfaction (cell IV). The attractive factor seat comfort (cell VI) requires low-priority improvement, while strong maintenance is required for ground service and airline seat class (cell V) as strength factors.

5.2. Implications

The following are the academic implications of this study. First, unlike previous studies that presented the asymmetry of attributes through quantitative data and surveys, this study confirmed the asymmetric relationship between customer opinions for quality attributes and satisfaction by employing topic modeling and Sentiment Analysis based on text mining. Although it is possible to derive sufficiently meaningful results from a survey-based study, it is also possible to derive results that reflect a variety of customer opinions through the use of unstructured big data of online reviews. By measuring the customer's opinion or expression of service satisfaction after using the service, online customer reviews can overcome the limitations of conventional survey techniques.

Second, it was confirmed that the sentiment scores of service quality attributes and airline satisfaction had an asymmetric relationship. This indicates that the attributes influencing satisfaction were not uniform, and there were variations in the importance and satisfaction based on the attributes' characteristics. In addition, there were asymmetries in the unstructured data that represented customer opinions and the quantitative data that described quality attributes.

Third, applying the three-factor theory (Kano et al., 1984) and the expectancy disconfirmation theory (Oliver, 1976), this study classified service quality attributes in the relationship between airline service quality attributes and customer satisfaction. In other words, the factors were categorized as fundamental, one-dimensional, and attractive, and the relationship between the attributes and customer satisfaction for each factor was con-

firmed. Although there are a variety of factors that affect customer satisfaction, reiterating that customer expectations determine satisfaction is the result.

Fourth, combining the airline service quality attributes extracted through topic modeling with the results of Sentiment Analysis yielded sentiment scores for each attribute. Thus, it was possible to examine not only the sentiment score for each customer review, but also the sentiment score for every extracted attribute. Finally, the most important component of this study is the Asymmetric-Sentiment Analysis (AISA) method proposal.

General asymmetry studies merely identified the relationship between service attributes and satisfaction, but this study presented a method for identifying the asymmetric relationship between customer sentiment regarding service quality attributes and satisfaction. This technique can be viewed as an improvement upon AISPA (Hu et al., 2020) and AIAPA (Pan et al., 2022). AISA was also used to derive resource allocation strategies for each factor. The practical implications are as follows.

First, it can help airline managers develop marketing strategies that are customer-centric. In other words, by analyzing online customer reviews, it is possible to anticipate an improvement in the quality of customer service by confirming that certain aspects of the service process are prioritized.

Second, it is possible to suggest improvement directions for service products and attributes actually experienced by customers, based on the AISA-identified factors, by identifying which factors must be improved first and which must be maintained. Finally, Asymmetric-Sentiment Analysis (AISA) identifies the same factors but different customer sentiments.

In actual airline service situations, there are instances in which customers do not have high expectations, but still feel bad, as well as instances in which they do not. Checking the difference in customer sentiment in advance during the customer service process of airline crew members can be used to provide more detailed service. In other words, it is possible to improve airline service satisfaction by confirming in advance that customer sentiment may vary despite identical service attributes.

5.3. Limitations and Future Works

In addition, this study can serve as a foundational framework for conducting further airline asymmetry research utilizing customer review data. By analyzing unstructured data such as customer reviews, researchers can delve deeper into understanding the nuanced relationship between service attributes and customer satisfaction. This approach allows for the identification of specific attributes that may hold varying levels of importance and significance in influencing customer perceptions, satisfaction, and loyalty. Such insights can enrich the theoretical understanding of asymmetry in service quality and provide a robust basis for academic and practical exploration of customer-centric strategies in the airline industry.

Moreover, the insights derived from customer review data can pave the way for comparative studies between domestic and international airlines. Through detailed analysis and comparison, researchers can identify unique differences in service quality attributes that resonate differently with domestic and international airline customers. For instance, certain service factors may hold greater significance for domestic travelers, such as convenience, punctuality, or affordability, whereas international travelers may prioritize comfort, in-flight entertainment, or long-haul service offerings. Understanding these differences not only highlights the cultural and contextual variations in customer expectations but also provides airlines with actionable insights to tailor their services accordingly.

Furthermore, such comparative studies can help identify gaps in service quality by analyzing the sentiment scores and customer satisfaction levels associated with specific

attributes for domestic versus international airlines. For example, while domestic airline customers might focus on efficiency and timely operations, international customers might be more influenced by factors like customer support, multilingual communication, and premium services. By exploring these distinctions, airlines can better allocate resources to address the most pressing concerns of their respective customer bases.

Lastly, this expanded perspective on airline service quality attributes allows for the identification of broader patterns and trends that can influence both operational decisions and strategic marketing efforts. Using customer review data as the foundation for comparative analysis, airlines can not only benchmark their performance against competitors but also gain insights into regional and global customer preferences. This comparison ultimately enables airlines to develop more targeted strategies to meet and exceed customer expectations, leading to enhanced satisfaction and competitive advantage in the industry.

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