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Retraction

Retracted: Foreign Muslim Workers' Perspectives of the Basic Needs of Muslim-Friendly Tourist Services: An Empirical Analysis of a Non-Muslim Destination

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] H. Yen, J. Chang, K. Ho, and H. Hung, "Foreign Muslim Workers' Perspectives of the Basic Needs of Muslim-Friendly Tourist Services: An Empirical Analysis of a Non-Muslim Destination," *Security and Communication Networks*, vol. 2022, Article ID 1676697, 17 pages, 2022.

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Research Article

Foreign Muslim Workers' Perspectives of the Basic Needs of Muslim-Friendly Tourist Services: An Empirical Analysis of a Non-Muslim Destination

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The rapid growth of Halal travel offers a tourism opportunity for countries, but non-Muslim countries often find it difficult to meet the multiple religious needs of Muslim tourists. This study verifies Muslim tourists' requirements for basic hotel and food services and identifies the categories in which to place these attributes and which ones need resources to increase Muslim tourists' satisfaction. Applying Taiwan as a non-Muslim destination, we surveyed 216 Indonesian Muslim foreign workers and used the recently developed Gradient Boosting Decision Trees, instead of a regression method, to overcome the nonlinear and multicollinearity issues of Penalty-Reward-Contrast Analysis. Impact-Range Performance Analysis and Asymmetric Impact-Performance Analysis were then applied to examine the basic attributes of Muslim foreign workers' tourist experiences. We learned that using Gradient Boosting Decision Trees provided advantages over the regression method. Empirical results indicated that hotel-related factors are prioritized over food services when Muslim tourists visit a non-Muslim country. In addition, religious observances play an essential part in Muslim tourists' hotel choices, and conveniently accessible Halal food is a desirable travel requisite for this group.

1. Introduction

The increasing Muslim population is one of the world's largest target markets, and Halal tourism has been the fastest-growing subtype of religious tourism in recent years [1–3]. Islamic beliefs influence Muslim attitudes and behavior when traveling and their destination choices [2, 4–8]. Muslim-majority countries, such as Indonesia, where the state and religion are closely linked to daily life, can offer a wide scope for the development of Halal tourism [6]. Conversely, promoting Halal tourism presents a challenge for non-Muslim countries, which lack a religious environment that follows Islamic laws of diet, attire, and other customs [3, 5, 9] and, thus, find it difficult to cater to these religious needs since they offer a wider range of activities than simply Halal tourism. However, research has been confined to the development of Halal tourism in Muslim-majority destinations [10–14], and few studies have focused on non-Muslim locations.

Halal tourism represents a potential opportunity to explore this market in both Muslim and non-Muslim countries [6, 15]. However, despite the market potential, there is a need to have better communication between organizations and consumers [16]. For example, at tourism destinations, efficient integrated marketing communication (e.g., visual media and online channels) will influence potential tourists' to travel to a considered destination [17, 18]. Guo and Shang [19] indicated that an accurate understanding of tourists' demands could reduce interactive communication problems. Hence, it is important to

understand Muslim tourists' requirements when creating effective marketing communication.

Nevertheless, a non-Muslim destination should consider the following issues before engaging in marketing communication with Muslim tourists. First, a non-Muslim country that targets Muslim tourists successfully should identify the attributes required by these tourists that subsequently affect their purchasing behaviors and satisfaction [2, 3, 20–23]. Several studies have found that consumers evaluate their postpurchase satisfaction for certain attributes [2, 10, 24, 25]. Second, since a customer can be satisfied and/or dissatisfied with different aspects of the same product, this complex situation is often combined with perceptions concerning the various attributes that create overall customer satisfaction [20]. Third, studies have found that attribute performance has an asymmetric or nonlinear influence on overall customer satisfaction [23, 25–29]. Therefore, an understanding of the asymmetric relationships between attributes and overall satisfaction (OS) enables us to comprehend the dynamic effect of attributes on satisfaction [25], while ignoring this relationship may result in model misspecification and poor predictive power [30]. Considering the issues, a systematic and straightforward tool for understanding the attributes of a destination for Muslim tourists is required.

The three-factor theory of customer satisfaction can be used as the conceptual framework for analysis [31, 32], which indicates that product attributes can be divided into basic, excitement, and performance factors based on the level of an attribute's performance impact on OS [33]. Penalty-Reward-Contrast Analysis (PRCA), initially developed by Brandt [34], is used to explore a three-factor structure. Mikulić and Prebežac [31] extended PRCA's reward and penalty indices to create a new Impact-Range Performance Analysis (IRPA). Subsequently, Caber et al. [28] introduced a revised method based on Mikulić and Prebežac's [31] Asymmetric Impact-Performance Analysis (AIPA). Regardless of the methods applied, it is important to present the incremental changes in OS, reflected in the penalty and reward indices features in PRCA, in extremely low/high attribute-performance cases [31]. Studies have applied these two sets of penalty and reward indices of attributes by using regression analysis [25, 27–29, 31, 35, 36].

However, a critical problem for regression analysis is that it may not precisely capture a nonlinear effect and may lead to bias when focused on an asymmetric effect [37, 38]. To overcome this problem, we propose a recently developed approach called Gradient Boosting Decision Trees (GBDT). This uses decision trees to classify predictors and calculate responses by minimizing loss function [39]. Compared with traditional linear regression analysis, a GBDT has advantages. First, it can illustrate nonlinear relationships between a set of dependent and independent variables [40, 41]. Second, this method effectively estimates the data with a small sample, including the missing values, and it deals with different types of independent variables [38]. Third, it addresses the multicollinearity issue as some of these attributes are relatively dependent on strong correlations [37, 42]. Finally, it does not assume a normal distribution for the dependent variable [37, 43, 44].

Consequently, this study verifies Muslim tourists' perceived attributes on basic services and fills the research gap by addressing the following research questions: (1) To what extent does a GBDT method contribute to understanding the asymmetric relationships between attribute needs and OS in a non-Muslim country that wants to develop Muslim tourism? (2) Based on integrating multimethods, which categories do these attributes belong to? (3) What resources should be allocated to attributes that may increase Muslim tourists' satisfaction while minimizing those that do not?

The contributions of this study are explained as follows: (1) In applying the concept of the three-factor theory, we can indirectly identify the importance of a product attribute based on its impact on OS instead of the importance perceived by the consumer [31, 32, 35]. (2) Although various fields of study have integrated the GBDT method to analyze respondents' satisfaction [43, 45–47], the method has seldom been used in tourism. The GBDT method classifies tourism service attributes into detailed categories and modifies the three-factor theory of regression analysis. (3) In our study, we considered the combined effects with factor scores rather than individual attributes. We then applied the IRPA and AIPA methods to interpret the influence of the attributes on OS through their asymmetric effect and performance. (4) This study selected Muslim workers who had lived in Taiwan for over one year instead of frequent short-stay tourists. The long-stay Muslim workers helped us ascertain their basic needs and reduce misunderstandings in the communication between destinations marketers and tourists. Furthermore, this case study identified Muslim workers' basic needs as tourists in a non-Muslim destination and enabled those destinations to be used as a guide for developing Muslim-friendly tourism.

The remaining sections of this paper are structured as follows: Section 2 reviews the existing literature; Section 3 describes analysis approaches and questionnaire design; Section 4 presents the empirical results; Section 5 presents the conclusions and recommendations for future research.

2. Related Literature

2.1. Muslim-Friendly Tourism and Basic Attributes. Although many scholars have defined the term "Halal tourism" and addressed the relationship between tourism and religion in many different ways [3–6, 8, 21, 48], few studies have focused on non-Muslim destinations and demonstrated in these destinations a desire to attract more Muslim tourists [5, 49]. El-Gohary [3], therefore, reviewed several Halal tourism packages provided by non-Muslim countries, noting that almost all of these packages met the needs of Muslim tourists in a Muslim-friendly way, but not with a fully Halal concept. Samori et al. [7] attempted to compare the current trends in Halal tourism in Muslim (Malaysia) and non-Muslim (Japan) countries and found that Muslim tourists could be an important niche market in Japan due to the increasing number of such tourists each year. Meanwhile, Yousaf and Xiucheng [21] observed the government websites of four non-Muslim Asian countries, indicating that a destination's positioning as Muslim-

friendly was one successful marketing strategy for enhancing Muslim tourists' experiences. Han et al. [22] explored Muslim tourists' possible Halal-friendly critical attributes (generic or basic) at a non-Muslim destination. Al-Ansi and Han [50] investigated Muslim tourists' behavior toward a Halal-friendly non-Muslim destination, examining the relationships between destination performance, perceived value, destination satisfaction, destination trust, and destination loyalty.

Although Halal tourism principles adhere to a religious point of view, each Muslim assesses these attributes differently by assigning differing degrees of importance to the principles and key requirements [3]. On the other hand, Rahman et al. [13] indicated the need to explore crucial resources for the Muslim tourist motivated, such as Halal food, alcohol-free drinks, and prayer places. Thus, it is important to meet the basic needs that allow Muslim tourists to comply with Islamic principles during their vacations.

Several studies have discussed the hotel and food-related factors that play a crucial role in satisfying the basic needs of Muslim tourists. Stephenson [51] indicated that hotel industry is codependent with tourism and often comprises a fundamental component of the tourism experience. Ignoring hotel functions within tourism could have a massive negative impact (i.e., low customer satisfaction) on performance [52]. In addition, Eid and El-Gohary [2] provided an integrated perspective of Muslim tourists' perceived value construction in the hotel and tourism industry, while Mohsin et al. [6] noted that the hotel industry can be a significant contributor to tourism by offering appropriate accommodation for Muslim tourists.

Likewise, in a study surveying Muslim interviewees, most indicated that the availability of Halal food is a basic requirement for all destinations [53]. When Muslim tourists are comfortable with food attributes, it often increases their OS [1, 7, 10] as well as their motivation to choose a specific tourist destination [1]. Accordingly, that destination is expected to experience higher growth in the tourist market [53, 54].

The perceived value of specific attributes for Muslim tourists' satisfaction will impact Muslim tourists' word of mouth to their family or friends [8, 23]. In this regard, several studies have discussed the hotel and tourism-related food industry corresponding to attributes of Muslims. For example, Battour et al. [55] indicated that Islamic hotels serve only Halal foods, are alcohol-free, have conservative TV channels, and provide women-only floors under universal Sharia rules. Rahman [56] found that local varieties of Halal foods are important attributes that affect the image of a tourist destination. Stephenson [51] discussed that Muslim-friendly hotels should normally possess the following attributes: (1) human resources: traditional uniforms for hotel staff and dress code for female staff; (2) private rooms: separate floors with rooms allocated to women and families, prayer mats, and copies of the Quran; (3) dining and banqueting facilities: Halal food with no pork, soft beverages only, and dining quarter provision for women and families; (4) other public facilities: no casino or gambling machines and separate leisure facilities. Putit et al. [57] examined the relationship between four Halal-friendly hotel attributes (i.e., prayer facilities, Halal food, Islamic dress code, and general Islamic morality) and customer satisfaction. In particular, the attribute of prayer facilities was found to have the most significant impact on customer satisfaction. Chang et al. [58] also found that core hotel service offerings (i.e., reception, housekeeping, food, and beverage personnel services) are the main factors influencing tourists' intention to revisit a hotel. When observing the quality of services, facilities, foods, and beverages in Halal-friendly hotels in non-Muslim countries, Jeaheng et al. [59] found that a hotel's service quality is crucial for the satisfaction of Muslim guest's high expectations.

Battour et al. [53] investigated Muslim travelers' religious requirements at destinations. They identified intangible attributes, including Islamic entertainment, dress codes, general Islamic morality, and Islamic call for prayer, while the tangibles comprise prayer facilities and Halal food. Their study showed that easily sourced Halal food, access to worship places, Islamic toilets, and entertainment are highly prioritized attributes. El-Gohary [3] proposed Halal tourism principles and/or key requirements comprising the basic needs expected, for example, Halal food, absence of alcohol, absence of ham or pork, a copy of the Quran in every room, prayer rooms, Islamic dress code for staff uniforms, prayer mats, markers indicating the direction of Mecca, and suitable guest dress codes. Yousaf and Xiucheng [21] summarized 27 attributes into five factors to compare four countries' Halal culinary and tourism marketing. The main attributes include Halal appraisal and certification, Halal cuisine features, recommended Halal food restaurants, Halal as a symbol of culinary diversity, and additional Halal services and facilities. Battour et al. [60] considered the impact on non-Muslim tourists of Muslim destinations' service attributes comprising general perception, gender segregation, Halal food, Islamic dress code, and Islamic ethics. They found that non-Muslim tourists may decrease their travel satisfaction in light of food restrictions (e.g., pork replacements and no alcoholic beverages) and the practice of gender segregation in hotels and resorts. Furthermore, Rahman et al. [61] also found that banning non-Halal services and implementing Halal food product services in Muslim tourist destinations are significantly related to the perspectives of non-Muslim tourists' travel experience and value.

2.2. Asymmetric Effects on Attribute Performance and Satisfaction. The direct or indirect methods assess the importance of attributes. The former evaluates important attributes directly from customers' viewpoints, recording their perceptions of the importance of attributes using a rating scale, while the latter indirectly derives attribute-importance from statistical inference to elicit abstract perceptions [31]. In particular, the indirect method of using a statistical approach to derive the implicit attributes from respondents has been popular in literature. For example, Kuo et al. [62] used regression analysis to explore the negative and positive asymmetric effects of tour guide service quality on tourist satisfaction. Tour guides should eliminate negative attitudes

to improve service quality. Similarly, curators should improve the negative asymmetry between a museums' interpretation of service quality and visitor satisfaction [24].

The application of a three-factor theory can be used as an indirect method to identify important attributes [35]. This three-factor theory can be divided into basic, excitement, and performance factors. Basic factors are referred to as must-be attributes. This type of attribute exerts a negative impact on OS in the case of low-level performance but does not have a significant positive impact on OS when its performance is high. Conversely, the excitement factor indicates attributes with a positive impact on OS when provided at high-level performance, but they do not have a significant negative impact on OS when performance is at a low level. These two factors have an asymmetric effect since OS is impacted differently by the level of each type of attribute's performance. In contrast, the performance factor reveals a linear and symmetrical style, where an attribute positively impacts OS during the high performance and negatively impacts OS during the low-level performance.

Studies have applied the concept of the three-factor theory, such as that by Fajriyati et al. [23], who classified generic and Islamic attributes as basic, performance, and excitement factors to identify the influence of satisfaction in Muslim tourists who had visited non-Muslim destinations. Hu et al. [63] introduced a novel asymmetric impact-sentiment-performance analysis to evaluate the impact-asymmetry of hotel service attributes on customer satisfaction. To avoid predefining service attributes from a researcher's perspective, they performed automated opinion mining on online reviews rather than closed-ended questionnaires. Furthermore, using three-factor theories, Lai and Hitchcock [64] explained how the structure of factors could influence the behaviors of new, repeat, and frequent travelers to Macau.

Based on a three-factor theory, the PRCA is a popular method for examining the asymmetric relationship between the performance of service attributes and customer satisfaction [31, 35, 64]. Following the PRCA, some studies have extended this analysis technique into a broad range of fields. Matzler and Renzl [33] assessed the asymmetric relationship between single satisfaction factors and overall employee satisfaction by using PRCA in the hotel industry. Mikulić and Prebežac [65] compared PRCA with the most commonly used approaches (e.g., importance grid and direct classification) to evaluate its validity and reliability for identifying asymmetric influences on product attributes. Albayrak and Caber [27] extensive literature review of PRCA classified three main phases and compared each literature with its different methodological techniques. Mikulić and Prebežac [31] used PRCA to develop new methods to help indicate an attribute's importance in explaining a customer's overall judgment of a service. Thereafter, Caber et al. [28] developed an extended version of Mikulić and Prebežac's [31] methods, which are used for AIPA instead of applying IAA.

2.3. Methods for Model Parameter Estimation. Albayrak and Caber [27] discussed that applications of PRCA contain an important phase of deciding each attribute's coefficients for measuring penalty or reward values. To determine these coefficients, the methodologies can generally be divided into statistical and nonparameter approaches [38, 41]. The former statistical methods are based on rigorous mathematical foundations and can thus explain the phenomena by interpreting the mechanism between the estimator and explanatory variables [66]. In general, the regression approach is the prevailing statistical method to estimate the attribute's coefficients [27]. Some researchers have used the regression approach for measuring penalty or reward values, such as service quality in the hotel industry [52], online tourism intermediaries [25, 36], and restaurant food [32].

However, the regression approach is mostly designed for inference and estimation and requires several hypotheses and restrictions to be satisfied before model development [41, 45]. Moreover, it lacks the ability to deal with nonlinear effects and multicollinearity issues between a set of dependent and independent variables and is easily sensitized to a small sample [37, 38, 42]. Chen et al. [67] developed a prediction system model to analyze the arrival time of waste collection vehicles. Compared with an alternate, linear regression method, their proposed prediction model is more efficient, better, and accurate.

Due to the weakness of the regression analysis, we can use different approaches, such as a nonparametric machine learning method [38]. Machine learning methods can detect deeply entrenched implicit relationships between variables, build nonlinear relationships between variables without prior knowledge, and are more accurate [45]. Nowadays, researchers have developed a wide variety of machine learning methods particularly suited to prediction and classification, such as Artificial Neural Network (ANN), Random Forests (RF), Support Vector Machine (SVM), and GBDT [41, 68, 69].

ANN models can handle complex relationships in datasets and have gained wide popularity in many fields [70]. For example, Feizollah et al. [71] used sentiment analysis to analyze Halal tourism and Halal cosmetics using Twitter data. Except for the deep learning approach, convolutional neural networks and recurrent neural networks improve accuracy and construct prediction models. Zhao et al. [72] analyzed 14 factors based on four aspects of the e-commerce platform by using ANN in their sales factor model. Yeh and Chen [73] used the ANN method to extract some important features for predicting the success of crowdfunding projects in the capital market. Zheng et al. [74] established a sports tourism function system that utilized three layers of neural networks concept, including the perception layer, network layer, and application layer. However, the drawback of ANN is the potential occurrence of overfitting or underfitting [38].

Another nonparametric model, the SVM algorithm, is a kind of supervised machine learning algorithm, potentially overcomes the drawbacks of neural networks, and addresses the issues of nonlinearity, small samples, high dimension, local minima, and overfitting [75]. Afzaal et al. [76] proposed hybrid approaches including SVM and random forest in their aspect-based sentiment classification framework to identify and classify tourist reviews on restaurants or hotels.

Chang et al. [77] described why travelers do not want to revisit destinations in the tourism and hospitality industry. They used the sentiment of text reviews to identify the passenger's motivations and utilized feature selection methods, such as SVM, Support Vector Machines Recursive Feature Elimination (SVM-RFE), and decision trees to discover the important nonrevisit factors. Cao et al. [69] improved the network traffic classification model based on an SVM. They overcame interferences between features that led to the degradation of the classification performance and improved grid search parameter optimization algorithms to prevent overfitting problems.

However, most machine learning models lack interpretability, limiting the application of prediction or classification [40]. Except for measuring coefficients in the PRCA phase, it is important to explain the incremental changes in penalty and reward values similar to regression coefficients. In contrast to the previous machine learning methods, the GBDT model can overcome many regression problems and interpretability parameters using the partial dependence concept [44, 45, 78]. Many studies have indicated that GBDT outperforms regression models [79], RF models [80, 81], ANN [82], and SVM [41].

To summarize, the GBDT supervised classification method has been widely used in feature selection and classification in other research fields. For example, according to the GBDT method, Rao et al. [83] proposed a novel feature selection method on cancer datasets, addressing problems of efficiency and informative quality when selecting features. Dong et al. [43] demonstrated that neighborhood attributes related to pedestrian satisfaction differ between gated and open communities. Cao et al. [46] found that important neighborhood attributes have asymmetric influences on generating resident satisfaction. Wu et al. [47] found that bus transit quality of service attributes had a nonlinear and asymmetric influence on rider satisfaction. These studies selected important attributes using the GBDT method, but they only focused on separate attributes, ignoring the analysis of the attributes' integrated effects in the same factor category. Moreover, these studies should carefully analyze the relationship between IA and performance to understand the degree of the factors/attributes influencing OS.

2.4. Tourism Behavior for Foreign Workers and a Given Group. Some studies have examined the tourism characteristics of a given group, such as the relationship between foreign workers in a particular destination and their leisure activities. For example, Hsu and Hsu [84] observed that although Indonesian care workers in Taiwan had limited discretionary time, they still participated in various leisure activities, such as travel. Tsai [85] focused on female blue-collar foreign workers and examined their leisure activities after work in Taiwan, observing that their leisure activities were affected by their countries or origin and their work arrangements. Furthermore, Tsai [86] also discussed foreign white-collar workers' leisure opportunities in Taiwan and showed that most respondents regularly participated in leisure or sports activities after work.

Another study by Boğan et al. [87] attempted to examine qualified prospective employees' perceptions or attitudes toward Muslim-friendly hotels. They showed that the factors enhancing job pursuit intention are organizational, job attractiveness, and person-organization fit. Alrwajfah et al. [88] explored females' perspectives on the economic impact of tourism in Jordan. The results found that women who are interested in gaining benefits economically from the tourism industry should not be hampered by social, religious, and educational restrictions. Meanwhile, researchers have attempted to examine their perception of the attractiveness of their study location as a tourism destination. Brown [89] and Bae and Song [90] indicated that international students are often considered long-term tourists with significant potential to influence and attract future visitors.

3. Research Methodology

3.1. The Processes of Penalty-Reward-Contrast Analysis. The PRCA is the most frequently used technology for explaining asymmetric effects on OS. Albayrak and Caber [27] discussed that applications of PRCA vary in three phases: (a) defining low- and high-performance levels, (b) obtaining penalty and reward values, and (c) attribute classification. These processes are described as follows.

3.1.1. Defining Low- and High-Performance Levels. In PRCA, two sets of dummy variables are created for each attribute. The first set measures the impact of extremely high attribute performance on OS, where the highest performance is recorded as "1" (scale = 5), and all other ratings are recoded as "0" (scale = 1, 2, 3, and 4); the second set measures the impact of extremely low attribute performance on OS, recoding the lowest performance as "1" (scale = 1) and others as "0" (scale = 2, 3, 4, and 5).

3.1.2. Obtaining Penalty and Reward Values through GBDT. In applying the regression model, Mikulić and Prebežac [31] showed that each attribute obtained from two regression coefficients representing penalty and reward indices showed an incremental increase/decrease in OS association with an extremely high/low attribute performance. Following the concept of the regression coefficient, we used partial dependence derived by Friedman [39] to illustrate the marginal effect of each variable on OS with a fit GBDT model. Achieving a fit GBDT model can be expressed as follows.

Given a training sample of (y, X), where y $(n \times 1)$ is a vector of the dependent variable and X $(n \times p)$ is a matrix of independent variables, the goal of GBDT is to search for an approximated predicted function of $F(x)$ that minimizes the loss function. Its basic algorithm is shown by the following three steps [39].

First, we determine the initialized predicted value with a constant (γ):

$$F_0(x) = \mathrm{argmin}_{\gamma} \sum_{i=1}^{n} L(y_i, \gamma), \tag{1}$$

where y_i $(i = 1, \ldots, n)$ is the observed value for the number of training samples and γ is the estimated value that minimizes the loss function of $L(y_i, \gamma)$.

In the second step, there are four substeps, (2a) to (2d), iterated until an M tree is achieved.

(2a) We compute the negative gradient of the loss function using equation (2) as an approximation of the residual.

$$r_{\mathrm{im}} = -\left[\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)}\right]_{F(x)=F_{m-1}(x)} \quad \text{for } i = 1, \ldots, n, m = 1, \ldots, \mathrm{M}. \tag{2}$$

(2b) Using the pairs of data (x_i, r_{im}), we can fit a regression tree and corresponding leaf node regions R_{jm} ($j = 1, \ldots, J_m$), where J_m is the number of leaf nodes.

(2c) For each sample in the leaf node, we find the best output value r_{jm} to minimize the loss function, as shown in equation (3).

$$r_{\mathrm{jm}} == \operatorname{argmin}_{\gamma} \sum_{x_i \in R_{jm}} L(y_i, F_{m-1}(x_i) + \gamma), \quad \text{for } j = 1, \ldots, J_m. \tag{3}$$

(2d) The last substep is to update the model (equation (3)) according to the results of equation (4).

$$F_m(x) = F_{m-1}(x) + \varphi \sum_{j=1}^{J_m} \gamma_{jm} \cdot I\left(x \in R_{\mathrm{jm}}\right), \tag{4}$$

where $I = 1$ if $x \in R_{\mathrm{jm}}$; otherwise, $I = 0$ if $x \notin R_{\mathrm{jm}}$; the learning rate $\varphi \in (0, 1]$ is used to prevent the overfitting problem of GBDT at each iteration [39].

After looping (2a) to (2d) until several M iterations are reached, the third step produces the final predicted results of the fitted CBDT model as follows:

$$F(x) = F_M(x). \tag{5}$$

Overall, the optimal performance of the GBDT model is influenced by the best combination of three parameters of the number of trees (M), learning rate (φ), and tree complexity. The first two parameters (M and φ) are a trade-off relationship to control the boosting speed. That is, a larger value for M added to the model will produce a lower φ for obtaining better performance [37, 45, 91]. Another parameter of tree complexity also influences the precision of the model. For a given learning rate parameter, increasing the value of tree complexity will induce more complex interactions among variables and thus requires fewer trees for a minimum error [40, 80].

To further investigate how these independent variables affect the dependent variable, we provide the concept of partial dependence to construct the reward and penalty index after a GBDT model has been fitted. Except for Mikulić and Prebežac [31] with regression analysis, our study is slightly different from those of Ding et al. [92] and Yin et al. [44] but uses the same GBDT model. Following is a discussion of how we use partial dependence.

Let X present the predictors in a model whose approximation prediction function is $\widehat{F}(X)$. If we can partition X into the features of interest subset Z_t and the remaining complement subset Z_c, where $Z_t \bigcup Z_c = X$, we can represent a partial dependence of $\widehat{F}(X)$ on the chosen target subset Z_t in equation (6).

$$\overline{F_t}(Z_t) = E_{Z_c}\left[\widehat{F}(Z_t, Z_c)\right] = \int \widehat{F}(Z_t, Z_c) \cdot \leq P_c(Z_c)\, \mathrm{d}Z_c. \tag{6}$$

Here, $P_c(Z_c) = \int P(X)\, \mathrm{d}Z_t$ is the complement marginal probability density of Z_c, and $P(X)$ is the joint density of all of X. By integrating overall values of Z_c, we can estimate by taking the average over a given training data set. Equation (6) is then simplified to the following equation (7):

$$\overline{F_t}(Z_t) = \frac{1}{n \cdot \sum_{i=1}^{n} \widehat{F}\left(Z_t, Z_{c,i}\right)}, \tag{7}$$

where $Z_{c,i}$ ($i = 1, 2, \ldots, n$) are the value of Z_c obtained from the training data. Equation (7) implies that $\overline{F_t}(Z_t)$ is all the other predictors (Z_c) averaged out in the model.

Let $Z_t = \mathrm{dum}_1$ be a single attribute-performance dummy variable. This variable has k values representing $\mathrm{dum}_{1,j}$ for $j = 1, 2, \ldots, k$ with unique values $\left\{\mathrm{dum}_{1,1}, \mathrm{dum}_{1,2}, \ldots, \mathrm{dum}_{1,k}\right\}$, and the partial dependence of the OS on dum_1 can be estimated from steps (3a) to (3c):

(3a) Hold the features of interest $\mathrm{dum}_{1,j}$ constant and find predictions over all other combinations of the complement set $Z_{c,i}$.

(3b) Compute the vector of predicted values from (a) modified training data.

(3c) Average out all the predictions across the supplied data set to obtain $\overline{F_t}(\mathrm{dum}_{1,j})$ and also one of the pairs $\left\{\mathrm{dum}_{1,j}, \overline{F_t}(\mathrm{dum}_{1,j})\right\}$.

After generating averages for each instance over a specified range of values, we can calculate the marginal effect between a dependent variable (i.e., OS) and a dummy variable (i.e., a particular attribute performance) as follows:

$$\frac{\Delta \mathrm{OS}}{\Delta \mathrm{dum}_1} = \left|\overline{F_t}\left(\mathrm{dum}_{1,1} = 0\right) - \overline{F_t}\left(\mathrm{dum}_{1,k} = 1\right)\right|. \tag{8}$$

Equation (8) indicates that a one-unit change of a dummy variable from zero (unhappen) to one (happen) affects the degree of change of OS. The degree of change can be assessed by the two absolute difference values between the mean prediction function change from zero to one. As such, the reward index (RI) is defined as the degree to which a dummy variable changes corresponding to extremely high attribute performance affecting OS. Similarly, a dummy variable change corresponding to the extremely low attribute performance is considered as the penalty index (PI) [31].

3.1.3. Attribute Classification. In merging the RI and PI, the Range of Impact on Overall Customer Satisfaction (RIOCS) can be calculated to define the dispersion of each attribute, as shown in equation (9).

$$\mathrm{RIOCS}_i = \mathrm{RI}_i + \mathrm{PI}_i. \tag{9}$$

Besides the RIOCS, Mikulić and Prebežac [31] suggested quantifying the extent of the indices of each attribute's Satisfaction-Generating Potential (SGP) and Dissatisfaction-Generating Potential (DGP). These two indices are calculated by RI, PI, and RIOCS to limit the range from 0 to 1 rather than −infinite to + infinite (see equations (10) and (11)).

$$\mathrm{SGP}_i = \frac{\mathrm{RI}}{\mathrm{RIOCS}_i}. \tag{10}$$

$$\mathrm{DGP}_i = \frac{|\mathrm{PI}|}{\mathrm{RIOCS}_i}. \tag{11}$$

Using the difference between SGP and DGP, the index of impact-asymmetry (IA) can be defined as equation (12).

$$\mathrm{IA}_i = \mathrm{SGP}_i - \mathrm{DGP}_i. \tag{12}$$

The IA shows the asymmetric influences of the attribute's performance on OS, which can be used as a criterion to categorize various levels of attributes. Caber et al. [28] extended Mikulić and Prebežac [31] concept with a classification similar to the three-factor theory; that is, IA scores (a) above 0.1 are labeled "excitement" factors; (b) below −0.1 are indicated as "basic" factors, and (c) between −0.1 and 0.1 are termed "performance" factors. The above idea is indirectly original from the reward and penalty indices. That is, when the value of the reward index is larger than that of the penalty index, this attribute tends toward an excitement factor. Likewise, it tends toward a basic factor when its value of reward index is smaller than its value of penalty index. Finally, the attribute is a performance factor if its value of reward index is approximately equal to its value of the penalty index [29]. Finally, the flow of the entire methods' framework in our study is shown in Figure 1.

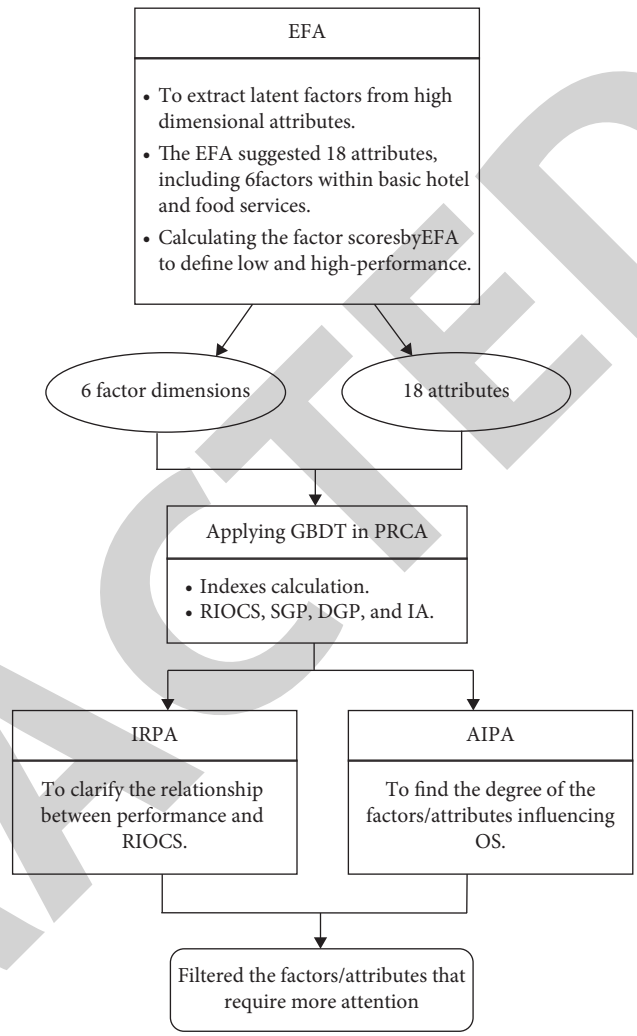

Figure 1: The flow of the entire methods' framework.

3.2. Questionnaire Design and Data Collection. This study selected respondents who were Indonesian Muslim workers who had lived in Taiwan for over one year. The majority of the sample lived in the Taoyuan industrial area. The language barrier represented a big problem during data collection, which we overcame by seeking assistance from foreign worker consultants to translate the questionnaire into the Indonesian language. Respondents were selected by conducting convenience sampling followed by in-person interviews with a paper-based survey. The survey was conducted between February to April 2018. There were a total of 240 questionnaires. To find a minimum sample size, the authors used the following equation:

$$\mathrm{n} = \frac{Z^2_{\alpha/2} \cdot \widehat{P} \cdot (1 - \widehat{P})}{E^2}, \tag{13}$$

where $\widehat{P}$ is the estimated proportion and E is the margin of error. The detailed calculation process is discussed as follows.

According to the Taiwanese Ministry of Labor, Indonesia's foreign workers in productive industrial sectors accounted for 71,446 out of 448,753 people (16%) in 2017. The Muslim population in Indonesia is about 80% [4]. Therefore, the authors could calculate the proportion of $\widehat{P}$ as 0.16 times 0.80 equals 0.13. The authors multiplied by 0.80 because not all Indonesians are Muslim. Using a common 95% confidence level $(1 - \alpha)$ and a margin of error of 5% (E), the minimum sample size (n) is approximately 171 people, of which 24 were omitted from analyses owing to missing values and incomplete data, resulting in a total of 216 useful responses. This study's structured questionnaire mainly comprised three topics: (a) hotel accommodation, (b) availability of Halal food, and (c) respondents' demographic characteristics. Each part featured multiple attributes regarding the hotel and food services in tourism. The first, hotel accommodation, comprised 17 attributes, while Halal food included 10 attributes. These attributes included the availability of tangible and intangible aspects in non-Muslim countries; for example, hotel facilities, food symbols and certification, entertainment, and dress codes follow Muslim-friendly norms and practices [53]. All attributes in the

questionnaire were derived from previous studies [3, 21, 51, 53, 55] discussed in the related literature in Section 2.1. Each attribute's items were measured on a 5-point Likert scale (1 = strongly disagree; 5 = strongly agree) in terms of satisfaction performance, and respondents' OS was measured related to all the topics of hotel and food services under the umbrella of Muslim-friendly tourism.

On the other hand, we chose Taiwan as a case to represent a non-Muslim destination for the following reasons. First, the Muslim population in Taiwan is small, but it has been listed in the top ten leading destinations out of 81 non-Muslim countries [93]. Taiwan has clearly made an effort to promote tourism and is worthy as a reference for other countries seeking to develop Halal tourism. Second, Taiwan faced a labor shortage in 1989 and consequently passed legislation permitting the introduction of foreign workers [84]. According to the Taiwanese Ministry of Labor, 706,850 foreign workers entered Taiwan at the end of 2018. Among them, the largest group originated from Indonesia (38% of the total). Indonesia, as a Muslim-majority country, is home to the largest Muslim population in the world [4]; thus, for the purposes of this study, we infer that Indonesian foreign workers in Taiwan are likely to be Muslim. Lastly, due to their time spent living in Taiwan, these foreign Muslim workers may expect more from their experiences since they are active travelers during their working period.

4. Results

4.1. Respondent Characteristics. As shown in Table 1, the majority of respondents were female (81.0%), with males accounting for 19.0% of the sample. This was to be expected since Indonesian Muslim workers in Taiwan are largely female. Approximately 56% of the respondents were aged between 26 and 35. More than half of the respondents (52.3%) were educated to the senior high school level, and their monthly incomes were mostly between $660 and $1,320 (48.1%).

4.2. Factor Extraction Technique. Due to the number of attributes (27) in the survey, we performed an Exploratory Factor Analysis (EFA) approach to extract latent factors from high dimensional attributes and prevent the negative skewness of data [25, 27, 32]. If the data distribution shows a negative skewness, the penalty coefficient is likely to be insignificant due to a few low-performance dummy variables data. Further, a particular attribute may be misclassified [94].

The EFA was based on the principal component approach with varimax rotation. The results are shown in Table 2. It was found that KMO was equal to 0.915, and Bartlett's test of sphericity was significant, which implied that EFA was appropriate for the application. The principles for deleting items are factor loadings lower than 0.4 or with high loadings on more than one factor. After extracting the attributes, the EFA suggested 12 attributes' items from four hotel service factors and six attributes' items related to factors of Halal food service. All six factors extracted in this analysis accounted for 70.771% of the total variance.

Table 1: Demographic characteristics of respondents ($n = 216$).

		Frequency	Percentage
Gender	Male	41	19.0
	Female	175	81.0
Age	16–25	67	31.0
	26–35	121	56.0
	36–45	23	10.6
	46 <	5	2.4
Education	No formal education	2	0.9
	Elementary school	19	8.8
	Junior high school	59	27.3
	Senior high school	113	52.3
	University or above	23	10.7
Income (monthly)	Under $660	94	43.6
	$660–$1,320	104	48.1
	$1,320–$1,980	13	6.0
	More than $1,980	5	2.4

According to the attributes' similar properties, the six factors were labeled hotel amenities (A1), hotel dining and banqueting facilities (A2), hotel staff (A3), hotel public facilities (A4), Halal food symbols and certification (F1), and Halal food restaurants (F2). The internal validity of the six-factor solution was tested through reliability analyses. Cronbach's alpha values for the dimensions ranged from 0.521 to 0.795, as presented in Table 2.

4.3. Empirical Analysis

4.3.1. Indexes Calculation and Model Comparison. We produced two types of penalty and reward indices. The first was a factor dimension using the factor scores from the EFA to define low- and high-performance impact on OS. Following Matzler and Renzl [33], we divided these factor scores into tertiles. When the factor score was located in the lowest performance tertile, they were coded as one dummy variable (value of 1). In contrast, the scores in the highest tertile were used for a second dummy variable (value of 1). The second type was evaluated for each attribute when the lowest performance (both Likert scales 1 and 2) was rated as "1," and the largest (both scales 4 and 5) was a rating of "1."

Using the GBDT technique, we set the learning rate at 0.01 because Friedman [39] indicated that smaller learning rate values are seen to result in better performance. Empirically, the learning rate $\phi < 0.1$ (i.e., between 0.01 and 0.001) usually yields dramatic improvements over boosting series instead of no shrinkage ($\phi = 1$) [78]. For the second parameter, we chose the tree complexity level of two in the GBDT. A higher level of tree complexity can capture more detailed information from the dataset, but its performance does not improve after the tree complexity value reaches a certain level [40]. Finally, before using the factor of 12 and the attributes of 36 independent variables, we initially set a

Table 2: Attributes obtained by Exploratory Factor Analysis.

	Eigenvalue/factor loading	Variance explained (%)	Cronbach's alpha
A1 Hotel amenities	7.538	41.875	0.795
A1-1 Separate wellness facilities such as gyms or swimming pools	0.566		
A1-2 Female staff for women and families	0.622		
A1-3 Al-Quran, prayer mats, and tasbih (rosary beads) in each room or at the front desk	0.558		
A1-4 Beds and toilet positioned so as not to face the direction of Mecca	0.630		
A1-5 Muslim toilets to be provided	0.567		
A2 Hotel dining and banqueting facilities	1.740	9.666	0.521
A2-1 No alcohol, pork, or similar products to be served	0.711		
A2-2 Conservative TV channels and appropriate music	0.701		
A3 Hotel staff	1.065	5.914	0.660
A3-1 An appropriate dress code worn by hotel staff	0.545		
A3-2 Muslim staff members	0.801		
A4 Hotel public facilities	0.899	4.994	0.582
A4-1 No casino or gambling machines	0.772		
A4-2 gender-segregated prayer rooms	0.528		
A4-3 Built-in wudhu facilities located outside prayer rooms	0.488		
F1 Halal food symbols and certification	0.778	4.323	0.699
F1-1 Description of Halal food menu not limited by language	0.796		
F1-2 Assurance that food meets the Halal standards being levied by the government	0.734		
F1-3 Only Halal food to be served	0.731		
F2 Halal food restaurants	0.720	3.999	0.760
F2-1 Halal food is cooked separately from non-Halal food	0.661		
F2-2 Certification of Halal food restaurants	0.732		
F2-3 Availability of Halal food at the destination	0.553		

Note. Total variance explained = 70.771%; KMO = 0.915; Bartlett's test of sphericity = 1776.675 (0.000).

maximum of 1,500 trees and iterations to get 1,437 and 448 optimal decision trees, respectively.

After the GBDT model has been fitted, we use the partial dependence to build the reward and penalty indices and then calculate all indices of RIOCS, SGP, DGP, and IA for the factor dimensions and attributes. Table 3 shows the results of all the indices on factor dimensions and attributes, and further detailed analyses of these indices are discussed in the following section.

To examine the difference between the GBDT and the regression method, the regression sets these two dummy variables ($\mathrm{dum}_{\mathrm{low},i}$, $\mathrm{dum}_{\mathrm{high},i}$) as independent variables and OS as a dependent variable, which are seen in the following equation:

$$\mathrm{OS} = \beta_0 + \sum_{i=1}^{n}\left(\beta_{\mathrm{low},i}\mathrm{dum}_{\mathrm{low},i} + \beta_{\mathrm{high},i}\mathrm{dum}_{\mathrm{high},i}\right) + \varepsilon. \quad (14)$$

In applying the regression model, each attribute obtains two regression coefficients. The first coefficient ($\beta_{\mathrm{low},i}$) is labeled PI, which indicates an incremental decrease in OS when the attribute is extremely low performing. The second coefficient ($\beta_{\mathrm{high},i}$), as the RI, represents an incremental increase in OS in cases of extremely high attribute performance. We also used the Wilcoxon signed-rank test to compare each pairwise index value (see Table 3) calculated by these two methods. We set the null hypotheses (H_0) so that the pairwise index values between the two methods were not different; in contrast, the alternative hypotheses (H_1) assume that the values from the two methods are different.

As shown in Table 4, H_0 were all rejected in the RI, PI, and RIOCS, indicating that the calculated coefficients between the GBDT and the regression methods were statistically different. This means that using other methods will incur different results for these critical indexes. Therefore, utilizing GBDT provides us with a greater abundance and more valuable information because operating nonlinear effect and multicollinearity issues is lacking in the regression method. On the other hand, SGP, DGP, and IA were nonreject H_0, implying no significant differences when using these two methods. The reason may be that these indexes are indirectly obtained by the two methods and are derived from subsequent arithmetic operations (see Section 3.1). This point of view is consistent with Ding et al. [79], Rao et al. [83], and Wu et al. [47].

4.3.2. Impact-Range Performance Analysis (IRPA). Using the RIOCS index (see Section 3.1), we found the range of incremental changes of one extremely low/high performance to influence the changes in OS. The range of RIOCS in factor dimensions was from 0.214 to 0.706 (see Table 3). The most influential factor was A2 (RIOCS = 0.706), followed by A1 (RIOCS = 0.611) and F1 (RIOCS = 0.402). Furthermore, the RIOCS in F2-3 (RIOCS = 0.417) was the highest of all attributes, followed by the same factor in F2-2 (RIOCS = 0.383). This means

Table 3: Results of indices for factors/attributes.

Factor/attribute	RI	PI	RIOCS	SGP	DGP	IA	Factor classification
A1 Hotel amenities	0.263	0.348	0.611	0.431	0.569	−0.139	Basic
A1-1 Separate wellness facilities such as gyms or swimming pools	0.005	0.017	0.022	0.225	0.775	−0.550	Basic
A1-2 Female staff for women and families	0.040	0.060	0.099	0.402	0.598	−0.197	Basic
A1-3 Al-Quran, prayer mats, and tasbih (rosary beads) in each room or at the front desk	0.002	0.032	0.034	0.059	0.941	−0.882	Basic
A1-4 Beds and toilet positioned so as not to face the direction of Mecca	0.006	0.067	0.073	0.077	0.923	−0.846	Basic
A1-5 Muslim toilets to be provided	0.016	0.106	0.122	0.129	0.871	−0.743	Basic
A2 Hotel dining and banqueting facilities	0.236	0.470	0.706	0.334	0.666	−0.331	Basic
A2-1 No alcohol, pork, or similar products to be served	0.014	0.054	0.067	0.202	0.798	−0.596	Basic
A2-2 Conservative TV channels and appropriate music	0.023	0.089	0.113	0.207	0.793	−0.587	Basic
A3 Hotel staff	0.063	0.198	0.261	0.241	0.759	−0.517	Basic
A3-1 An appropriate dress code worn by hotel staff	0.109	0.048	0.157	0.696	0.304	0.392	Excitement
A3-2 Muslim staff members	0.037	0.011	0.048	0.774	0.226	0.548	Excitement
A4 Hotel public facilities	0.116	0.273	0.388	0.298	0.702	−0.404	Basic
A4-1 No casino or gambling machines	0.006	0.001	0.007	0.811	0.189	0.622	Excitement
A4-2 Gender-segregated prayer rooms	0.013	0.066	0.079	0.169	0.831	−0.663	Basic
A4-3 Built-in wudhu facilities located outside prayer rooms	0.029	0.100	0.129	0.226	0.774	−0.548	Basic
F1 Halal food symbols and certification	0.188	0.214	0.402	0.468	0.532	−0.063	Performance
F1-1 Description of Halal food menu not limited by language	0.118	0.156	0.274	0.430	0.570	−0.140	Basic
F1-2 Assurance that food meets the Halal standards being levied by the government	0.031	0.114	0.145	0.211	0.789	−0.578	Basic
F1-3 Only Halal food to be served	0.055	0.173	0.228	0.243	0.757	−0.514	Basic
F2 Halal food restaurants	0.138	0.076	0.214	0.644	0.356	0.287	Excitement
F2-1 Halal food is cooked separately from non-Halal food	0.016	0.123	0.139	0.117	0.883	−0.766	Basic
F2-2 Certification of Halal food restaurants	0.140	0.243	0.383	0.366	0.634	−0.268	Basic
F2-3 Availability of halal food at the destination	0.117	0.300	0.417	0.280	0.720	−0.439	Basic

Note. (1) RI: reward index; PI: penalty index; RIOCS: Range of Impact on Overall Customer Satisfaction; SGP: Satisfaction-Generating Potential; DGP: Dissatisfaction-Generating Potential; IA: impact-asymmetry. (2) Following Caber et al. [28], IA scores (a) above 0.1 are labeled "excitement" factors, (b) below −0.1 are indicated as "basic" factors, and (c) between −0.1 and 0.1 are termed "performance" factors.

Table 4: Wilcoxon signed-rank test between the GBDT and the regression method.

Hypotheses	Z value		P value
H_0: RI_GBDT = RI_regress H_1: RI_GBDT ≠ RI_regress	−3.157	∗∗	0.002
H_0: PI_GBDT = PI_regress H_1: PI_GBDT ≠ PI_regress	−4.143	∗∗	0.000
H_0: RIOCS _GBDT = RIOCS_regress H_1: RIOCS _GBDT ≠ RIOCS_regress	−2.971	∗∗	0.003
H_0: SGP _GBDT = SGP_regress H_1: SGP _GBDT ≠ SGP_regress	−1.557		0.119
H_0: DGP _GBDT = DGP_regress H_1: DGP _GBDT ≠ DGP_regress	−1.557		0.119
H_0: IA_GBDT = IA_regress H_1: IA_GBDT ≠ IA_regress	−1.571		0.116

Note. "∗∗" indicates significance at the 5% level.

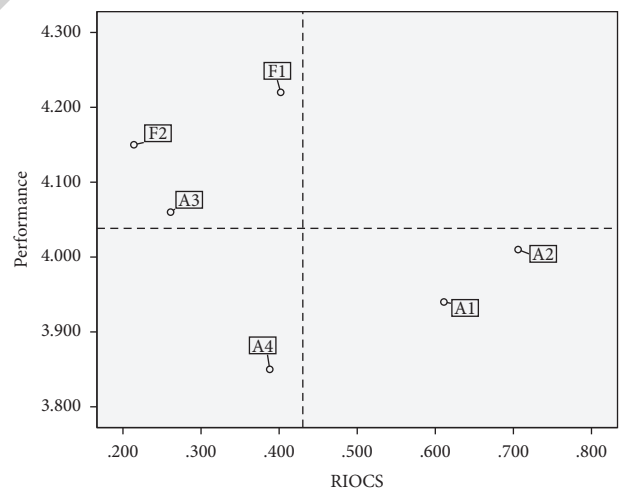

Figure 2: Impact-Range Performance Analysis of factor dimensions.

that no matter whether the impact is positive or negative, the RIOCS reflects the quantity of one attribute's performance sensibility on its OS.

To clarify the relationship between performance and RIOCS, we further plotted the two dimensions graphically in a figure that listed mean values of performance along the vertical axis and RIOCS along the horizontal axis. Using the grand mean values of the RIOCS and performance, we divided four quadrants. Mikulić and Prebežac [31] indicated that an object deserves more attention when it is located in the highest RIOCS and lowest performance quadrant (i.e., quadrant IV). Therefore, Figure 2 reveals that A1 and A2, which are positioned in this area, should be carefully considered. In contrast, A3, F1, and F2 are not such a priority because their RIOCS is below mean, while their performance is above mean.

In Figure 3, we present six separate scatter plots of each attribute within its factor because every regression model

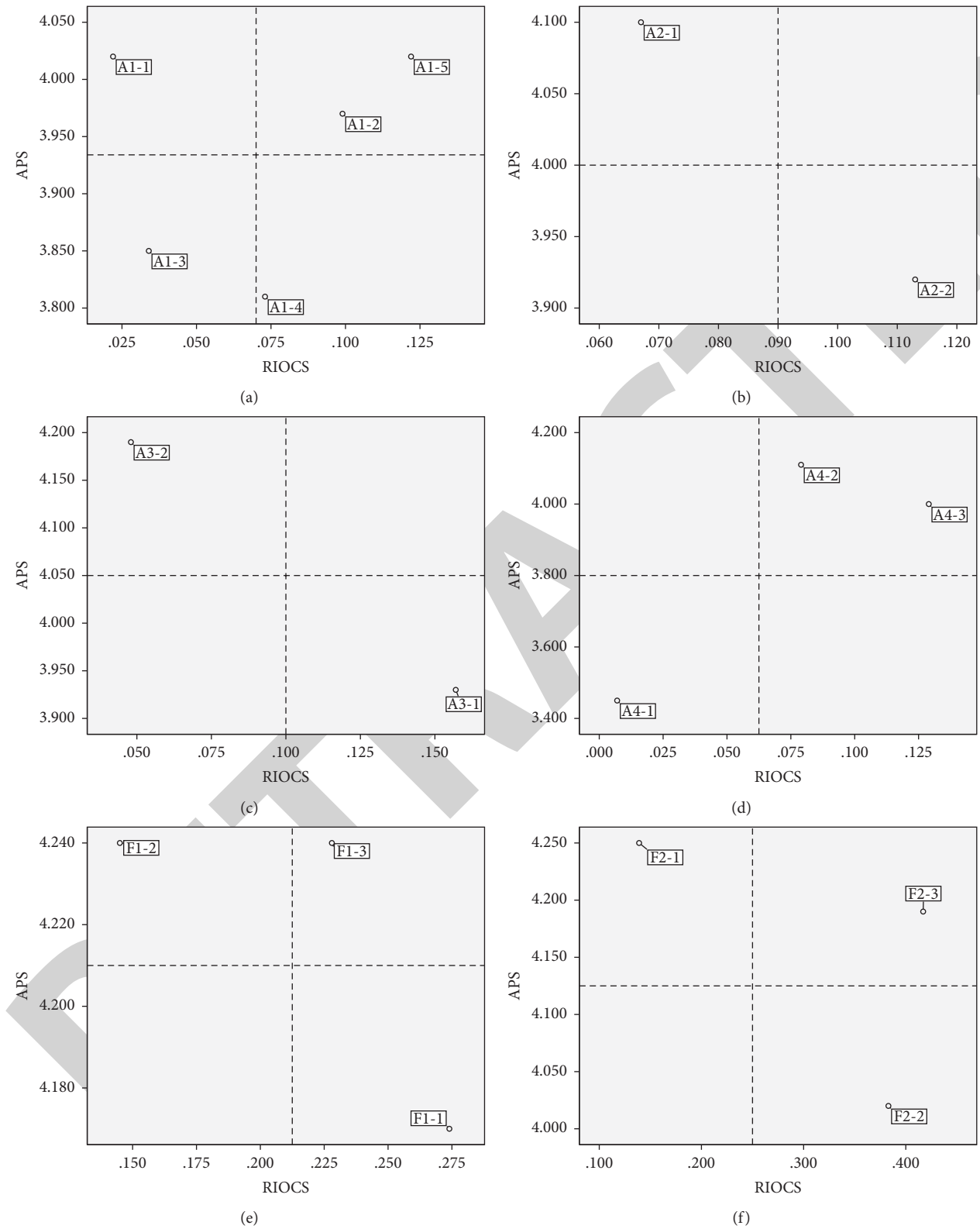

Figure 3: Impact-Range Performance Analysis of attributes. (a) Hotel amenities. (b) Hotel dining and banqueting facilities. (c) Hotel staff. (d) Hotel public facilities. (e) Halal food symbols and certification. (f) Halal food restaurants.

produced different grand mean values for attribute-performance score (APS) and RIOCS [32]. Notably, except (d) hotel public facilities, A1-4 (see Figure 3(a)), A2-2 (Figure 3(b)), A3-1 (Figure 3(c)), F1-1 (Figure 3(e)), and F2-2 (Figure 3(f)) fall into quadrant IV areas (i.e., lower APS and higher RIOCS), and all of these attributes require greater attention.

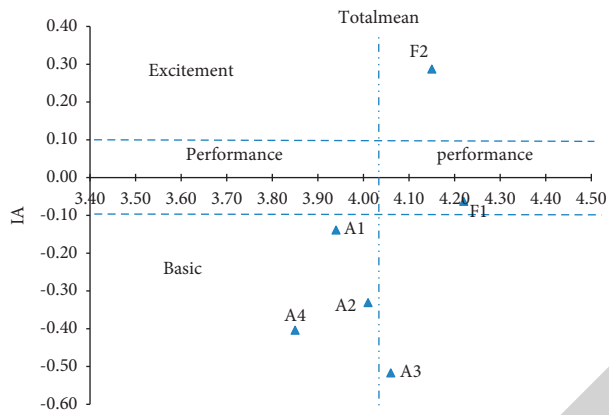

Figure 4: Asymmetric Impact-Performance Analysis of factor dimensions.

4.3.3. Asymmetric Impact-Performance Analysis (AIPA). To find the degree of the factors/attributes influencing OS, we used the IA index to measure the asymmetric effect. The IA index is evaluated by the difference between SGP and DGP, followed by the use of Caber et al. [28] concept to classify these factors/attributes based on the level of the IA index (see Section 3.1). The results of all IA scores and factor classifications are shown in Table 3.

It was found that categories of the "basic" comprised more than half of both the factor dimensions (4 out of 6, 66.67%) and more than 80% of both attributes (15 out of 18, 83.33%). This implies that basic services for Muslim tourism are must-be-provided factors, and they will lead to high customer dissatisfaction if absent. Next, the excitement factors show a more significant impact on satisfaction when implemented, and they do not trigger dissatisfaction when absent [23, 95]. This shows that F2 and A3-1, A3-2, and A4-1 belong to the excitement factors. When most Muslim respondents encounter these factors/attributes, they are very satisfied; however, a lack of these factors has little influence on their satisfaction level. Finally, F1 is the only performance factor. It is different from the basic and excitement factors, as it shows a particularly symmetrical link to Muslim respondents' satisfaction and dissatisfaction.

Moreover, to determine which characteristics of the factors/attributes should be identified and how an appropriate strategy should be devised with limited tourism resources, we employed Caber et al.'s [28] AIPA, which also presents a two-dimensional graphic between IA and performance scores. The IA scores along the vertical axis of 0.1 to −0.1 classified three types of excitement, performance, and basic factors. The performance scores along the horizontal axis are divided into low- and high-performance areas based on the vertical line of each factor and total mean value.

Following factor dimensions in Figure 4, A1 to A4 are all indicated as basic factors, but A1, A2, and A4 show low performance (to the left of the vertical dotted line of the total mean value). When performance is low, their characteristics exert a strong influence on OS. Hence, it would be useful to improve the current performance of these three factors. F2 was denoted as an excitement factor and positioned in the high-performance area. Due to its high performance, this condition's influence on OS was also high. The best strategy in this situation is to maintain or increase the number of resources available for this factor.

In Figure 5, six attributes (A1-3, A1-4, A2-2, A3-1, F1-1, and F2-2) belonged to the basic factors, but their performance trend was low with their mean value (vertical dotted lines of each factor). When an attribute's performance is low, it will highly influence Muslim tourists' OS. As such, these types of attributes should be dealt with immediately with several strategies to promote performance for increasing Muslim tourists' satisfaction. In contrast, the attributes of A3-1, A3-2, and A4-1 were the excitement factor, but A3-1 and A4-1 currently have a low performance based on their vertical mean line. Promoting the performance of this attribute could, thus, positively influence Muslim tourists' OS.

After analyzing IRPA and AIPA, we further screened the asymmetric effects of basic and excitement services of the factors/attributes located in the highest RIOCS and lowest performance areas (i.e., more attention area). As shown in Table 5, we found the factor dimensions of A1, "hotel amenities," and A2, "hotel dining and banqueting facilities," as well as the attributes of A1-4, "beds and toilet positioned so as not to face the direction of Mecca," and A2-2, "conservative TV channels and appropriate music." For the religious needs of Muslim tourists, it is recommended that strategies are immediately employed to improve these factors' performance and avoid future displeasure. Similarly, the food-related attributes of F1-1, "description of Halal food menu not limited by language," and F2-2, "certification of Halal food restaurants," are also considered important basic attributes to modify quickly. The result responses indicate that food outlets with appropriate, conveniently identifiable confirmation of Halal are sought-after by Muslim tourists [21].

Another interesting finding is that the excitement attribute A3-1, "an appropriate dress code is worn by hotel staff," was also positioned as requiring attention (see Table 5). This result was also found by Boğan et al. [87], who advised that hotel employees should boost their awareness of how to increase their overall image for Muslim travelers. Addressing excitement factors, however, is not as urgent as addressing basic factors, but they can increase Muslim tourists' OS when provided.

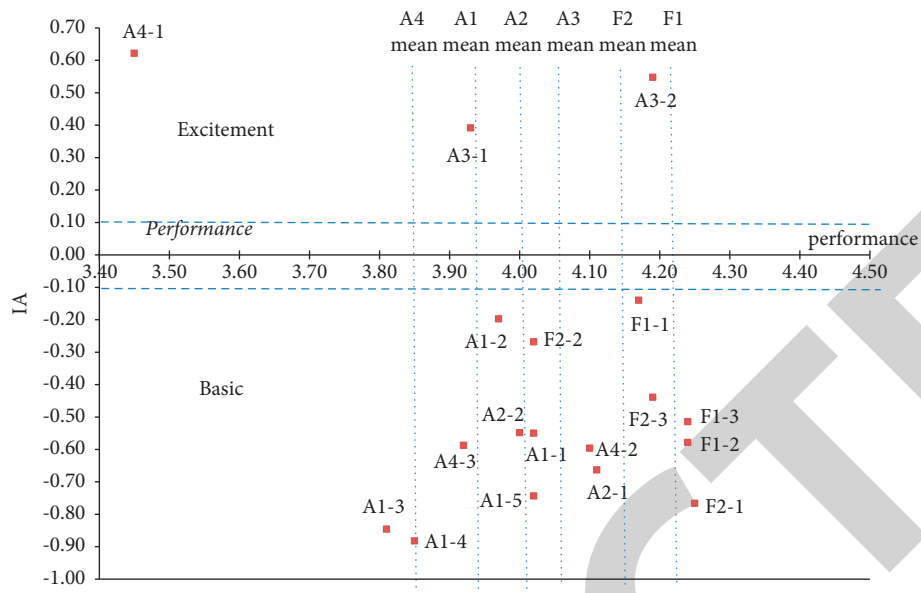

Figure 5: Asymmetric Impact-Performance Analysis of attributes.

Table 5: Asymmetric services' factors/attributes that require more attention.

IRPA		AIPA	Items	
Highest RIOCS	Lowest performance/APS	IA classification	Factor dimensions	Attributes
More attention area (quadrant IV)		Basic	A1	A1-4
			A2	A2-2
				F1-1
				F2-2
		Excitement		A3-1

5. Conclusions

Our study was to verify hotel and food tourism services that Muslim tourists perceived as basic needs while visiting a non-Muslim destination. Using a convenience sampling method, we selected 216 respondents from Indonesian Muslims working and living in Taiwan for more than one year. The EFA approach then suggested 18 attributes, including six factors within basic hotel and food services. Using GBDT methods instead of regression analysis, we produced a partial dependence to calculate the penalty and reward indices, which show the marginal effects of extremely low- and extremely high-performance incremental changes of OS. The Wilcoxon signed-rank test found that GBDT and the regression method are statistically different among the RI, PI, and RIOCS indexes and provide few advantages over the regression method. Subsequently, the IRPA and AIPA methods were used to examine the characteristics of each factor/attribute and devise an appropriate strategy.

Our proposed model was applied to understand Muslim tourists' important factors/attributes regarding basic hotel and food services provided by non-Muslim destinations. The theoretical implications are as follows. First, we found that the GBDT is different from the regression method by using the Wilcoxon signed-rank test. This implies that using the GBDT has several advantages to overcome the weakness of regression in PRCA analysis. Hence, it is important to find an efficient algorithm to extend insight into the relationship between attribute performance and OS when these attributes are available. Second, our study used multiple methods (i.e., EFA, GBDT, IRPA, and AIPA) to provide a more meaningful guideline for extracting the characteristics of crucial attributes. This means that Halal tourism practices applied in some destinations could be used as a benchmark for other destinations to target Muslim tourists [5].

According to the empirical results, the practical implications are listed as follows. One result found that hotel-related factors prioritize food-related services for many Muslim respondents. Putit et al. [57] and Jeaheng et al. [59] attempted to discover the important attributes of Halal-friendly hotel services, which significantly impact Muslim guests' satisfaction. This objective aligned with our study since prioritizing influential attributes contributes to cost savings and to high rankings. However, this study was different from ours because it ignored the effects of the combined indices (e.g., RIOCS and IA) and illustrated the attributes' position using figures. In addition, a basic hotel-related attribute factor, meeting the religious needs of Muslim respondents, requires significant attention. Similarly, Putit et al. [57] found that prayer facilities in Halal-friendly

hotels have the most significant impact on guest satisfaction. Hence, providing basic religious needs for Muslim tourists is a primary issue for Muslim-friendly hotels. A food-related basic attribute factor that needs to be addressed is appropriate Halal confirmation in restaurants and on menus. This implies that customers (Muslim tourists) pay more attention to the seller guarantees (Halal confirmation) except for the price [72]. Thus, when a Muslim decides to buy a tourism product, the religious aspect of the selection criteria is considered very important. Appropriate strategies to address basic and must-be-provided attributes should immediately improve the satisfaction levels of Muslim tourists and avoid their displeasure. Moreover, ensuring that an appropriate dress code is worn by hotel staff will also increase Muslim tourists' OS, but this is not as urgent.

Finally, we present some limitations and directions for further research. First, the GBDT method effectively illustrates the nonlinear relationship between variables but cannot produce confidence intervals and identify the statistically insignificant variables [37, 44]. Furthermore, the current study cannot substantiate the causal relationship between variables; future work should provide a more detailed model to determine the relationships and statistical inferences. Second, our study focused on the Muslim tourists' basic hotel and food service requirements when traveling to a non-Muslim destination. Therefore, apart from religion-related attributes, future studies may extend the scope of the topic to Muslim tourists. For example, considering the commercial dimension, the attributes of location, pricing, advertisement, goodwill, and the purpose of Muslim tourism can be explored. Third, extending from the Indonesian Muslim sample in our case, future studies could involve participants from different Muslim countries. Muslim perceptions can become a word-of-mouth tool to attract potential customers, such as when Muslims share their experience at non-Muslim destinations with their friends and families.

Data Availability

Data are available upon request from the authors.

Consent

Informed consent was obtained from all individual participants included in the study.

Conflicts of Interest

All authors declare that they have no conflicts of interest.

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