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The Integration Model of Kano Model and Importance-Performance and Gap Analysis—Application of Mutual Information

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Abstract: Service quality research has traditionally focused either on identifying Kano two-dimensional quality categories or detecting service quality deficiencies. However, integrating these perspectives remains a challenge due to the Kano model's nonlinear characteristics and the importance-performance and gap analysis (IPGA) model's linear approach. This study proposes the Kano-IPGA (KIPGA) model, incorporating mutual information (MI) to bridge the gap between these two models. The KIPGA model first employs moderated regression analysis to classify service attributes into Kano's quality categories. MI is then used to calculate the relative importance (RI), while relative performance (RP) is determined using the original IPGA approach. The results are mapped into the KIPGA strategic matrix, categorizing service attributes into eight management strategies. An empirical analysis of Taiwan's online insurance systems demonstrates the model's effectiveness in simultaneously identifying Kano categories and prioritizing service quality improvements. The findings reveal that critical improvement and enhanced improvement regions require immediate attention. The proposed KIPGA model offers a systematic approach for service quality management, providing decision-makers with a structured framework to allocate resources effectively and enhance customer satisfaction. This study contributes to service quality research by offering an integrated model that accounts for both linear and nonlinear quality assessment perspectives.

Keywords: service quality; Kano model; importance-performance and gap analysis (IPGA); mutual information (MI); KIPGA

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1. Introduction

In today's highly competitive market environment, service quality has become a crucial factor for enterprises to gain a competitive advantage. As customer expectations for services continue to rise, businesses must continuously enhance service quality to meet customer needs, increase satisfaction, and foster customer loyalty [1]. Chang and Cheng [2] further highlighted the need to evaluate and enhance service attributes to foster customer loyalty. However, the traditional service quality analysis method, importance-performance analysis (IPA), provides a means of identifying priority areas for service quality improvement [3]. Nevertheless, it has certain limitations in its application. As a result, many scholars have proposed improved methods. Notably, approaches such as simultaneous importance-performance analysis (SIPA) [4], revised importance-performance analysis [5], importance-performance and gap analysis (IPGA) [6], competitive importance-performance

analysis (CIPA) [7], and competitive importance-performance and gap analysis (CIPGA) [8] have been developed to provide a more comprehensive evaluation of service deficiencies. Among them, the IPGA model, which integrates IPA with service quality gap analysis, was proposed in our earlier work [6]. This integration effectively identifies service quality issues that require improvement and serves as a basis for resource allocation. The IPGA model has been applied in recent studies to identify priority service quality attributes in the online food delivery sector [9]; assess the relative importance and implementation status of corporate digital responsibility (CDR) measures [10]; prioritize improvement needs of airport service attributes based on passenger expectations [11]; explore the influence of sustainability initiatives on hotel guest satisfaction [12]; evaluate the importance and performance of pedestrian facilities for urban policy planning [13]; and examine service gaps to understand how airline safety services affect customer loyalty [14].

On the other hand, the Kano model has become a crucial tool for analyzing customer service needs due to its ability to classify service attributes into different quality categories [15]. Many scholars have adopted the Kano model for service quality classification. A notable research trend is the integration of the Kano model with importance-performance analysis (IPA) to enhance service quality assessment. For instance, Lin and Chan [16] integrated Kano's model with IPA to strengthen service quality improvement strategies. Similarly, Chen and Liu [17] combined the Kano model with IPA to explore student needs in synchronous distance learning environments incorporating gamification. Chen [18] adopted a revised IPA model with Kano to evaluate tourist satisfaction in airport terminals. In another study, Munawar et al. [19] applied the integration of SIPA and a modified Kano model to analyze telecommunication service quality. However, this integration is limited by the shortcomings of IPA, making it unable to effectively identify service quality gaps. Therefore, combining the Kano model with the IPGA model enables the simultaneous identification of Kano's two-dimensional quality categories and the prioritization of service quality improvements.

The Kano model considers nonlinear relationships. In contrast, the IPGA model is primarily based on linear correlation analysis. As a result, the IPGA model fails to fully capture the nonlinear relationships, leading to differences in the identification of key improvement items compared to the Kano model. To address the above issues, this study proposes introducing mutual information (MI) as an analytical tool. MI can measure the total correlation between two variables, including both linear and nonlinear relationships, providing more comprehensive information than traditional correlation coefficients. Therefore, this study intends to incorporate MI to integrate the Kano model and IPGA model, developing a comprehensive KIPGA model.

Through the KIPGA model, businesses can simultaneously identify the Kano quality categories of service quality attributes and analyze the improvement priority of each service quality factor. This allows businesses to effectively identify key service-quality factors in need of improvement. Moreover, this study will establish a strategic matrix based on the developed integrated model. This will assist businesses in formulating service quality management strategies, optimizing resource allocation, enhancing service quality, meeting customer needs, and strengthening market competitiveness.

In summary, this study aims to integrate the Kano two-dimensional quality model, the IPGA model, and mutual information (MI) to provide a more precise and comprehensive tool for service quality analysis. This tool will help businesses develop effective service quality improvement strategies under limited resources, addressing the limitations of existing models in identifying nonlinear relationships between service quality and target performance. The research objectives are as follows:

(1) To utilize the characteristics of mutual information (MI) in analyzing both linear and nonlinear relationships between two variables, and to develop an integrated model—

KIPGA—that combines the Kano model and the IPGA model. This model will enable the simultaneous identification of Kano two-dimensional quality categories and the prioritization of service quality improvements. As a result, it can help identify key service quality factors that require improvement.

(2) Based on the developed integrated model, this study aims to formulate a strategic matrix according to Kano two-dimensional quality categories and the prioritized improvement order of service quality factors. This matrix will serve as a foundation for developing effective service quality management strategies.

2. Literature Review

2.1. IPA and IPGA

The concept of importance-performance analysis (IPA) involves using surveys to understand users' perceptions of the "importance" and "performance" levels of quality attributes. A two-dimensional matrix of importance and performance levels is then used to categorize these attributes into four quadrants: Keep Up the Good Work, Concentrate Here, Low Priority, and Possible Overkill [3]. While the IPA model is widely regarded by researchers as a simple tool for performance evaluation and quality management, it also presents certain practical issues in application and decision-making. These issues include the inability to differentiate quality attributes within the same quadrant, the lack of consideration for service gaps, variations in the importance of quality attributes, and subjective conflicts [6]. Therefore, many scholars have proposed methods for improvement. Among them, our previous work [6] introduced the importance-performance and gap analysis (IPGA) model. This model integrates importance-performance analysis (IPA) with service quality gap analysis by replacing the IPA model's coordinate axes with relative importance (RI) and relative performance (RP). Similar to the traditional IPA model, the IPGA model divides resource allocation into four quadrants with different strategic implications.

The IPGA model applies transformation functions to the two coordinate axes. If the importance of the j-th attribute is significantly lower than its service performance, it indicates that the attribute has not met consumer expectations. Thus, its position in the matrix should fall into a high-priority range for resource allocation. Conversely, if the importance of the j-th attribute is significantly higher than its service performance, it suggests that the attribute has exceeded consumer expectations. Therefore, its position in the matrix should be in a lower priority range for resource allocation. When an attribute is located in Quadrant II of the IPGA matrix, it represents high relative importance and low relative performance. In other words, attributes in Quadrant II are highly important but exhibit lower service performance than expected. On the other hand, when an attribute is farther from the intersection point within Quadrant II, the priority for resource adjustment increases (as shown in Figure 1 [6], Attribute A has a higher resource adjustment priority than Attribute B).

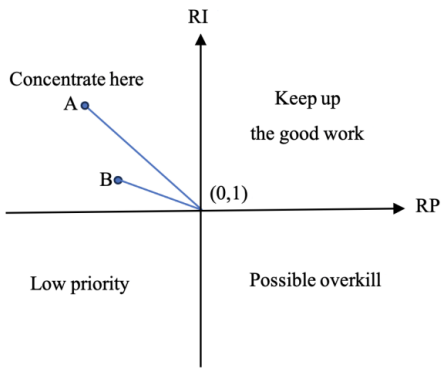


Figure 1. IPGA matrix diagram [6].

2.2. KANO Two-Dimensional Quality

The Kano two-dimensional quality model, proposed by Noriaki Kano in 1984, is a framework used to analyze customer needs and satisfaction [15]. The model classifies quality attributes into five categories based on their impact on customer satisfaction: must-be quality, one-dimensional quality, attractive quality, indifferent quality, and reverse quality. The significant contribution of the Kano model lies in its ability to help businesses understand the varying effects of different quality attributes on customer satisfaction. This understanding enables organizations to optimize resource allocation and design products and services that align with customer needs, thereby improving customer satisfaction and loyalty. Additionally, the model highlights the dynamic nature of quality attributes over time and with increasing market competition. Specifically, attributes classified as attractive quality may gradually transition to one-dimensional quality or even evolve into must-be quality [15].

In the Kano two-dimensional quality identification method, Kano et al. (1984) proposed the model and designed a questionnaire analysis approach [15]. Berger et al. (1993) further refined the application of the questionnaire analysis method [20]. This method primarily collects customer responses to specific attributes through a questionnaire, using functional questions and dysfunctional questions, and classifies attributes based on these responses.

Additionally, the moderated regression analysis method used in this study was originally proposed by one of the co-authors in a previous work [21] to identify the attribute categories of various service items. This method examines the relationship between customers' evaluations of all service attributes and the target performance using moderated regression analysis. The target performance can include overall satisfaction, continuous use, or recommendation to others. This method facilitates questionnaire design in empirical analysis and can be integrated with IPGA for further analysis. Therefore, this study adopts this method to identify Kano two-dimensional quality categories.

2.3. Mutual Information (MI)

In 1948, Claude Shannon proposed the concept of mutual information (MI), defining it using the joint probability function. The distinguishing feature of MI lies in its ability to capture both the linear and nonlinear relationships between variables. This makes it particularly advantageous when dealing with high-dimensional or nonlinear data. When analyzing data associations, MI provides a more comprehensive correlation analysis compared to traditional statistical methods (e.g., Pearson correlation coefficient), which only measure linear relationships [22]. For datasets with nonlinear patterns, MI can detect a broader range of dependencies, whereas correlation coefficients may underestimate these associations. For example, if $Y = X^2$, the Pearson correlation coefficient might approach 0, yet MI can accurately reflect the dependency between X and Y.

Regarding the applications of MI, Laarne et al. (2022) utilized MI to explore nonlinear relationships among atmospheric variables [23]. Their study highlighted that this method effectively identifies significant associations in complex datasets and captures nonlinear patterns, particularly excelling in handling data with exponential distributions. Compared to traditional correlation analyses (e.g., Pearson correlation coefficient), MI demonstrates significant advantages. Dionisio, Menezes, and Mendes (2004) applied MI in financial research to detect nonlinear relationships between time series [24]. The study emphasized that MI better describes nonlinear associations between two variables compared to traditional correlation coefficients. Young et al. (2023) employed MI to investigate critical features of variables in epidemiologic data [25]. The study specifically highlighted the following three characteristics of MI:

(i) Its ability to capture all types of relationships, including both linear and nonlinear.
(ii) It equals zero only when the random variables are independent.
(iii) It serves as a robust measure of relationship strength.

On the other hand, Vergara and Estévez (2014) reviewed MI's application scenarios and noted that compared to other related indices (including correlation coefficients), MI proves significantly more effective in handling nonlinear or high-dimensional data [26].

Regarding the relationship between MI and the correlation coefficient, when the relationship between two variables is primarily linear and (X,Y) follows a bivariate normal distribution [27]:

$$MI(X,Y) = -\frac{1}{2}\log(1-r^2)$$

where r^2 is the squared correlation coefficient.

The above formula indicates that MI and the correlation coefficient can exhibit similar relative magnitudes. This means that as the correlation coefficient increases, MI also becomes larger.

In summary, MI is an important tool for measuring the relationship between variables. It not only captures both linear and nonlinear relationships but also effectively handles high-dimensional and complex data, addressing the limitations of traditional correlation coefficients.

Although IPA and IPGA are widely used for service quality evaluation, these models primarily focus on the linear relationships between service attributes and customer perceptions, making them insufficient for capturing nonlinear effects. In contrast, the Kano model considers nonlinear relationships, but it lacks a structured approach to prioritizing improvement efforts. To address this gap, this study integrates the Kano model with IPGA and introduces mutual information (MI) to quantify the impact of service attributes on customer perceptions. The proposed KIPGA model not only identifies Kano two-dimensional quality categories but also prioritizes service quality improvements based on relative importance (RI) and relative performance (RP) values. By bridging the gap between linear performance evaluation and nonlinear customer perception analysis, this model provides a comprehensive and systematic framework for service quality management and resource allocation.

3. Research Method

3.1. Development of KIPGA Mode

This study aims to integrate the Kano and IPGA models to develop a comprehensive framework, referred to as the Kano-IPGA (KIPGA) model. This framework will enable the simultaneous identification of service quality attribute types, key service quality attributes requiring improvement, and their prioritized improvement order. However, since the Kano model considers both linear and nonlinear relationships, while the IPGA model is based solely on a linear approach, this study incorporates mutual information (MI) to modify the IPGA model.

The IPGA model calculates relative importance (RI) and relative performance (RP). In the calculation,

$$RI_i = \frac{I_i}{\overline{I}} \tag{1}$$

where I_i represents the importance of the i-th service quality attribute and $\overline{I}$ represents the average importance of the service quality attributes. The calculation of relative performance (RP) is as follows, as shown in Table 1:

This study will retain the relative performance (RP) of the IPGA model while modifying the relative importance (RI). The revised model is explained as follows:

Table 1. Rules for calculating relative performance (RP).

Importance and Performance Analysis of Attribute *i*	***Results of the Paired Sample t-Test***	***Calculation of RP Value***
$P_i > I_i$	*Significance* ($p < 0.05$)	$P_i/\overline{P}$
$P_i < I_i$	*Significance* ($p < 0.05$)	$-(P_i/\overline{P})^{-1}$
$P_i \geq I_i$ *or* $P_i < I_i$	*Non-significance* ($p > 0.05$)	*0*

Note: The performance of attribute i is P_i and its importance is I_i. The average performance of all attributes is $\overline{P}$.

Let I_i denote the impact of the i-th attribute on the target performance (e.g., overall satisfaction), which corresponds to the mutual information value (MI) between the i-th attribute and the target performance. That is as follows:

$$I_i = MI(S_i, OS). \tag{2}$$

where S_i represents the evaluation of the i-th attribute and OS represents the target performance (e.g., overall satisfaction).

The value $MI(S_i, OS)$ is used to replace the importance measure in the IPGA model. Combined with the Kano two-dimensional quality categories, this study calculates the relative importance (RI) value as follows:

1. One-dimensional Quality: When the i-th attribute is a one-dimensional quality, its relative importance (RI) is as follows:

$$RI_i = \frac{I_i}{\overline{I}_P} \tag{3}$$

where $\overline{I}_P$ represents the average mutual information (MI) between all attributes belonging to the one-dimensional quality category and the target value, expressed as $\overline{I}_P = \frac{\sum_{i \in P} I_i}{\#\{P\}}$, where P represents the set of one-dimensional quality attributes and $\#\{P\}$ denotes the number of elements in the set P. The relative importance (RI_i) differs from the RI value in IPGA and is normalized based on MI values. This ensures that the importance measure reflects both the linear and nonlinear relationships between attributes and the target performance.

2. Attractive Quality: When the i-th attribute is an attractive quality and its performance is greater than or equal to 0 ($RP_{\mathrm{i}} \geq 0$), the relative importance of this attribute is as follows:

$$RI_i = \max_{k \in P} RI_k + \xi_1 \times \frac{I_i}{\max_{j \in E} I_j} \tag{4}$$

where E represents the set of attractive quality (excitement needs) attributes, $\xi_1 > 0$.

This formula was developed in this study to address the integration of Kano's nonlinear classification with the IPGA model while utilizing mutual information (MI) to refine the calculation of relative importance. When the attribute belongs to the excitement quality category and its performance is greater than or equal to 0, it indicates that quality improvement at this stage can yield higher benefits. This signifies that its relative importance is higher than all performance quality attributes. The rationale behind this formulation is as follows:

(1) **Ensuring Relative Importance Consistency:** The term $\max_{k \in P} RI_k$ guarantees that attractive quality attributes are assigned a higher relative importance than all one-dimensional quality attributes. This aligns with the principle that attractive quality attributes tend to have a disproportionate positive impact when improved.

(2) **Normalization and Scaling Adjustment:** The term $\xi_1 \times \frac{I_i}{\max\limits_{j\in E} I_j}$ serves as a scaling factor that normalizes the relative importance values within the attractive quality category. This ensures that attributes within this category are appropriately positioned in the KIPGA strategic matrix while maintaining differentiation in their impact levels.

(3) **Enhancing Matrix Visualization:** The introduction of ξ_1 facilitates better visualization in the two-dimensional matrix. By normalizing values towards 1, it maintains clarity in distinguishing between different attractive quality attributes while ensuring that the importance measure remains interpretable.

For the subsequent formulas, a similar approach is applied to ensure that the classification and. prioritization of service quality attributes align with the theoretical underpinnings of Kano's model while maintaining compatibility with IPGA's resource allocation framework.

3. Must-be Quality: When the *i*-th attribute is a must-be quality and its performance is less than 0 ($RP_{\mathrm{i}} < 0$), the relative importance of this attribute is as follows:

$$RI_i = \max_{k\in P} RI_k + \xi_2 \times \frac{I_i}{\max\limits_{j\in B} I_j} \tag{5}$$

where B represents the set of must-be quality (basic needs) attributes, ξ_2>0.

The reason for selecting ξ_2 is the same as that for ξ_1, which is also for the visualization of the two-dimensional matrix coordinates. When the attribute belongs to the must-be quality category and its performance is less than 0, failing to improve its quality could cause a significant negative impact on the target. This signifies that its relative importance is higher than all one-dimensional quality attributes. For attributes that also belong to the must-be quality category, to facilitate visualization in the matrix while still reflecting the differences in their impact on the target, their values are normalized (unitized) towards 1.

4. Must-be Quality: When the *i*-th attribute is a must-be quality and its performance is greater than or equal to 0 ($RP_{\mathrm{i}} \geq 0$), the relative importance of this attribute is as follows:

$$RI_i = \min_{k\in P} RI_k - \xi_3 \times \frac{\max\limits_{j\in B} I_j - I_i}{\max\limits_{j\in B} I_j} \tag{6}$$

where B represents the set of *basic factors*, $\xi_3 > 0$.

The reason for selecting ξ_3: is the same as that for ξ_1 and ξ_2. When an attribute belongs to the must-be quality category and its performance is greater than or equal to 0, quality improvements will have only a minimal impact on the target. This indicates that its relative importance is lower than all one-dimensional quality attributes. For attributes within the must-be quality category, normalization is applied to facilitate visualization in the matrix while still reflecting differences in their impact on the target. This formula indicates that the greater the difference between the MI value of this attribute and the maximum MI value, the lower its relative importance.

5. Attractive quality: When the *i*-th attribute is an attractive quality and its performance is less than 0 ($RP_{\mathrm{i}} < 0$), the relative importance of this attribute is as follows:

$$RI_i = \min_{k\in P} RI_k - \xi_4 \times \frac{\max\limits_{j\in E} I_j - I_i}{\max\limits_{j\in E} I_j} \tag{7}$$

where E represents the set of *excitement factors*, $\xi_4 > 0$.

The reason for selecting ξ_3: is the same as that for ξ_1, ξ_2, and ξ_3. When an attribute belongs to the attractive quality category and its performance is less than 0, improving this quality attribute will have only a minimal impact on the target. This indicates that its relative importance is lower than the one-dimensional quality. For attributes within the

attractive quality category, normalization is applied to facilitate visualization in the matrix while still reflecting differences in their impact on the target. This formula indicates that the greater the difference between the MI value of this attribute and the maximum MI value, the lower its relative importance.

The mathematical model summarizing the above explanation is as follows:

$$RI_i = \begin{cases} \frac{I_i}{\overline{I}_P} & ,i \in P \\ \max\limits_{k\in P} RI_k + \xi_1 \times \frac{I_i}{\max\limits_{j\in E} I_j} & ,i \in E \cap RP_{\mathrm{i}} \geq 0 \\ \max\limits_{k\in P} RI_k + \xi_2 \times \frac{I_i}{\max\limits_{j\in B} I_j} & ,i \in B \cap RP_{\mathrm{i}} < 0 \\ \min\limits_{k\in P} RI_k - \xi_3 \times \frac{\max\limits_{j\in B} I_j - I_i}{\max\limits_{j\in B} I_j} & ,i \in B \cap RP_{\mathrm{i}} \geq 0 \\ \min\limits_{k\in P} RI_k - \xi_4 \times \frac{\max\limits_{j\in E} I_j - I_i}{\max\limits_{j\in E} I_j} & ,i \in E \cap RP_{\mathrm{i}} < 0 \end{cases} \quad (8)$$

where P represents the set of *performace quality* attributes; B represents the set of basic *quality attributes*; E represents the set of *attractive quality* (*excitement needs*) attributes; $I_i = MI(S_i, OS)$, $\xi_i > 0$, S_i represents the evaluation of the i-th attribute, $i = 1, 2, 3, 4$; OS represents the target performance, $\overline{I}_P = \frac{\sum_{j\in P} I_j}{\#\{P\}}$.

According to the above formula, the range of RI values calculated by MI is determined by the rating scale of importance and performance. If both importance and performance scores range from 1 to k, then the resulting RI values will be within the range of 0 to k + ξ_i. Generally, ξ_i is assigned a small value less than 1. However, RI does not exhibit monotonicity, as MI captures the nonlinear dependencies between attributes and target performance, meaning that RI values do not necessarily increase or decrease in a strictly ordered manner. This characteristic reflects the varying influence of different service attributes on the target performance.

3.2. Strategic Matrix Management Implications of the KIPGA Model

Based on the KIPGA model, this study divides the two-dimensional coordinates into eight regions. The strategic matrix diagram uses (0, 1) as the center point, with relative performance (RP) as the X-axis and relative importance (RI) as the Y-axis. Two parallel dashed lines are added (line1: $x1 = \max\limits_{k\in P} RI_k$, line2: $x2 = \min\limits_{k\in P} RI_k$) to create an eight-region strategic matrix diagram, as shown in Figure 2.

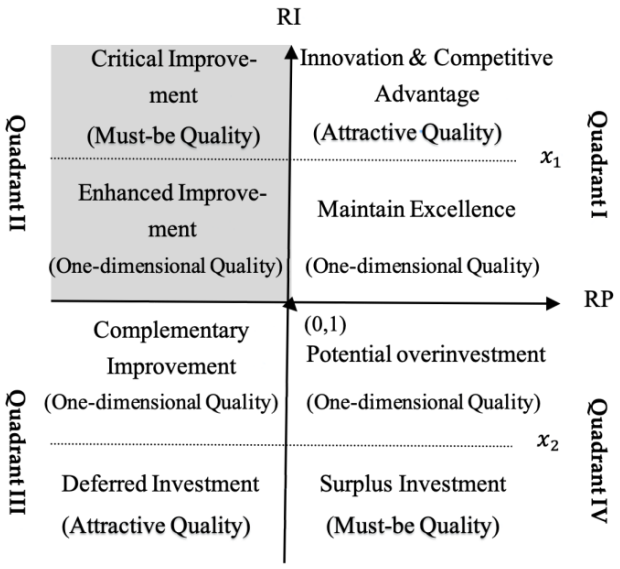


Figure 2. KIPGA strategic matrix.

The management strategies for the eight regions are described as follows:

Quadrant I: This quadrant consists of high relative importance and positive performance attributes. Based on its strategic implications, it is further divided into two regions.

(1) **Innovation and Competitive Advantage** (Upper Region of Quadrant I)

Attributes in this region belong to the attractive quality category for strategic objectives. This means that investing resources in these attributes yields a positive nonlinear effect, generating significantly greater benefits than other attributes. As a result, these attributes exhibit high relative importance. Additionally, customers currently rate these attributes higher than their expectations, reflecting a positive performance. This indicates that customers are already perceiving the company's efforts in these areas. Thus, attributes in this quadrant can be regarded as competitive advantage factors, and companies should continue investing in them. If resources are sufficient, further investment in these attributes will enhance differentiation and competitiveness.

(2) **Maintain Excellence** (Lower Region of Quadrant I)

Attributes in this region belong to the one-dimensional quality category for strategic objectives. This means that investing resources in these attributes yields a positive linear effect, generating relatively higher benefits compared to other attributes (except for Innovation and Competitive Advantage attributes). Consequently, these attributes have a high relative importance. Additionally, customers currently rate these attributes higher than their expectations, indicating positive performance. Managers should continue maintaining the current level of investment, while service providers should consistently monitor their performance to ensure sustained quality.

Quadrant II: This quadrant consists of attributes with high relative importance and. negative performance. Based on its strategic implications, it is further divided into two regions.

(3) **Critical Improvement** (Upper Region of Quadrant II)

Attributes in this region belong to the must-be quality category for strategic objectives. However, customers currently rate these attributes lower than their expectations, indicating negative performance. This indicates that customers perceive the provided level of these attributes as insufficient. Additionally, investment in this region yields nonlinear effects, meaning that improving these attributes will generate significantly greater benefits than other attributes, making them highly important. Therefore, attributes in this quadrant should be regarded as key priority monitoring attributes, requiring increased investment and improvement until customers rate them above their expectations, achieving positive performance. This region is the top priority for improvement.

(4) **Enhanced Improvement** (Lower Region of Quadrant II)

Attributes in this region belong to the one-dimensional quality category for strategic objectives. This indicates that resource investment has a positive linear effect on the target, generating relatively higher benefits compared to other attributes (except for critical improvement attributes). However, customers currently rate these attributes lower than their expectations, indicating negative performance. This means that customers perceive the provided level of these attributes as insufficient. Therefore, additional resources should be allocated to improve these attributes until customer ratings exceed expectations and achieve positive performance.

Quadrant III: This quadrant consists of attributes with low relative importance and negative performance. Based on its strategic implications, it is further divided into two regions.

(5) **Complementary Improvement** (Upper Region of Quadrant III)

Attributes in this region belong to the one-dimensional quality category for strategic objectives. This means that resource investment in these attributes yields a positive linear effect, but the benefits generated are relatively low. As a result, these attributes have low relative importance. However, customers currently rate these attributes lower than their expectations, indicating negative performance. This indicates that customers perceive the provided level of these attributes as insufficient. Therefore, resource allocation to improve these attributes should only be considered after higher-priority attributes have been addressed. Once improvements in more important areas are completed, additional resources can be invested in this region until customer ratings exceed expectations and achieve positive performance.

(6) **Deferred Investment** (Lower Region of Quadrant III)

Attributes in this region belong to the attractive quality category for strategic objectives. This means that resource investment in these attributes yields a positive nonlinear effect. However, customers currently rate these attributes lower than their expectations, indicating negative performance. This indicates that customers have not yet perceived the company's development efforts in these areas. Although the benefits generated by improving these attributes are higher, these attributes have not been a major focus in the past, meaning that significant resource investment would be required for improvement. From the perspective of resource allocation order, these attributes have low relative importance. Therefore, after addressing higher-priority attributes, companies may consider investing resources in these attributes if additional capacity is available.

Quadrant IV: This quadrant consists of attributes with low relative importance and. positive performance. Based on its strategic implications, it is further divided into two regions.

(7) **Potential Overinvestment** (Upper Region of Quadrant IV)

Attributes in this region belong to the one-dimensional quality category for strategic objectives. This means that resource investment in these attributes yields a positive linear effect, but the benefits generated are relatively low. Customers rate these attributes as meeting their expectations, indicating positive performance. This means that customers already perceive the provided level of these attributes as sufficient. Therefore, managers should evaluate whether these services are at risk of oversupply. However, continuous monitoring is necessary to ensure performance does not decline, and resource adjustments should be made if needed.

(8) **Surplus Investment** (Lower Region of Quadrant IV)

Attributes in this region belong to the must-be quality category for strategic objectives. Customers rate these attributes as meeting their expectations, indicating positive performance. This means that customers already perceive the provided level of these attributes as sufficient. At this stage, additional resource investment in these attributes would generate significantly lower benefits compared to other attributes. Therefore, managers should evaluate whether these services are already overinvested, and resource adjustments should be made if necessary.

3.3. Priority of Resource Adjustment

In the KIPGA strategic matrix, Quadrant II represents the primary improvement area. Quadrant II is further divided into critical improvement and enhanced improvement. The following section explains the priority order for resource adjustments in these two key regions.

(1) **Critical Improvement**

For the critical improvement region, this study identifies the intersection point $(0, a)$ of the x1 line with the *y*-axis in the KIPGA strategic matrix, where $x1 = \max_{k \in P} RI_k$. When the coordinate of attribute k in this region is $(RP_k,\ RI_k)$, the standardized distance between $(RP_k,\ RI_k)$ and $(0, a)$ is calculated using the following formula:

$$DI_{CI}(k) = \sqrt{[|RP_k| / \max_{r \in CI}(|RP_r|]^2 + [(RI_k - a) / \max_{r \in CI}(RI_r - a))]^2} \quad (9)$$

where CI represents the critical improvement region in Quadrant II. The larger this value, the higher the priority of this attribute for improvement.

(2) **Enhanced Improvement**

For the enhanced improvement region, when the coordinate of attribute k in this region is $(RP_k,\ RI_k)$, the standardized distance between $(RP_k,\ RI_k)$ and the coordinate center point $(0, 1)$ is calculated using the following formula:

$$DI_{EI}(k) = \sqrt{[|RP_k| / \max_{r \in EI}(|RP_r|]^2 + [(RI_k - 1) / \max_{r \in EI}(RI_r - 1))]^2} \quad (10)$$

where EI represents the enhanced improvement region in Quadrant II. The larger this value, the higher the priority of this attribute for improvement in the region.

3.4. Implementation Steps of the KIPGA Model

According to the development framework of the KIPGA model, this study outlines its implementation steps as follows.

Step 1. Determine Kano two-dimensional quality categories.

Use the moderated regression analysis method to determine the Kano two-dimensional quality categories [22]. This method analyzes the relationship between customers' evaluations of all service attributes (S_{ij}) and the target performance (OS_j) using moderated regression analysis. The target performance can include overall satisfaction, continuous use, or recommendation to others. The analysis model is as follows:

$$OS_j = \beta_0 + \beta_1 S_{ij} + \beta_2 S_{ij} * Z_{ij} \quad (11)$$

where $Z_{ij} = \begin{cases} 1, & S_{ij} < m \\ 2, & S_{ij} = m \\ 3, & S_{ij} > m \end{cases}$, m represents the moderate evaluation value and $\beta_0, \beta_1, \beta_2$ are the regression coefficients.

The classification criteria for each service category factor are shown in Table 2 [23].

Table 2. Classification of factors identified through moderated regression analysis [23].

Factor Category	Attractive Quality	Basic Quality	One-Dimensional Quality	Indifferent Quality	Reverse Quality
β_2	>0	<0	=0	=0	=0
β_1	any value	any value	>0	=0	<0

Step 2. Calculate MI values.

Use the concept of mutual information proposed by Shannon (1948) to calculate the MI value as follows [22]:

$$MI(X, Y) = \sum_{x \in X} \sum_{y \in Y} f(x, y) log \frac{f(x, y)}{g(x)h(y)} \quad (12)$$

where $f(x, y)$ represents the joint probability distribution of the random variables (X,Y).

$g(x), h(y)$ represent the marginal probabilities of X and Y, respectively.

Step 3. Calculate RP values.

Use the rules in Table 1 to calculate the relative performance (RP).

Step 4. Calculate RI values.

Use Formula (8) to calculate the relative importance (RI).

Step 5. Classify attributes in the KIPGA strategic matrix.

Use Figure 2 to classify the service attributes within the KIPGA strategic matrix based on Kano two-dimensional quality categories and the RP and RI values.

Step 6. Determine the key critical improvement factors

For the critical improvement region, use Formula (9) to calculate the standardized distance: $DI_{CI}(k)$. For the enhanced improvement region, use Formula (10) to calculate the standardized distance: $DI_{EI}(k)$.

4. Empirical Analysis

This study aims to enhance the continuous use of online insurance systems in Taiwan by conducting an empirical analysis of KIPGA service quality categories and improvement strategies. In this research, the E-S-QUAL mobile service quality scale was used as a foundation [21,24]. Additionally, key functions of various online insurance platforms in Taiwan and the characteristics of insurance services were integrated to develop a service quality scale for online insurance systems. This scale consists of nine dimensions with a total of 26 attributes, including efficiency (3 attributes), fulfillment (4 attributes), system availability (2 attributes), privacy and security (3 attributes), responsiveness (2 attributes), compensation (2 attributes), contact (3 attributes), personalization (5 attributes), and tangibility (2 attributes). Table 3 provides detailed information.

The research participants are Taiwanese individuals who have previously used online insurance systems. This study adopts a 5-point Likert scale for measurement, followed by data collection through an online survey. A total of 357 valid responses were collected, evaluating the importance and satisfaction of all quality attributes, as well as the users' willingness to continue using the system. This study focuses on individuals as the research subjects under the age of 50. In terms of sample composition, 52.8% were male, and 47.2% were female. Participants under 30 years old account for 43.1%, those aged 30–40 make up 33.9%, and those aged 40–50 constitute 23%. Additionally, 39.8% of the respondents were married, while 60.2% were unmarried.

For the importance scale, the Cronbach's α of each dimension ranged from 0.686 to 0.939, with standardized factor loadings > 0.5 and average variance extracted (AVE) > 0.5. For the satisfaction scale, the Cronbach's α of each dimension ranged from 0.880 to 0.969, with standardized factor loadings > 0.5 and AVE > 0.5. These results indicate that the questionnaire demonstrated good reliability and validity.

First, this study conducted a descriptive analysis and paired *t*-test for each research variable. The analysis results are summarized in the table below.

Table 3. Descriptive analysis and paired *t*-test of research variables.

Dimension	Attribute	Code	Importance		Performance		Paired *t*-Test
			Mean	Std	Mean	Std	
Efficiency	Available at any time	EF1	4.350	0.799	4.353	0.741	0.069 (ns)
	Easy to use	EF2	4.574	0.770	4.314	0.809	−6.367 *
	Fast completion of the insurance process	EF3	4.451	0.787	4.322	0.775	−3.154 *

Table 3. *Cont.*

Dimension	Attribute	Code	Importance		Performance		Paired *t*-Test
			Mean	Std	Mean	Std	
Fulfillment	Real-time and accurate insurance information	PF1	4.616	0.739	4.373	0.756	−6.086 *
	Complete insurance information	PF2	4.597	0.730	4.336	0.793	−6.458 *
	Comprehensive insurance application process	PF3	4.543	0.758	4.375	0.753	−4.196 *
	Comprehensive claims process and details	PF4	4.591	0.735	4.339	0.786	−5.518 *
System Usability	System operates normally	SA1	4.597	0.742	4.375	0.749	−5.424 *
	Stable system without crashes	SA2	4.566	0.722	4.3	0.809	−5.909 *
Privacy and Security	Secure password and key login mechanism	PS1	4.527	0.736	4.426	0.737	−2.821 *
	Secure and fast biometric login mechanism	PS2	4.423	0.785	4.336	0.789	−2.293 *
	Information security management mechanism	PS3	4.644	0.618	4.451	0.696	−5.960 *
Responsiveness	Provides clear error messages when issues occur	RE1	4.639	0.623	4.336	0.807	−7.601 *
	Quickly responds with solutions when problems arise	RE2	4.675	0.567	4.331	0.830	−8.053 *
Compensation	Refunds available in case of insurance errors due to system malfunction	CP1	4.669	0.620	4.317	0.841	−8.863 *
	Compensation available for losses caused by system malfunctions	CP2	4.661	0.636	4.314	0.839	−8.407 *
Contact	Customer service email provided	CT1	4.375	0.756	4.227	0.808	−4.169 *
	Telephone customer service hotline available	CT2	4.549	0.675	4.291	0.789	−7.302 *
	Online intelligent customer service available	CT3	4.303	0.837	4.16	0.874	−3.737 *
Personalization	Provides personalized professional insurance information	PE1	4.499	0.681	4.263	0.823	−5.652 *
	Offers a personalized user interface	PE2	4.468	0.697	4.286	0.802	−4.770 *
	Provides insurance needs estimation function	PE3	4.557	0.666	4.314	0.788	−6.273 *
	Offers policy health check service	PE4	4.459	0.712	4.275	0.823	−4.529 *
	Provides personalized historical insurance records	PE5	4.454	0.739	4.283	0.772	−4.413 *
Tangibility	Visually appealing interface	TG1	4.039	0.914	4.092	0.841	1.262 (ns)
	Well-designed user experience	TG2	4.255	0.760	4.221	0.824	−1.037 (ns)
Continuous use	-	CU	-	-	4.255	0.786	-

Note. * indicates $p < 0.05$; "ns" indicates a non-significant result ($p > 0.05$).

This study applies the implementation steps of the KIPGA model for further analysis based on the aforementioned analysis results.

Step 1. Determine Kano two-dimensional quality categories.

Using each respondent's evaluated continuous use as the target performance (OS_j) and each attribute as the independent variable (S_{ij}), Formula (11) is applied to perform

moderated regression analysis. The results are interpreted using the classification criteria in Table 2 to determine the Kano two-dimensional quality categories. The results of this analysis are presented in the 'Quality Category' column of Table 4.

Step 2. Calculate MI values.

The relative frequency distributions from the sample data were used to calculate $g(x), h(y)$, and $f(x, y)$. Subsequently, mutual information (MI) values were derived using Formula (12), with the corresponding results presented in the MI column of Table 4.

Step 3 and 4 Calculate RP values and RI values.

Following the rules in Table 1 and applying Formula (8), the relative performance (RP) and relative importance (RI) were calculated. These results are presented in the RP and RI columns of Table 4.

The overall analysis results are presented in the table below.

Table 4. KIPGA analysis for enhancing the continuous use of online insurance systems.

Dimension	Code	Quality Category	Performance Gap	MI	RP	RI	KIPGA Matrix
Efficiency	EF1	P	NS	0.202	0.000	0.923	CPI
	EF2	B	Neg	0.194	−0.999	1.371	CI
	EF3	P	Neg	0.199	−0.997	0.909	CPI
Fulfillment	PF1	P	Neg	0.227	−0.985	1.037	EI
	PF2	P	Neg	0.204	−0.994	0.932	CPI
	PF3	P	Neg	0.200	−0.985	0.914	CPI
	PF4	P	Neg	0.171	−0.993	0.781	CPI
System Usability	SA1	P	Neg	0.211	−0.985	0.964	CPI
	SA2	B	Neg	0.190	−1.002	1.370	CI
Privacy and Security	PS1	P	Neg	0.199	−0.973	0.909	CPI
	PS2	P	Neg	0.199	−0.994	0.909	CPI
	PS3	P	Neg	0.220	−0.968	1.005	EI
Responsiveness	RE1	IN	Neg	0.231	−0.994	0.000	---
	RE2	P	Neg	0.225	−0.995	1.028	EI
Compensation	CP1	B	Neg	0.217	−0.998	1.380	CI
	CP2	P	Neg	0.202	−0.999	0.923	CPI
Contact	CT1	P	Neg	0.224	−1.019	1.023	EI
	CT2	P	Neg	0.242	−1.004	1.106	EI
	CT3	B	Neg	0.247	−1.036	1.393	CI
Personalization	PE1	B	Neg	0.224	−1.011	1.383	CI
	PE2	P	Neg	0.283	−1.005	1.293	EI
	PE3	P	Neg	0.249	−0.999	1.138	EI
	PE4	B	Neg	0.240	−1.008	1.390	CI
	PE5	B	Neg	0.231	−1.006	1.386	CI
Tangibility	TG1	B	Neg	0.248	0.000	1.393	CI
	TG2	P	Neg	0.264	0.000	1.206	EI

Note. P: one-dimensional quality (performance needs); B: must-be quality (basic needs); IN: indifferent quality; NS: non-significance; Neg: negative performance; CI: critical improvement; EI: enhanced improvement; CPI: complementary improvement.

Based on Step 5, service attributes are classified within the KIPGA strategic matrix using Figure 2, according to Kano's two-dimensional quality categories and the RP and RI values. These results indicate that the service quality attributes contributing to the continuous use of online insurance systems in Taiwan fall into three categories: must-be quality, one-dimensional quality, and indifferent quality, as presented in Table 5.

Table 5. Service quality categories for enhancing the continuous use of online insurance systems.

Quality Category	Must-Be Quality	One-Dimensional Quality	Nondifference Quality
Attribute	EF2, SA2, CP1, CT3, PE1, PE4, PE5, TG1	EF1, EF3, PF1, PF2, PF3, PF4, SA1, PS1, PS2, PS3, RE2, CP2, CT1, CT2, PE2, PE3, TG2	RE1

From Table 5, it can be seen that the service quality categories aimed at enhancing the continuous use of the online insurance system include the following as must-be quality attributes: "Easy to use" under efficiency, "Stable system without crashes" under system usability, "Refunds available in case of insurance errors due to system" under compensation, "Online intelligent customer service available" under contact, "Provides personalized professional insurance information", "Offers policy health check service", and "Provides personalized historical insurance records" under personalization, and "Visually appealing interface" under tangibility. Additionally, "Provides clear error messages when issues occur" under responsiveness is classified as an indifferent quality attribute. Apart from this, the remaining attributes are classified as one-dimensional quality attributes.

Furthermore, following Step 6, Formula (9) is used to calculate $DI_{CI}(k)$, and Formula (10) is used to calculate $DI_{EI}(k)$, to determine the key critical improvement factors, enhanced improvement factors, and their improvement priorities. The summary of these findings is shown in Table 6.

Table 6. KIPGA categories and distances for enhancing the continuous use of online insurance systems.

CI (Critical Improvement)			EI (Enhanced Improvement)		
Item	**Distances**	**Rank**	**Item**	**Distances**	**Rank**
CT3	1.4113	1	PE2	1.4045	9
PE4	1.3724	2	PE3	1.0866	10
PE5	1.3457	3	CT2	1.049	11
PE1	1.33	4	CT1	1.0032	12
CP1	1.3016	5	RE2	0.9806	13
EF2	1.2417	6	PF1	0.9749	14
SA2	1.234	7	PS3	0.9498	15
TG1	1.0000	8	TG2	0.7037	16

According to the KIPGA analysis results, eight attributes fall into the critical improvement region, and another eight attributes fall into the enhanced improvement region. Using Formulas (4) and (5), the distances $DI_{CI}(k)$ and $DI_{EI}(k)$ can be calculated. Based on these distances, the priority order for improvement is summarized in the table below. The analysis results indicate that to enhance the continuous use of online insurance systems by Taiwanese users, the top three service quality attributes are "Online intelligent customer service available" under contact, "Offers policy health check service" under personalization, and "Provides personalized historical insurance records" under personalization.

5. Discussion and Conclusions

In service quality research, the Kano model classifies service attributes into different quality categories, making it an essential tool for analyzing customer service needs [15]. Additionally, in identifying service quality deficiencies, the IPGA model integrates IPA and gap analysis to identify service quality deficiencies that require improvement [6]. Among these two models, the Kano model considers a nonlinear approach, while the IPGA model adopts a linear approach. Therefore, to integrate the Kano model and the IPGA model for simultaneously analyzing Kano's two-dimensional quality categories and identifying service quality deficiencies, model adjustments are necessary. In response to this, this study introduces mutual information to calculate the RI value and develops an integrated model combining the Kano model and the IPGA model. This integrated model is referred to as the KIPGA model in this study.

In the KIPGA model, this study first employs a moderated regression model to identify the Kano two-dimensional quality categories. Next, based on their classification within the Kano model, mutual information (MI) is introduced to calculate the relative importance (RI) value. At the same time, the original IPGA model is used to compute the relative performance (RP) value. Finally, the obtained (RP_k, RI_k) coordinates are used to plot the KIPGA matrix, which is then divided into eight different regions, each assigned a distinct management strategy. Based on the analysis from the implementation steps of the KIPGA model, this study categorizes the KIPGA matrix into the following eight categories: (1) innovation and competitive advantage (upper region of Quadrant I); (2) maintain excellence (lower region of Quadrant I); (3) critical improvement (upper region of Quadrant II); (4) enhanced improvement (lower region of Quadrant II); (5) complementary improvement (upper region of Quadrant III); (6) deferred investment (lower region of Quadrant III); (7) potential overinvestment (upper region of Quadrant IV); (8) surplus investment (lower region of Quadrant IV).

Among the eight categories mentioned above, the highest priority improvement region is the critical improvement region. This region represents a must-be quality, where performance does not meet customer expectations. To further analyze the improvement priority within this region, Formula (4) can be used to calculate the standardized distance between the attribute's coordinate and (0, a), where (0, a) is the intersection point of the x_1 line with the y-axis in the KIPGA strategic matrix. Additionally, the second priority improvement region is the enhanced improvement region. This region represents one-dimensional quality, where performance also fails to meet customer expectations. To further analyze the priority for improvement within this region, Formula (5) can be used to calculate the standardized distance between the attribute's coordinate and the coordinate center point (0,1). The larger the distance value, the higher the improvement priority.

After establishing the model, this study further conducts an empirical analysis of the KIPGA model with the objective of enhancing the continuous use of online insurance systems in Taiwan. The research findings confirm that the KIPGA model can effectively classify service quality factors into different Kano two-dimensional quality categories while identifying the key factors that require improvement. Furthermore, the model can analyze and determine the priority order for improvement.

The following is a comparative analysis table of IPGA, the Kano model, KIPA (the Kano model and IPA), and KIPGA (see Table 7).

Overall, previous service quality research has primarily focused either on identifying Kano two-dimensional quality categories or detecting service quality deficiencies. In contrast, this study differs from the past research by not only integrating the Kano model with the IPGA model, which identifies service quality deficiencies, but also considering the differences between the two models. By incorporating mutual information (MI), this study

successfully integrates the Kano model and the IPGA model, establishing the KIPGA model. This integrated model can accurately classify service quality attributes into Kano two-dimensional quality categories while also identifying the key factors requiring improvement and determining their priority for enhancement. The KIPGA model provides a valuable reference for service quality managers to develop service quality strategies and address service quality deficiencies effectively under limited resource conditions.

Table 7. Comparative analysis of IPGA, Kano model, KIPA, and KIPGA.

Criteria	IPGA	Kano Model	KIPA	KIPGA
Model Type	Linear	Nonlinear Consideration	Does not integrate linear and nonlinear models	Integration of linear and nonlinear
Identifies Service Quality Deficiencies	Yes	No	No	Yes
Categorizes Service Quality Attributes	No	Yes	Yes	Yes
Provides Prioritization of Improvements	Yes	No	Partially (limited prioritization using IPA quadrants)	Yes
Integrates Importance and Performance	Yes	No	Yes	Yes
Limitation	Does not consider nonlinear customer perceptions	Does not quantify importance levels	Does not identify service quality gaps, limited prioritization effectiveness	Requires additional computation for MI and classification

6. Limitations and Future Research

While this study successfully integrates the Kano model and IPGA through mutual information (MI) to enhance service quality assessment, several limitations should be acknowledged. First, the research primarily focuses on a specific domain—online insurance services in Taiwan—limiting its generalizability to other industries or regions. The reason most attributes fall into two types in the second quadrant is due to the nature of the selected case study. The online insurance systems in Taiwan are still in their early stages of implementation, meaning that most service attributes exhibit a performance gap rather than exceeding customer expectations. Future studies could apply the KIPGA model to more mature industries or conduct longitudinal analyses to examine how the distribution of attributes evolves over time.

Second, this study relies on self-reported survey data, which may introduce biases such as social desirability or response inconsistencies. Future research could incorporate objective performance metrics or customer behavior data to complement the subjective assessments and strengthen the robustness of the model.

Third, while the KIPGA model effectively refines service quality prioritization, its computational complexity increases due to the integration of MI. Further research could explore alternative methodologies or simplified approaches to enhance computational efficiency without compromising accuracy.

Fourth, service attributes may be interrelated and jointly influence customer satisfaction and service quality. To address this limitation, future studies can incorporate structural equation modeling (SEM) or network analysis to identify and quantify these interdependencies, thereby improving the accuracy and robustness of the model in characterizing complex service systems.

Additionally, this study does not consider the potential impact of external factors such as technological advancements, market trends, or policy regulations, which may influence

customer perceptions over time. Longitudinal studies could be conducted to assess how service quality attributes evolve and how the KIPGA model adapts to these changes.

For practitioners, the KIPGA model provides a strategic decision-making tool for resource allocation in service quality management. However, businesses should carefully interpret the RI and RP values in relation to their operational constraints and customer expectations. Future studies could develop decision-support systems or software tools that automate the KIPGA analysis, making it more accessible for industry practitioners.

By addressing these limitations and exploring future research directions, the KIPGA model can be further refined and extended, contributing to more effective service quality evaluation and management strategies.

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