



Enhancing E-Commerce Customer Satisfaction: A Multi-Method Approach Using Sentiment Analysis, IPA, and PGCV

Muhammad Alief Rivaldi Maulana¹, Kifayah Amar^{2*}

^{1,2} Department of Industrial Engineering, Hasanuddin University, Indonesia

ABSTRACT: The advancement of information technology has enabled rapid expansion in e-commerce, establishing one of the platforms as a leading company in Indonesia. Subsequently, the authors name the e-commerce platform as XZ to preserve the anonymity of the research subject. This research intends to evaluate consumer sentiment regarding XZ's e-service quality utilizing opinion mining based in the Support Vector Machine (SVM) method, while also determining enhancement priorities through Importance Performance Analysis (IPA) and Potential Gain in Customer Value (PGCV). The dataset comprises 50,000 data from the Google Play Store, categorized into positive and negative comments. The findings reveal that factors including the promptness in addressing customer complaints, the effectiveness of refund procedures, and XZ's reliability in delivering promotional commitments, including shipping discount vouchers, are primary customer concerns. The IPA technique indicated that key service components should be emphasized to improve customer satisfaction, particularly attributes such as P4, P13, and P14. The PGCV methodology strengthened these results by determining the enhancement opportunities that would most significantly elevate service value, particularly attribute P4 associated with the promptness of addressing customer complaints. Also, P13 regarding the effectiveness of refund procedures for incorrectly shipped or defective products, and lastly P14 pertaining to XZ's reliability in delivering on promotional commitments such as shipping discount vouchers. The results of this study have the potential to provide a benchmark for the businesses in formulating more efficient service enhancement plans and assist in advancing the field of quality management within the e-commerce industry.

KEYWORDS: E-Commerce, E-Service Quality, Importance Performance Analysis, Potential Gain in Customer Value, Support Vector Machine.

INTRODUCTION

The fast expansion of e-commerce, driven primarily by breakthroughs in information technology, has altered the way businesses operate and consumers shop [1]. E-commerce platforms have become important to modern trade, enabling convenience and accessibility to a broad audience [2]. In Indonesia, XZ has developed as one of the top e-commerce platforms, playing a significant role in the digital marketplace [3]. As a prominent player, XZ is continually under pressure to upgrade its service quality to match the ever-increasing demands of its clients and keep its competitive edge. The impact of customer satisfaction cannot be emphasized. It directly effects customer retention, brand loyalty, and the overall performance of a platform [2], [4], [5]. XZ, like many e-commerce platforms, relies significantly on great customer experiences to support its growth [6]. However, maintaining high levels of customer satisfaction is tough due to the changing nature of consumer expectations and the varied range of services supplied by e-commerce platforms [7].

Despite XZ's dominant position in the market, it has suffered fluctuations in consumer satisfaction, as indicated by its changing Top Brand Index (TBI) scores over the years [8]. These changes are generally attributable to specific service-related difficulties that customers have noted, such as slow resolution of complaints and differences in delivering promotional offers [7], [9]. Negative consumer comments, particularly on public sites like the Google Play Store, can dramatically harm the brand's reputation and user base [10]. Addressing these difficulties needs a full awareness of the consumer feelings and the factors impacting their satisfaction levels. This study tries to bridge this gap by employing sentiment analysis to systematically categorize and understand customer comments. By doing so, the research intends to provide practical insights that can assist XZ prioritize and implement service enhancements successfully.

The topic of sentiment analysis, also known as opinion mining, has attracted substantial attention in recent years due to its applicability in different domains [11], [12], [13] including e-commerce [10]. Several studies have proved the efficacy of sentiment



analysis in extracting significant insights from vast amounts of unstructured text data [14], [15], such as customer evaluations. Techniques like Support Vector Machine (SVM), Naïve Bayes, and K-Nearest Neighbors have been extensively utilized for this purpose, with SVM often producing greater accuracy rates [15], [16], [17]. Previous research has also studied the use of Importance Performance Analysis (IPA) [6], [18], [19], [20] and Potential Gain in Customer Value (PGCV) [6], [21], [22], [23] to prioritize service enhancements. These strategies have been beneficial in identifying significant areas for improvement by mapping service attributes based on their perceived relevance and existing performance levels. This study builds on this existing body of work by merging sentiment analysis with IPA and PGCV to provide a holistic approach to service quality improvement in e-commerce.

The original component of this research originates in its integrated methodology, which blends classic sentiment analysis with modern performance evaluation methodologies. This research adopts a multi-faceted strategy that integrates sentiment analysis with IPA and PGCV to examine and enhance XZ's service quality. The sentiment analysis will classify responses from consumers into positive and negative comments, offering a baseline picture of the general customer attitude. Subsequently, IPA will be used to identify which service aspects are most essential to consumers and how well XZ is performing in those areas. PGCV will then be applied to estimate the potential advantages of increasing various traits, so helping XZ prioritize its efforts properly.

The primary objective of this research is to examine consumer sentiment towards XZ's service quality and identify critical areas for improvement. By merging sentiment analysis with IPA and PGCV, the study intends to provide XZ with a deep insight of consumer attitudes and actionable recommendations for service enhancements. Ultimately, this study attempted to make a contribution to the broader subject of e-commerce service quality management by demonstrating the value of combining sentiment analysis with performance evaluation approaches.

METHODS

Data was acquired from two main sources: First is a dataset of 50,000 customer evaluations from the Google Play Store, where the reviews were scraped using Python in Google Colab, a cloud-based tool that supports large-scale data processing. Python was deployed to collect 50,000 recent user reviews of the Y Application from the Google Play Store between June 2024 and January 2023. Second is replies to the distribution of a customer satisfaction survey questionnaire employing Google Forms. Sub-attributes within the questionnaire were created from the most frequent terms detected in customer sentiment research. The questionnaire measures five dimensions of service quality which are reliability (3 questions), responsiveness (3 questions), assurance (3 questions), efficiency (3 questions), and fulfillment (4 questions), utilizing 16 questions in total. For each topic, respondents submit two assessments based on a Likert scale: one for the level of importance and another for the level of performance. The target demographic of questionnaire for this study consists of all users of the XZ Application within the geographical boundaries of Makassar City. To ensure data richness and handle the research aims effectively, purposive sampling was utilized. This selection procedure highlighted individuals with extensive experience and the capacity to contribute in-depth and relevant information pertinent to the research issues. The dataset of user reviews reflects a varied spectrum of consumer experiences, delivering a rich source of information for sentiment analysis. The questionnaire supports this by giving structured responses that can be used to validate and expand on the conclusions from the review data. Together, these data sources offer a full snapshot of individual perceptions. Following data collecting, the succeeding phase required detailed examination of data. XZ user reviews are part of this analysis, specifically looking at the sentiment conveyed within them, alongside a customer satisfaction rating utilizing gap analysis. Furthermore, the Importance-Performance Analysis (IPA) technique then applied to define priority areas for service improvement, thus delivering significant insights for the organization. Finally, the Potential Gains from Customer Value (PGCV) technique was applied to quantify the projected advantages arising from improvements pertaining to key features.

1. Opinion Mining and Sentiment Analysis

Sentiment analysis then performed using the Support Vector Machine algorithm, a robust technique known for its excellent accuracy in text categorization applications. Before applying SVM, many preprocessing processes were taken to the data. This was necessary because scraped data can be unreliable for direct analysis due to issues such as missing entries, duplicate information, unexpected data points, and inappropriate formatting. Data preparation involves numerous stages [24], including:

- a. Case Folding, changing all text to lowercase to maintain consistency.
- b. Cleansing, deleting special characters, digits, and punctuation that do not contribute to sentiment.

- c. Tokenization, breaking text into distinct words or tokens for faster processing.
- d. Normalization, normalizing words to their base forms, for as reducing "running" to "run."
- e. Stopword Removal, deleting common terms that do not contain substantial significance, such as "and" or "the."
- f. Stemming, reducing words to their base forms to unite diverse versions of the same word.

Following data cleaning, the dataset was partitioned into discrete training and testing subsets. The training subset serves as input for model training, whereas the testing subset is utilized to evaluate the model's predicted performance on previously unencountered data. Common data splitting ratios including 60:40, 70:30, and 80:20. For instance, an 80:20 split allocates 80% of the data for training and the remaining 20% for testing, with equivalent proportions applied to various splitting ratios.

The SVM technique was utilized for sentiment analysis classification. SVM aims to discover the best border, known as a hyperplane, that efficiently separates data points belonging to distinct sentiment classes. In higher dimensions, this hyperplane creates a more complex decision boundary. To assess model performance, the accuracy of predictions on both the training and testing datasets was examined. Training accuracy represents the model's performance on data used for training, while test accuracy examines its ability to generalize to previously unseen data.

The outputs of the opinion mining technique were subsequently visualized through the production of a word cloud. This graphic depiction displays the frequency of the most frequent phrases. The selected high-frequency words served as the foundation for the development of a customer satisfaction questionnaire, which was later circulated for data collecting and analysis.

2. Importance Performance Analysis (IPA) and Potential Gain in Customer Value (PGCV)

IPA and PGCV were employed to select service enhancements based on their potential influence on customer satisfaction. IPA entails plotting service attributes on a two-dimensional grid to measure their value to customers and XZ's performance in those areas. This graphic helps identify traits that require urgent attention or those that are performing well. PGCV expands this research by estimating the potential advantages of enhancing certain qualities. By measuring the predicted gain in customer value from increasing particular service features, PGCV provides a clear framework for decision-making. This technique ensures that XZ can allocate resources effectively to areas that will offer the best returns in customer satisfaction. Together, IPA and PGCV offer a strategic approach to service quality improvement, allowing XZ to make educated decisions based on empirical evidence. This combined methodology enhances conventional sentiment research by integrating customer input directly to effective company strategy.

RESULTS & DISCUSSION

Opinion Mining

The initial phase of this research was undertaking sentiment analysis. The data was acquired by scraping the Google Play Store for the most recent consumer reviews of the XZ application. A total of 50,000 reviews were successfully extracted. The distribution of reviews across different star ratings is depicted in Figure 1.

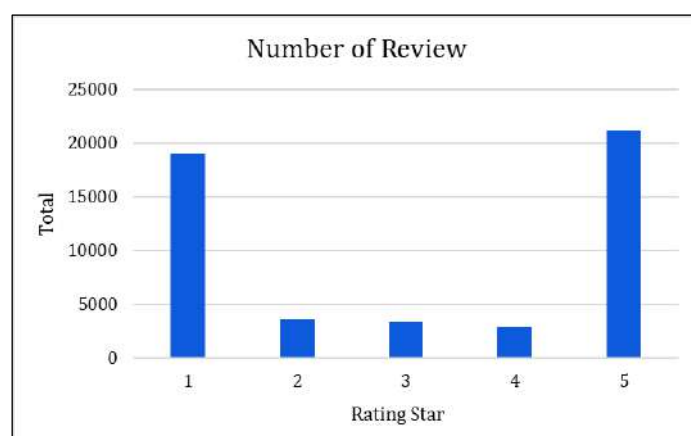


Figure 1. Classification results

Figure 1 displays the distribution of user ratings, with 21,140 five-star reviews, 2,886 four-star reviews, 3,346 three-star reviews, 3,630 two-star reviews, and 18,998 one-star reviews. A binary classification technique was then employed, designating reviews with five or four stars as "positive" (label 1) and those with three, two, or one stars as "negative" (label -1). This resulted in 24,026 positive comments and 25,974 negative reviews.

For the purpose of model creation and validation, the dataset then partitioned into training set (75%) and testing set (25%). The Support Vector Machine (SVM) technique was then applied to do sentiment categorization on these subsets. The model obtained a peak accuracy of 88.56%, suggesting its usefulness in capturing consumer-based sentiment. A summary of the sentiment analysis conclusions derived from 25% of the data set is presented in Figure 2.

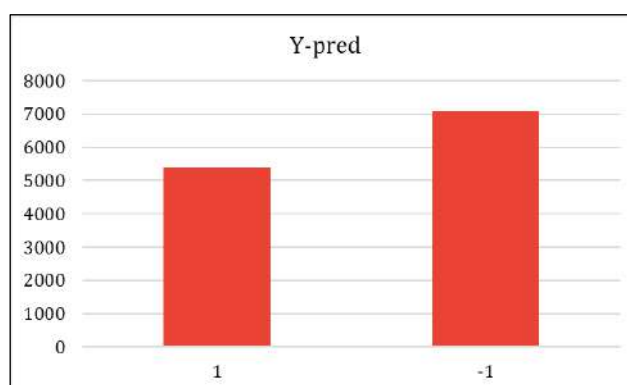


Figure 2. Classification results

Figure 2 demonstrates that among the 12,500 reviews utilized as the testing dataset, 5,393 (43.14%) indicated positive sentiment, whereas 7,107 (56.86%) conveyed negative sentiments. This means that 56.86% of XZ application users within the testing sample reported dissatisfaction with the services they received.

The final stage entailed testing the model's accuracy. The Support Vector Machine (SVM) technique attained a classification accuracy of 88.56%. This reaches the 80% threshold, indicating its effectiveness in doing opinion mining on XZ application review data. A thorough classification report, comprising a precision, confusion matrix, F1-score, and recall, was then created from the trained model. Figure 3 displays a visual depiction of the classification outputs produced using the SVM-based method.

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Accuracy of SVM Classifier on test set 0.885600
[[6081 404]
 [1026 4989]]

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	precision	recall	f1-score	support
-1	0.86	0.94	0.89	6485
1	0.93	0.83	0.87	6015
accuracy			0.89	12500
macro avg	0.89	0.88	0.88	12500
weighted avg	0.89	0.89	0.89	12500

Figure 3. Confusion matrix outcome

Subsequently, the most frequent phrases within consumer sentiment expressions were determined. These significant terms will serve as the foundation for building a thorough questionnaire targeted at analyzing customer satisfaction. Certain words that influence unfavorable consumer attitude have been detected, such as XZ, application, cost, buy, disappointed, send, buy, pay, store, and free. The higher occurrence of particular words in customer reviews shows a greater influence on sentiment. Consequently, these phrases are crucial for understanding consumer needs and will inform the formulation of focused sub-attributes in the customer satisfaction questionnaire. This concentrated approach will allow for a more specific identification of necessary improvements to satisfy customer expectations.

Customer Satisfaction Analysis**1. Respondents Demographics**

Customer satisfaction was measured using a five-point Likert scale within a two-part questionnaire. The first section collected demographic information from respondents, while the second part focused on evaluating service quality. Table 1 presents a summary of the respondent demographics.

Table 1. Respondent demographics

Demographics	Item	Frequency	Percentage
Gender	Male	67	41.6%
	Female	94	58.4%
Age	17-24	155	96.3%
	25-34	3	1.9%
	35-44	1	0.6%
	Over 45	2	1.2%
Job	Student	150	93.2%
	Employees	4	2.5%
	Housewives	2	1.2%
	Civil Servants	2	1.2%
	Freelancer	2	1.2%
	Doctor	1	0.6%
Length of uses	Less than 1 year	79	49%
	1-2 years	41	25.5%
	More than 2 years	41	25.5%

2. Validity and Reliability Test

To ensure the validity of research instrument, a validity test was conducted. The validity of each statement was assessed by comparing the estimated r-value with the critical r-value from the table. If the calculated r-value exceeded the table r-value, the statement was declared valid. All statements in the questionnaire demonstrated a calculated r-value greater than the table r-value, supporting the validity of all items. A reliability test was also performed to examine the questionnaire's consistency. Cronbach's Alpha was chosen as the reliability measure. The coefficient value above 0.6 shows acceptable reliability. The results reported in Table 3 show that all dimensions within the questionnaire obtained Cronbach's Alpha is greater than 0.6, confirming their reliability and consistency.

Table 2. Validity test

No	Dimension	r-value of Performance	r-value of Expectation	r-table	Result
1	Reliability	0.637	0.825	0.154	Valid
		0.639	0.767	0.154	Valid
		0.660	0.765	0.154	Valid
2	Responsiveness	0.732	0.864	0.154	Valid
		0.710	0.840	0.154	Valid
		0.686	0.804	0.154	Valid
3	Assurance	0.663	0.820	0.154	Valid
		0.610	0.789	0.154	Valid
		0.764	0.813	0.154	Valid
4	Efficiency	0.596	0.805	0.154	Valid

		0.739	0.861	0.154	Valid
		0.641	0.776	0.154	Valid
		0.662	0.771	0.154	Valid
5	Fullfilment	0.705	0.843	0.154	Valid
		0.708	0.815	0.154	Valid
		0.754	0.854	0.154	Valid

Table 3. Outcome of reliability test

Dimension	Cronbach's Alpha of Performance	Cronbach's Alpha of Expectation	Parameter	Result
Reliability	0.769	0.881	0.6	Reliable
Responsiveness	0.798	0.886	0.6	Reliable
Assurance	0.760	0.857	0.6	Reliable
Efficiency	0.733	0.872	0.6	Reliable
Fulfillment	0.800	0.910	0.6	Reliable

Table 4. Gap analysis outcome

Dimension	Item	Performance	Expectation	Gap
Reliability	P1	3.931	4.286	-0.355
	P2	3.950	4.248	-0.298
	P3	4.087	4.354	-0.267
Responsiveness	P4	3.559	4.236	-0.677
	P5	3.602	4.161	-0.559
	P6	3.634	4.068	-0.434
Assurance	P7	3.627	4.211	-0.584
	P8	3.776	4.124	-0.348
	P9	3.652	4.211	-0.559
Efficiency	P10	3.820	4.230	-0.410
	P11	3.950	4.236	-0.286
	P12	3.894	4.342	-0.448
Fulfilment	P13	3.571	4.224	-0.653
	P14	3.658	4.224	-0.566
	P15	3.925	4.255	-0.330
	P16	3.913	4.354	-0.441
AVERAGE		3.784	4.235	-0.451

Table 4 highlights the outcomes of this analysis for XZ's services. Notably, all service dimensions exhibited negative gaps, with an average gap value of -0.451. This reveals a large difference between perceived performance and user expectations across all service dimensions. The most noticeable gap was identified in the 'responsiveness' dimension, particularly in item P4. A gap rating of -0.677 means that XZ's handling of consumer purchasing concerns and complaints is much slower than what people expect.

Importance-Performance Analysis (IPA) was applied to prioritize improvement efforts based on relative importance of each service aspect and its present performance level. Questionnaire items were subsequently mapped into a Cartesian diagram, graphically ordering them from most to least important. This graphical representation supports the prioritization of improvement initiatives to successfully satisfy consumer expectations. Figure 4 presents the results of the Importance-Performance Analysis for XZ's services, illustrating the relative importance of each item.

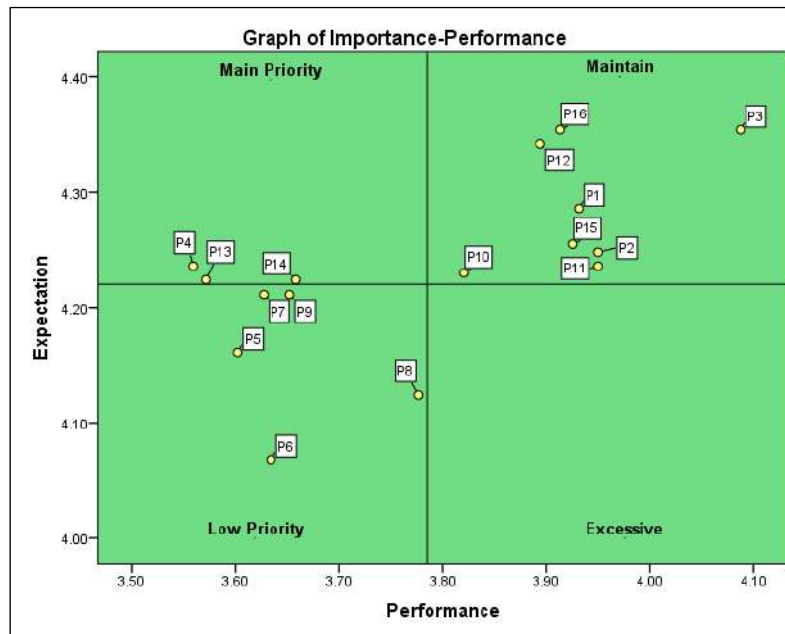


Figure 4. The IPA diagram

The above figure reveals that three items fall within a Quadrant I (High Importance, Low Performance), highlighting key areas for service improvement for XZ, as indicated in Table 5.

Table 5. Quadrant I

No	Statement
P4	I am satisfied with XZ's timely resolution of purchase-related issues and complaints.
P13	I can request a refund when the item I receive is incorrect or damaged.
P14	I feel that XZ always keeps its promises (for example: providing a shipping discount voucher when purchasing a minimum of IDR 10,000).

Attributes demonstrating both high importance and high performance are classified within a Quadrant II, denoting areas of strength that require consistent management. Table 6 presents a thorough listing of the Quadrant II attributes pertinent to XZ's services.

Table 6. Quadrant II

No	Statement
P1	Important information about the order is directly sent to the customer.
P2	Order tracking information is available until the order is received by the customer.
P3	The XZ application can be accessed at any time.
P10	The XZ application interface is easy to understand.
P11	Easy to make payments.
P12	Easy to find the desired product.
P15	Customers can cancel and re-order.
P16	The product received matches the customer's order.

Attributes in Quadrant III reflect low priority and are associated with low customer expectations. Consequently, they are given less priority for improvement, as shown in Table 7 for XZ's services.

Table 7. Quadrant III

No	Statement
P5	XZ's responses generally fast through email or chat.
P6	XZ's email address and call center are displayed in the application.
P7	Trust in the sellers and products offered on the platform.
P8	XZ's privacy policy is accessible.
P9	Guarantee that products and services will meet customer needs.

The IPA analysis suggested that there was no attribute was found to be excessive (Quadrant IV).

In the importance-performance graph, there are three attributes located in Quadrant I, an area requiring the company's concentrated efforts. These three attributes will then be selected for improvement so that the XZ can build a service quality improvement strategy for the attributes in Quadrant I based on the priority ranking measured using the PGCV approach.

Potential Gain in Customer Value

This approach is implemented subsequent to acquiring the outcomes of the Importance Performance Analysis (IPA). The outcomes of the IPA analysis enable the identification of attributes situated in Quadrant I, which denote the highest priority. The characteristics in this quadrant are deemed highly important by users yet exhibit poor performance, necessitating focus for improvement. The primary position in Quadrant I signifies the attribute that need to be the company's main emphasis, since it directly impacts overall service efficacy and customer satisfaction. By recognizing this attribute, the organization can distribute resources and efforts to enhance quality in the domains that significantly influence favorable customer perception, thereby preserving high customer satisfaction.

The development of the PGCV index seeks to quantitatively assess customer satisfaction regarding the quality of service delivered. The PGCV index data will be examined to determine key attributes requiring quick improvement. The weighted PGCV index, which accounts for the relative weight of each attribute, will be the foundation for establishing improvement priorities.

Table 8. PGCV Index based on Quadrant I

No	Attribute	Performance	Importance	Gap	ACV	UDCV	PGCV	Rank
1	P4	3.559	4.236	-0.677	15.076	21.180	6.104	1
2	P13	3.571	4.224	-0.653	15.082	21.118	6.036	2
3	P14	3.658	4.224	-0.566	15.450	21.118	5.668	3

Table 8 indicates that the priority ranking according to the PGCV Index is P4, followed by P13, and then P14. The suggestions for enhancing service are outlined as follows:

- XZ must enhance its customer care system by integrating a cutting-edge AI-driven chatbot that operates around the clock to address basic queries and offer preliminary assistance to customers.
- XZ must streamline the refund request process to enable consumers to submit issues more swiftly and effortlessly via the application. A user-friendly reporting mechanism and sequential instructions can reduce customer confusion.
- XZ must guaranty that advertized promotions are consistently accessible in alignment with explicit and transparent terms and conditions. XZ has the potential to enhance the automation system to facilitate voucher deployment, ensuring customers encounter no issues when fulfilling the requirements.

CONCLUSION

The main findings of the research demonstrate that opinion analysis utilizing the SVM algorithm effectively categorized XZ reviews into negative and positive comments. The research identified essential dimensions of service quality and ranked areas needing enhancement, particularly in managing customer complaints, ensuring refund processes, and promotional consistency. These conclusions seem reasonable and correspond with the reported outcomes, as the examination explicitly connects user input to



enhancement goals. Analysis of XZ reviews on the Google Play Store, utilizing the SVM algorithm with an accuracy of 88.56%, indicated that 56.86% of the evaluations conveyed negative sentiment, whilst 43.14% reflected positive feedback. An examination of negative reviews revealed five principal dimensions of service quality determined by word frequency: reliability, responsiveness, assurance, efficiency, and fulfillment. These dimensions represent essential factors affecting customer satisfaction. The Importance Performance Analysis (IPA) identified three service attributes necessitating immediate enhancement: the promptness in addressing customer issues (P4), the effectiveness of refund procedures for incorrect or defective items (P13), and the reliability in delivering promotional commitments, including free shipping vouchers (P14). These attributes, while significantly valued by users, were assessed as lacking in performance. Employing the PGCV approach, the sequence for enhancement commences with P4, followed by P13 and P14, highlighting the necessity for focused initiatives to elevate user satisfaction.

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