

The Impact of Perceived and Interactive Attributes of Personalized Hotel Services on Customer Satisfaction: A Text Analysis Based on Online Reviews

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DOI: <https://dx.doi.org/10.47772/IJRISS.2025.907000253>

Received: 08 July 2025; Revised: 16 July 2025; Accepted: 19 July 2025; Published: 12 August 2025

ABSTRACT

In the increasingly competitive hotel industry, personalized services have gradually become an important factor affecting customer satisfaction. This study explores the impact of perceived attributes and interactive attributes in hotel personalized services on customer satisfaction. By analyzing the online review data of hotel customers on Ctrip.com, combined with text analysis, sentiment analysis, and regression analysis, the key influencing factors in customer feedback were explored. The results show that perceived attributes (such as room comfort and facilities) affect customer satisfaction through functionality and emotional value, while interactive attributes (such as employee responsiveness, communication, and empathy) improve customer satisfaction by enhancing customer participation and personalized experience. It is found that focusing on strengthening interaction with customers can significantly improve overall satisfaction. This study provides relevant empirical support for the role of personalized services in the hotel industry and provides practical suggestions for hotel managers to optimize customer experience.

Keywords: personalized service, customer satisfaction, text analysis, sentiment analysis

INTRODUCTION

With the continuous development of the accommodation industry in China's tertiary industry⁴² and the significant recovery of the number of tourists after the epidemic²⁴, consumers' demand for high-quality services and diversified, differentiated and personalized services has continued to increase². As an important part of the accommodation industry, the hotel industry has been unable to meet the ever-increasing service needs of customers under the traditional business model, which has led to intensified competition in the service market. In this context, personalized services have received widespread attention from the industry as an important means for hotels to improve customer satisfaction and enhance brand competitiveness. Personalized services are not a single-dimensional concept, but a complex system involving multiple interactive factors²⁹.

Although relevant research has been discussed in theory and practice, there is still room for further research on the specific impact of different dimensions of hotel personalized services on customer satisfaction. Especially in the big data environment, online reviews are an important source of real customer feedback. How to extract and mine customers' perceived content and emotional reactions to service experience through natural language analysis technology is gradually becoming a new research perspective.

This study takes "Shanghai S Hotel" as a case study and collects customer online review data of the hotel on the Ctrip

platform based on Python technology. By constructing an empirical analysis framework based on user-generated content (UGC)¹⁹, combined with natural language processing (NLP)¹⁸ technology and regression analysis, the perceived attributes and interactive attributes of the hotel's personalized services are classified, identified and quantified, so as to further analyze the differences in the impact of the two dimensions on customer satisfaction. The data acquisition method used in this study breaks through the limitations of the traditional questionnaire method and reflects the service experience feedback of customers in a natural state. Through the combined analysis of multiple research methods, it effectively addresses the skewed distribution of comment data and the practical problems that are difficult to meet traditional statistical tests, and to a certain extent reduces the dependence on P values¹⁶. It enhances the scientificity and explanatory power of the analysis results, and the research conclusions can also provide practical reference value for related text data research. At the same time, the UGC analysis framework constructed in the study also has a certain degree of generalizability, which can effectively reveal the influencing mechanism and weight ratio of different dimensions of hotel personalized services, and can also provide hotel managers with relevant data support and strategic suggestions on service optimization and management decision-making.

Future research can be carried out from the following aspects: first, further subdivide the personalized service dimensions and deeply explore the impact mechanism of each dimension on customer satisfaction; second, innovate research methods, and comprehensively use a variety of research methods to improve the accuracy and depth of research; third, strengthen industry case studies, combine China's consumption characteristics, and build a personalized service system suitable for the Chinese market; fourth, expand the scope of research, explore the application of personalized services in different types of hotels and other service industries, and provide more targeted suggestions for industry development. Based on the research objectives and the analysis of UGC online reviews, this study addresses the following research questions:

RQ1: How are the perceptual and interactive attributes of personalized hotel services reflected in customer online reviews?

RQ2: To what extent do perceptual and interactive attributes influence customer satisfaction, and are there significant differences between them?

RQ3: How do different types of personalized service practices contribute to enhancing customer satisfaction in the hotel industry?

THEORETICAL BACKGROUND

Perceived attributes of personalized services

mainly reflected in the customer's subjective cognition and feelings during the service process, including four aspects: perceived value, information transparency, perceived risk, and expectation management^{41,5}. Perceived value not only covers functionality and emotion, but also social value. Hotels can enhance customer sense of belonging through data analysis and customized services^{31,2}. In terms of information transparency, if the basis of personalized recommendations is not stated, customers are prone to privacy concerns⁵. If the data source and recommendation logic can be clarified, trust can be enhanced¹. In terms of perceived risk, unfair prices, technical failures, etc. will cause customer dissatisfaction^{9,13}. In addition, customer satisfaction is affected by the difference between expectations and actual experiences²⁶. If promises are over-promising and deliverables are insufficient, the experience will be reduced²³. This gap can be alleviated through real-time feedback mechanisms¹⁴.

Interactive attribute of personalized service

focusing on the two-way communication and service response between the hotel and the customer, emphasizing the immediacy and emotional connection of the service process. Based on social exchange theory, customers expect to obtain efficient returns in interaction⁴, and service response speed and flexibility have been proven to

be the core factors affecting satisfaction³. Highly flexible service mechanisms can be dynamically adjusted according to customer preferences, improving relationship stickiness and brand loyalty³⁴. In addition, interaction is not limited to rational exchanges, but also involves deep emotional connections³². Studies have shown that the degree of emotional interaction is highly correlated with customer satisfaction¹⁴. With the development of AI and big data technology, the form of service interaction has gradually become intelligent, but emotional temperature is still the key to differentiated experience²².

Personalized service and customer satisfaction

With the advancement of big data and artificial intelligence, personalized hotel services not only meet functional needs, but also pay more attention to immersive experience and emotional connection, becoming an important path to improve customer satisfaction¹¹. Studies have shown that personalized services not only affect transactional satisfaction, but also have a profound effect on cumulative satisfaction and brand loyalty^{25,21}. For example, Widiastini et al.³⁷ found that employees' emotional management, empathy, and professional service delivery significantly enhance customer satisfaction in the hotel industry. Furthermore, Widiastini et al.³⁸ emphasized that during the pandemic, MSMEs maintained customer satisfaction by innovating services and strengthening customer interactions, highlighting that adaptive service strategies remain crucial in difficult contexts. At the same time, strategic collaborations and service diversification were also proven to enrich customer experiences and increase their satisfaction in tourism villages³⁹.

In addition, customers' tolerance for service failures also plays an important role in satisfaction, Trianasari et al.³³ found that guests with higher cultural familiarity are less tolerant of interpersonal service failures, leading to lower satisfaction levels. This suggests that personalized hotel services must consider not only functional and emotional aspects but also cultural expectations to ensure customer satisfaction. By continuously providing experiences that exceed expectations, hotels can stimulate customers' 'sense of belonging and willingness to repurchase. In addition, immersion theory and self-determination theory suggest that high involvement and autonomy are also key psychological mechanisms for improving customer satisfaction⁸. Especially in social media scenarios, personalized responses can further strengthen brand emotional stickiness³⁶.

Based on previous research results and theoretical support, and on the basis of the research framework, the following hypotheses are proposed:

H1: The perceived attributes of personalized services positively affect customer satisfaction.

H2: The interactive attributes of personalized services positively affect customer satisfaction.

H3: The interactive attributes of personalized services have a greater impact on customer satisfaction than the perceived attributes.

These hypotheses will be demonstrated in subsequent data analysis to clarify the specific relationship between hotel personalized services and customer satisfaction.

METHODOLOGY

This study adopts a mixed research method⁷ to explore how the perceived attributes and interactive attributes of hotel personalized services affect customer satisfaction. In quantitative research, it refers to Villa-Turek's³⁵ VADER sentiment analysis and LDA topic modeling, and Palkast's²⁷ study combining topic modeling and sentiment analysis methods and other natural language processing techniques; therefore, this study uses Ctrip's Shanghai case hotel reviews as the data basis, use Python to crawl online review data, and extract keywords and topics through text preprocessing, LDA topic modeling and K-Means clustering to assist in identifying perceptual attributes and interactive attributes in personalized services; Further combine semantic network

analysis to identify the semantic structure between attributes, use sentiment analysis to quantify customer satisfaction, and finally verify the influence trend and significance of each attribute on satisfaction through multivariate regression analysis.

EMPIRICAL FINDINGS/RESULT

Text Topic Modeling Analysis

This study uses LDA topic modeling to identify the core concerns in customer reviews, and selects 2774 valid reviews from the original 2781 reviews. After data preprocessing, the TF-IDF word frequency matrix is constructed, and the number of topics (K) is set from 2 to 9. The optimal parameters are evaluated by topic consistency and perplexity. The results show that when K=6, the consistency score is the highest (about 0.53), and the perplexity is in a reasonable range of a downward trend. Therefore, 6 topics are selected for analysis. Word Cloud word cloud diagram display:



Fig. 1 (a) Theme 1



Fig. 1 (b) Theme 2

Source: 2025 processed original data, Python3.10

After keyword induction and semantic interpretation, the six topics were divided into two attributes. For example, in Topic 1, keywords such as " clean, comfortable, quiet, facility, " and other perceptual words related to the cleanliness of the room and the comfort of the facilities appeared; while in Topic 2, keywords such as "staff, service, reception, patient," and other interactive words related to whether the staff are enthusiastic, patient, and

proactive in solving problems appeared. Attribute classification results:

Table I. Attribute Classification Table

Topic Number	Name	Attributes
1	Guest room environment and infrastructure experience	Perceived Attributes
2	Staff service attitude and front desk response	Interactive Attributes
3	Dining experience and diverse services	Perceived Attributes
4	Space design and artistic atmosphere	Perceived Attributes
5	Overall stay satisfaction and willingness to recommend	Perceived Attributes
6	Employee attitudes and subjective emotional expression	Interactive Attributes

Source: 2025 processed original data, Python3.10

Through LDA visualization using PyLDAvis, we found that Topic 1 (guest room environment) is close to Topic 3 (accommodation comfort), reflecting customers' attention to the linkage between hardware and comfort in their evaluations; Topic 6 (service response) is independently distributed, indicating that the service experience evaluation is independent; Topic 2 is far away from Topic 4, indicating that there is a clear semantic differentiation between “dining experience” and “space design”.

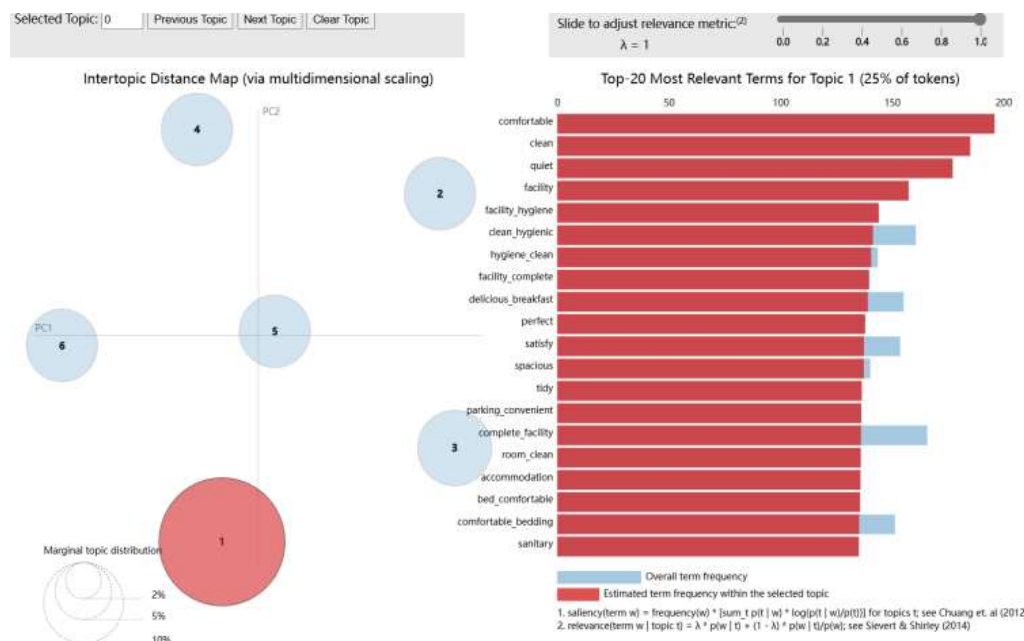


Fig. 2 Topic 1 modeling visualization diagram

Source: 2025 processed original data, Python3.10

K-Means Text Clustering

The study used the K-Means algorithm to cluster customer reviews, and evaluated the effect through the elbow method and silhouette coefficient. Finally, the number of clusters $K=4$ was selected. After clustering, the review text was divided into four categories. Figure.3 shows the cluster visualization distribution:

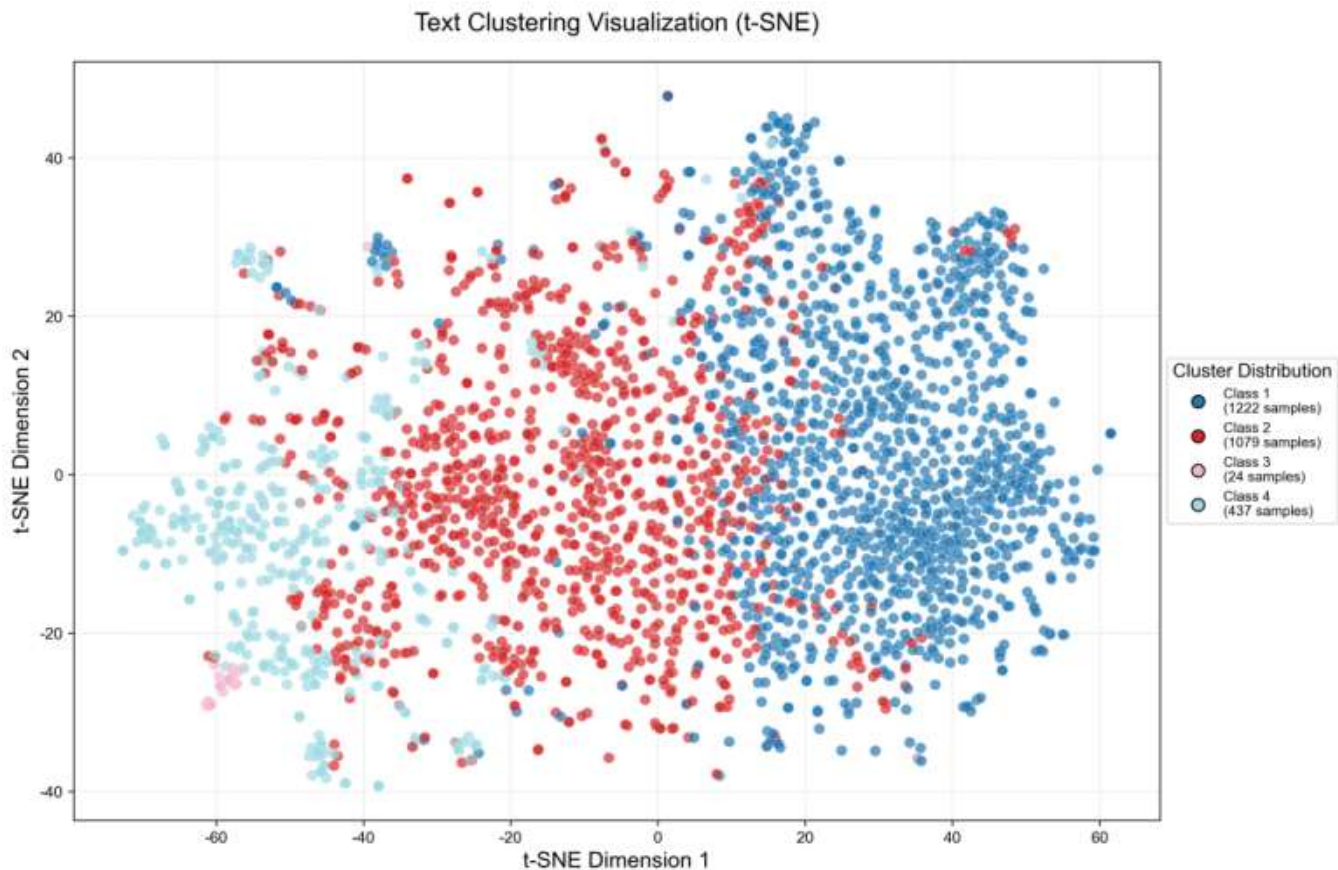


Fig. 3 Cluster distribution visualization

Source: 2025 processed original data, Python3.10

Cluster topic keyword characteristics and proportions:

Cluster 1 (1,222 reviews, approximately 44.1%): Keywords include “good, hotel, room, service, environment”, etc. The reviews are generally long and rich in content, focusing on hotel design, room facilities, service experience, and catering. Customers have a strong sense of experience and often contain more specific descriptions of usage scenarios and feelings.

Cluster 2 (1,079 items, approximately 38.9%): Keywords include "comfortable, clean, quiet", etc. The evaluation focuses on conventional experience dimensions such as comfort, hygiene, and service. The text structure is short, the tone is concise, and the language is conventional, reflecting customers' general recognition of basic services.

Cluster 3 (24 items, about 0.9%): Keywords include "ok, hahaha, bad", etc. The text is short and repetitive, with frequent appearance of "OK" or similar expressions. The semantics are clear but lack details, and may also contain some emotional expressions.

Cluster 4 (437 items, about 15.8%): Keywords include "satisfied, facilities, experience", etc., which mostly reflect certain positive emotions and sense of identity. The structure is short but the vocabulary has emotional tendencies.

Semantic Network Analysis

In order to present the keyword structure in the comments, a semantic network diagram was constructed . The visualization results of the semantic network analysis show a clear overall network structure and obvious clustering, which reflects the customers' focus on the personalized service dimension.

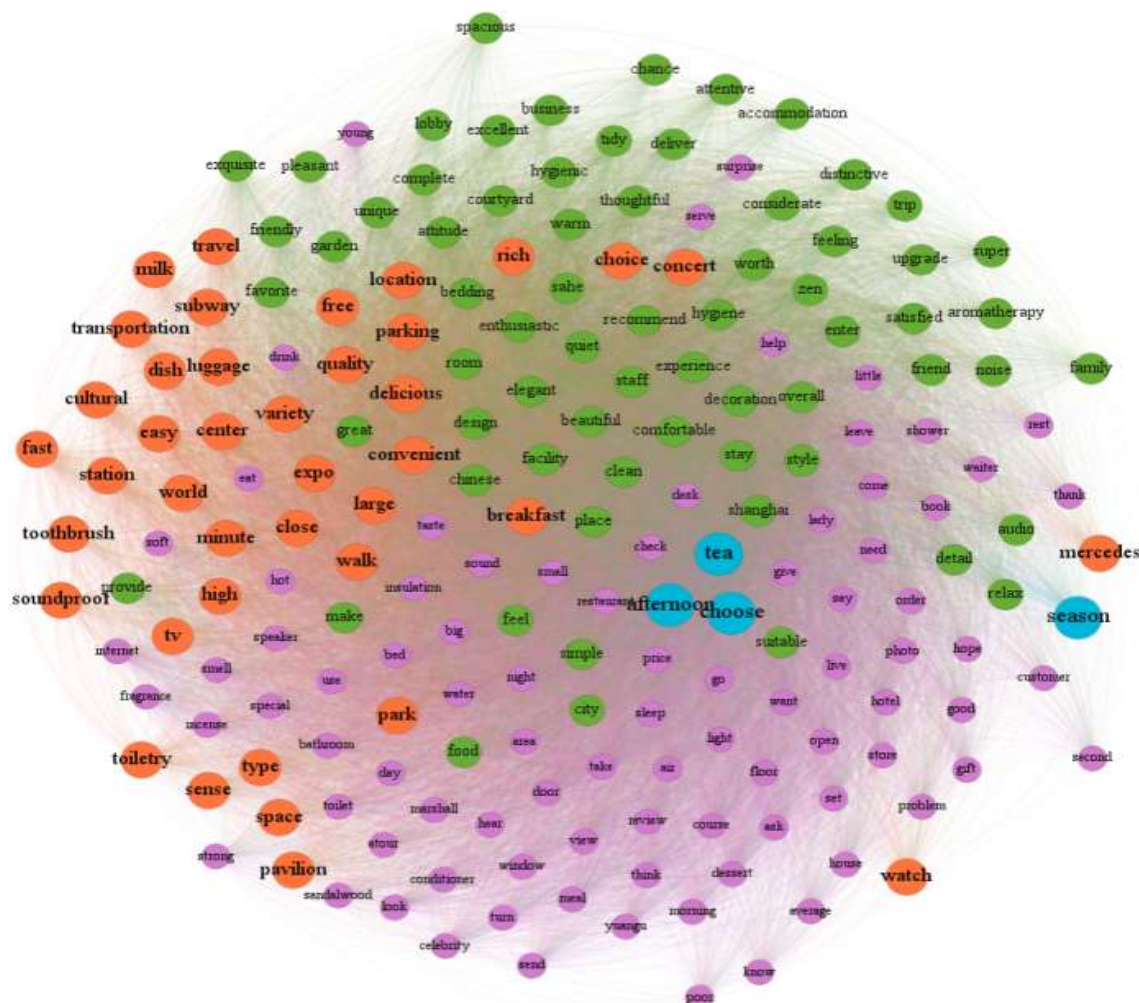


Fig. 4 Semantic network diagram

Source: 2025 processed original data,Python3.10

In terms of perceived attributes, words such as "room", "clean", "quiet" and "comfortable" are at the core, indicating that the environment and facilities are still the most direct factors for customers to feel. "Breakfast" appears frequently and is associated with "delicious" and "rich", showing an important impact on satisfaction.

In terms of interactive attributes, "service" is at the center, and related high-frequency words include "friendly", "considerate", "timely", "smile", etc., reflecting customers' high attention to service attitude and response efficiency. At the same time, words such as "special" and "surprise" are related to customized service experience, such as aromatherapy selection, meditation activities, etc., reflecting the role of hotel interactive services in enhancing emotional experience.

Sentiment Analysis

Figure.5 (a) Sentiment Score Distribution (per 0.1 interval, log scale) shows the frequency distribution of the sentiment score of the comments. The data shows that the comments are mainly concentrated in the positive interval (score > 0.5), among which the number of comments in the interval of 0.9 to 1.0 is the largest (697); neutral and negative comments account for a small proportion, and the overall distribution is skewed.

Figure.5 (b) Sentiment Distribution (Donut Chart) shows the distribution ratio of the three types of sentiment labels in the form of a donut chart. Positive sentiment comments account for 90.1%, neutral comments account for 5.6%, and negative comments account for 4.3%. The results of the two figures show that the sample data is mainly positive sentiment.

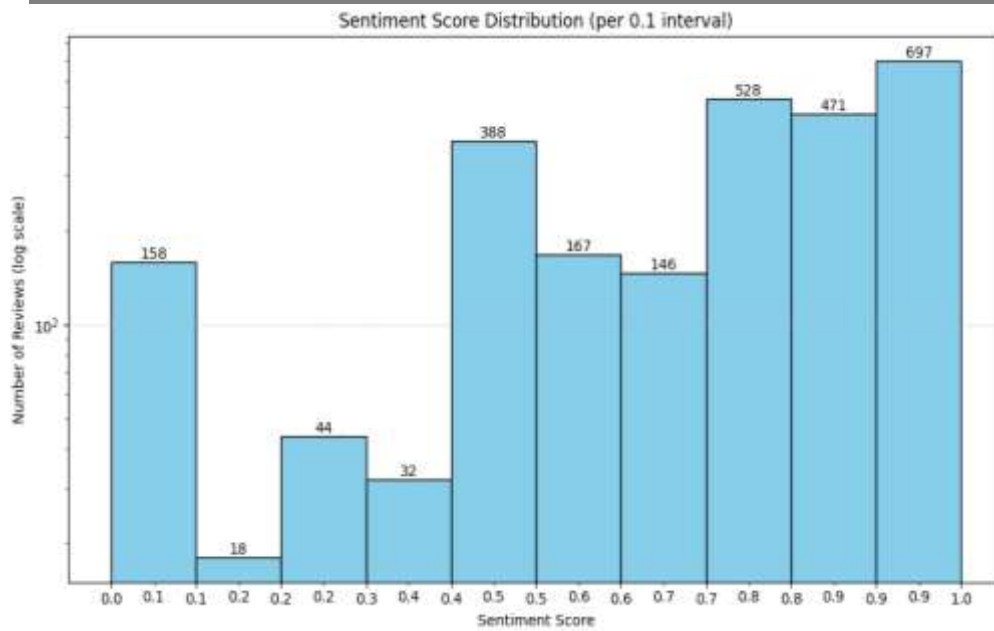


Fig. 5 (a)

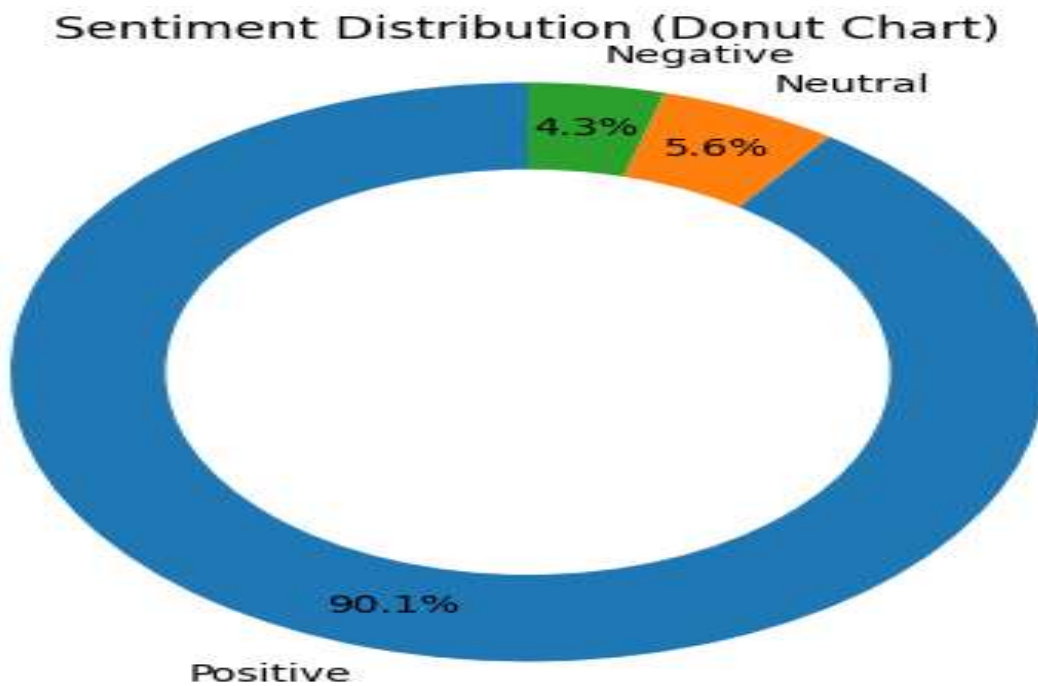


Fig. 5 (b)

Source: 2025 processed original data, Python3.10

Regression analysis

1) Calculating attribute scores

For a certain comment, the calculation formula for its perceptual attribute score is:

$$Perceptual_{score} = P(topic1) + P(topic3) + P(topic4) + P(topic5) \quad (1)$$

The calculation formula for the interactive attribute score is:

$$Interactive_{score} = P(topic2) + P(topic6) \quad (2)$$

Where $P(\text{Theme } X)$ is the probability of the comment on topic X calculated by the LDA model.

2) Regression analysis results

The sentiment score results show that the weighted sentiment scores of the six topics are all in the positive area (all above 0.61), among which the topics related to service interaction (Topics 2 and 6) have relatively higher sentiment scores, which are 0.6671 and 0.6697 respectively. In addition, the sentiment scores of the overall comments are concentrated between 0.5 and 1, and the overall sentiment is positively skewed, indicating that the hotel review data are mainly positive and the overall customer satisfaction is high.

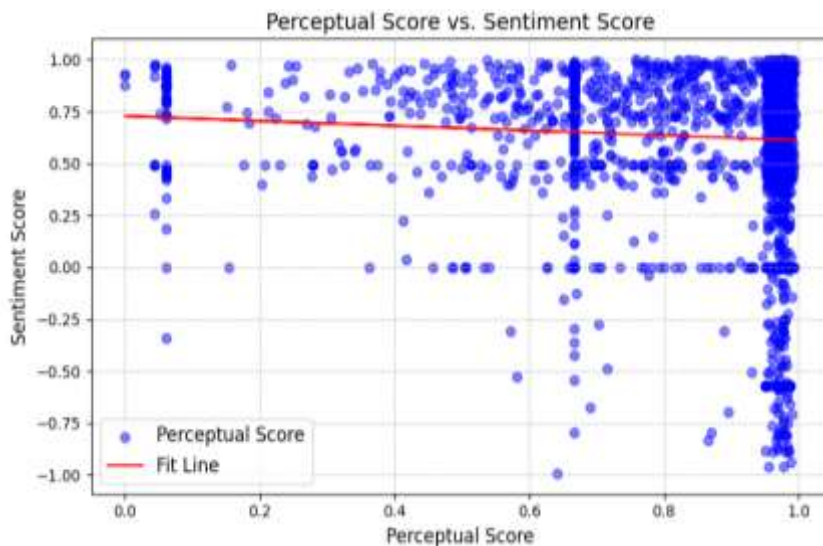


Fig. 6 (a)

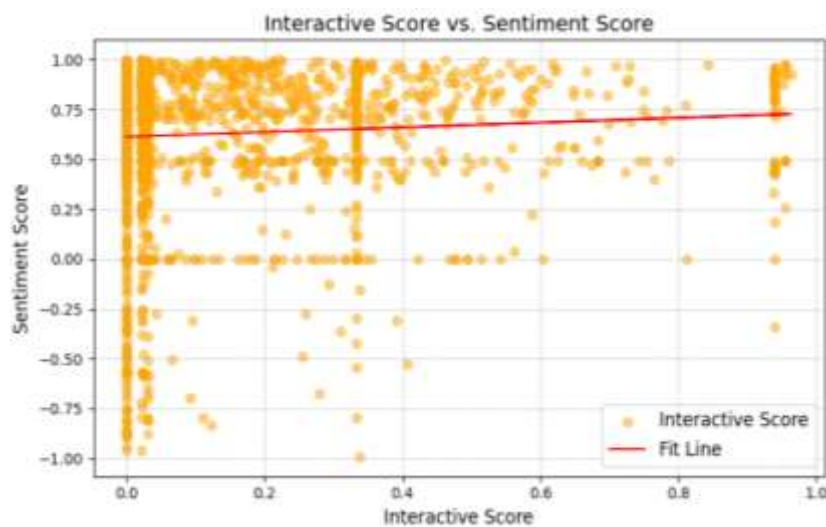


Fig 6 (b)

Source: 2025 processed original data, Python3.10

Figure.6 (a) (Perceptual Score vs. Sentiment Score) The regression results show that the regression coefficient of the perceived attribute score is positive (0.6018). In addition, the sentiment score distribution is more dispersed when the perceived attribute score of a large number of reviews is close to 1, indicating that customers have diversified cognition in their evaluation of perceived content such as environment, room, breakfast, etc.

Figure.6 (b) (Interactive Score vs. Sentiment Score) The regression results show that the regression coefficient of the interactive attribute score is positive (0.7135). It can be observed from the figure that the interactive score

and the sentiment score show a clear positive relationship, and the overall slope of the fitting line is positive .

DISCUSSION

This study verified the hypothesis that both perceptual attributes and interactive attributes in personalized services have a positive impact on customer satisfaction, and the impact of interactive attributes is more significant. In terms of perceptual attributes, customers mainly focus on physical facilities such as room environment, dining experience and space design; in interactive attributes, service response and employee emotional expression are particularly critical, indicating that customers are highly sensitive to attitude and efficiency in the service process. Although perceptual attributes account for a higher proportion in comments, the weight of interactive attributes has increased significantly in negative feedback, which is the main source of dissatisfaction. Through the cross-validation of "topic classification + sentiment analysis + semantic network", it is found that although there are defects in perceived attributes such as poor sound insulation and mosquito infestation, the intensity of negative reviews mainly depends on the interactive attribute performance of the hotel: if the staff can respond in time (such as changing rooms, apologizing), the user's dissatisfaction will be alleviated; if the service is indifferent or the handling is delayed, the dissatisfaction will be amplified, and the focus of the comments will shift to interactive links such as "service attitude" and "response efficiency". The semantic network further shows that the negative association density of interactive attribute keywords is much higher than that of perceived attributes, and interactive defects often escalate minor problems into strong dissatisfaction. The overall comments are positively skewed (90.1% are positive), indicating that the perceived attributes have basically met the standards, and the interactive problems exposed by a small number of negative reviews confirm the service profit chain theory⁶, that is, when the hardware meets the basic needs, emotional interaction becomes the key to improving user satisfaction and forming a differentiated competitive advantage. However, cluster analysis reveals that different customer groups have different concerns about satisfaction, High-quality experience customers pay more attention to emotional and detailed services, while basic service customers pay more attention to cleanliness and facility completeness.

The results of this study are consistent with existing literature, such as Gretzel et al.¹¹ and Wang et al.³⁶, which both emphasize the positive role of personalized services on satisfaction. Unlike previous studies that mostly stayed at the macro level, this study refined the service attributes and found that the interactive attributes had a greater impact on satisfaction, which is highly consistent with the service profit chain perspective proposed by Chathoth et al.⁶. At the same time, service response, as a key touchpoint of negative emotions, confirms the effectiveness of Kim & So²⁰ "service failure and remedy" mechanism, and emotional expression, as a way to measure satisfaction, also fits the application trend of sentiment analysis in service marketing proposed by Feldman¹⁰. Although the regression analysis in this study is mainly used for trend verification, the OLS methodology used is consistent with the least squares regression principle described by Yudiatmaja⁴⁰ in "*Analisis Regresi dengan Menggunakan Aplikasi Komputer Statistik*"; and there are also related studies that confirm the rationality of using Python for regression analysis³⁰.

Based on the empirical results, the study constructed a customer satisfaction evaluation system that combines perceptual attributes and interactive attributes. According to the regression coefficient, the model sets the weight of interactive attributes to 55% and perceptual attributes to 45%. Through sentiment analysis and keyword frequency, the scores of various indicators are extracted to form a satisfaction calculation formula, Satisfaction score = perceived attribute score×45% + interaction attribute score×55%. Further combined with the importance-performance analysis (IPA)¹⁷, the service elements are divided into four management areas: Keep up the Good work (such as personalized butler services, catering, and meditation courses) should continue to be refined; Concentrate Here (such as sound insulation and pest problems) need to be included in the priority rectification; Low Priority (such as smart facilities) can maintain the status quo; Possible Overkill (such as parent-child facilities and cultural experiences) are recommended to introduce child-

friendly designs and cultural derivative services. This system has constructed a closed-loop optimization path of "perception-interaction-technology". By modifying the secondary indicators can be extended to personalized service industries such as cultural tourism and catering. Provide practical tools for enterprises to achieve customer satisfaction management.

CONCLUSIONS

Based on the experiment, the management optimization strategy for the hotel is proposed. In terms of perceptual attributes, it is recommended to optimize the basic facilities such as sound insulation and bedding in the guest rooms, provide customized catering and theme menus, introduce cultural experiences such as meditation and tea ceremony in combination with Zen space design, and use mini programs to enhance customers' recognition of brand culture. In terms of interactive attributes, to improve response efficiency and emotional service quality, it is recommended to combine AI customer service and exclusive butler mechanism, improve user stickiness through social media interaction, and employees should use "service scripts" to achieve personalized communication experience. In terms of service quality monitoring, NLP technology is used to identify negative emotions in real time, establish an early warning mechanism, and introduce undercover personnel and rapid trial and error mechanisms to improve service processes. In terms of differentiated competition, service products are created around the needs of different customer groups, such as business efficiency packages, parent-child rooms, meditation and healing projects, etc., and the "Zen Life" brand IP is created through the development of cultural and creative products and cultural joint activities to enhance brand recognition. Cost investment should focus on optimizing interactive attributes to maximize satisfaction.

In theory, the study divides personalized services into perceived attributes and interactive attributes, innovates the measurement path, and expands the theoretical framework of personalized service satisfaction research; in practice, it clarifies interactive attributes as the key dimension affecting satisfaction, proposes executable optimization solutions, and provides data support for Same Type mid- to high-end hotels to improve service response and customer emotional connection.

Although the research has achieved rich results, there are still some shortcomings. First, the research sample is online reviews on the Ctrip platform. This is mainly because its reviews are only allowed to be written by users who have actually stayed in the hotel, ensuring that the content is authentic and reliable. In addition, as China's leading OTA platform, Ctrip has a large number of reviews with detailed content and strong representativeness. Studies have also verified the academic value of Ctrip reviews in hotel management and consumer behavior research¹⁵. Compared with other platforms, Ctrip provides the most diverse types of review data and the largest number of reviews for the case hotel. It is more suitable as the main platform for studying online reviews of Chinese hotels. At the same time, future studies on other types of hotels or cross-platform comparisons could also incorporate data from platforms such as Booking and Meituan to further enrich the depth and scope of personalized service research. Secondly, the overall comment data is positively skewed (Shapiro-Wilk = 0.808, $p < 0.001$). However, the regression analysis in this study is a trend verification. Gelman¹² and Ioannidis¹⁶ pointed out that the p value is not the only criterion for measuring the significance of variable relationships. Therefore, this study combines LDA topic modeling, sentiment analysis and other methods for cross-validation to enhance stability and explanatory power; The hotel is a mid- to high-end hotel that provides a variety of personalized services (such as meditation, yoga, singing bowl experience courses, service robots, exclusive butlers, etc.), and has rich online review data and is representative to a certain extent; but its service model may be different from that of economy hotels or resort hotels, which limits its direct universal applicability. In the future, the data sample range can be expanded to hotels of different star ratings, regions and brands. Differences in customer perception and interaction preferences under different national cultural backgrounds, and interviews and quantitative research can be combined to improve explanatory power. In addition, the study did not use a questionnaire survey and could not

obtain a standardized satisfaction score. Therefore, the sentiment score was used as a proxy variable. Studies have shown that it can reflect the emotional state of customers and is widely used in satisfaction measurement^{10,28}. At the same time, in the future, we can further explore other attribute dimensions of personalized services, explore the cross-scenario adaptability of the model in experience-based service industries such as cultural tourism and catering, and enhance its promotion and practical value. In the future, AI-driven review sentiment tracking can be combined to monitor customer feedback in real time to help hotels optimize service experience in a timely manner. These limitations provide directions for future research.

REFERENCES

1. Aguirre, E., Roggeveen, A. L., Grewal, D., & Wetzels, M. G. M. (2016). The personalization–privacy paradox: Implications for new media. *Journal of Consumer Marketing*, 33(2), 98–110. <https://doi.org/10.1108/JCM-06-2015-1458>
2. Batat, W. (2019). *Experiential marketing: Consumer behavior, customer experience and the 7Es*. Routledge.
3. Berry, L.L. (1995). Relationship marketing of services—Growing interest, emerging perspectives. *Journal of the Academy of Marketing Science*, 23(4), 236–245. <https://doi.org/10.1177/009207039502300402>
4. Blau, P.M. (1964). *Exchange and power in social life*. New York: Wiley.
5. Bleier, A., De Keyser, A., & Verleye, K. (2018). Customer engagement through personalization and customization. In R. Palmatier, V. Kumar, & C. Harmeling (Eds.), *Customer engagement marketing* (pp. 75–94). Palgrave Macmillan. https://doi.org/10.1007/978-3-319-61985-9_4
6. Chathoth, P. K., Ungson, G. R., Harrington, R. J., & Chan, E. S. W. (2016). Co-creation and higher order customer engagement in hospitality and tourism services: A critical review. *International Journal of Contemporary Hospitality Management*, 28(2), 222–245. <https://doi.org/10.1108/IJCHM-10-2014-0526>
7. Creswell, J.W., & Plano Clark, V.L. (2018). *Designing and conducting mixed methods research* (3rd ed.). Sage Publications.
8. Deci, E.L., & Ryan, R.M. (2000). The “what” and “why” of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry*, 11(4), 227–268. https://doi.org/10.1207/S15327965PLI1104_01
9. Featherman, M.S., & Pavlou, P.A. (2003). Predicting e-services adoption: A perceived risk facets perspective. *International Journal of Human-Computer Studies*, 59(4), 451–474. [https://doi.org/10.1016/S1071-5819\(03\)00111-3](https://doi.org/10.1016/S1071-5819(03)00111-3)
10. Feldman, R. (2013). Techniques and applications for sentiment analysis. *Communications of the ACM*, 56(4), 82–89. <https://doi.org/10.1145/2436256.2436274>
11. Gretzel, U., Sigala, M., Xiang, Z., & Koo, C. (2015). Smart tourism: foundations and developments. *Electronic Markets*, 25(3), 179–188. <https://doi.org/10.1007/s12525-015-0196-8>
12. Gelman, A. (2013). P values and statistical practice. *Epidemiology*, 24(1), 69–72. <https://doi.org/10.1097/EDE.0b013e31827886f7>
13. Geng, C., Wang, P., & Meng, Y. (2021). Research on customer emotions and post-purchase behavior under hotel dynamic pricing: Evidence from online reviews. *Tourism Research*, 13(2), 57–70. <https://doi.org/10.3969/j.issn.1674-5841.2021.02.005>
14. Hennig-Thurau, T., Gwinner, K.P., & Gremler, D.D. (2002). Understanding relationship marketing outcomes: An integration of relational benefits and relationship quality. *Journal of Service Research*, 4(3), 230–247. <https://doi.org/10.1177/1094670502004003006>
15. Hou, Z., Cui, F., Meng, Y., Lian, T., & Yu, C. (2019). Opinion mining from online travel reviews: A comparative analysis of Chinese major OTAs using semantic association analysis. *Tourism*

- Management, 74, 276–289. <https://doi.org/10.1016/j.tourman.2019.03.009>
16. Ioannidis, J.P.A. (2005). Why most published research findings are false. *PLoS Medicine*, 2(8), e124. <https://doi.org/10.1371/journal.pmed.0020124>
17. Jou, R.-C., & Day, Y.-J. (2021). Application of revised importance–performance analysis to investigate critical service quality of hotel online booking: A three-dimensional IPA approach. *Sustainability*, 13(4), 2043. <https://doi.org/10.3390/su13042043>
18. Jurafsky, D., & Martin, J.H. (2020). *Speech and Language Processing* (3rd ed.). Draft. Stanford University.
19. Kaplan, A.M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of social media. *Business Horizons*, 53(1), 59–68. <https://doi.org/10.1016/j.bushor.2009.09.003>
20. Kim, H., & So, K. K. F. (2023). The evolution of service failure and recovery research in hospitality and tourism: An integrative review and future research directions. *International Journal of Hospitality Management*, 114, Article 103457. <https://doi.org/10.1016/j.ijhm.2023.103457>
21. Kotler, P., & Keller, K.L. (2016). *Marketing management* (15th ed.). Pearson.
22. Kumar, V., & Reinartz, W. (2016). Creating enduring customer value. *Journal of Marketing*, 80(6), 36–68. <https://doi.org/10.1509/jm.15.0414>
23. Li, H., & Zhang, A. (2020). Thoughts on personalized hotel services. *China Business Review*, (18), 116–117. <https://doi.org/10.19699/j.cnki.issn2096-0298.2020.18.116>
24. National Bureau of Statistics. (2025). National Bureau of Statistics of china . <https://data.stats.gov.cn/easyquery.htm?cn=C01>
25. Oliver, R.L.(1999). Whence consumer loyalty? *Journal of Marketing*, 63(Special Issue), 33–44. <https://doi.org/10.2307/1252099>
26. Parasuraman, A., Zeithaml, V.A., & Berry, L.L. (1988). SERVQUAL: A multiple-item scale for measuring consumer perceptions of service quality. *Journal of Retailing*, 64(1), 12–40. Retrieved from ResearchGate :https://www.researchgate.net/publication/225083802_SERVQUAL_A_multiple-Item_Scale_for_measuring_consumer_perceptions_of_service_quality
27. Palkast. (2023). Unveiling sentiments and themes in social media news using topic modeling and OpenAI-enhanced sentiment analysis [GitHub project]. GitHub. Retrieved from <https://github.com/palkast/Unveiling-Sentiments-and-Themes-in-Social-Media-News-using-Topic-Modeling>
28. Pang, B., & Lee, L. (2008). Opinion mining and sentiment analysis. *Foundations and Trends® in Information Retrieval*, 2(1–2), 1–135. <https://doi.org/10.1561/15000000011>
29. Peppers, D., & Rogers, M. (1993). *The One-to-One Future: Building Relationships One Customer at a Time*. Currency Doubleday.
30. Sargent, T. J., & Stachurski, J. (2025). Linear regression in Python — Intermediate quantitative economics. QuantEcon. Retrieved from <https://python.quantecon.org/ols.html>
31. Sweeney, J.C., & Soutar, G.N. (2001). Consumer perceived value: The development of a multiple item scale. *Journal of Retailing*, 77(2), 203–220. [https://doi.org/10.1016/S0022-4359\(01\)00041-0](https://doi.org/10.1016/S0022-4359(01)00041-0)
32. Thomson, M., MacInnis, D.J., & Park, C.W. (2005). The ties that bind: Measuring the strength of consumers' emotional attachments to brands. *Journal of Consumer Psychology*, 15(1), 77–91. https://doi.org/10.1207/s15327663jcp1501_10
33. Trianasari, N., Butcher, K., & Sparks, B. (2018). Understanding guest tolerance and the role of cultural familiarity in hotel service failures. *Journal of Hospitality Marketing & Management*, 27(1), 21–40. <https://doi.org/10.1080/19368623.2017.1329677>
34. Verhoef, P.C., Lemon, K.N., Parasuraman, A., Roggeveen, A., Tsiros, M., & Schlesinger, L.A. (2009). Customer experience creation: Determinants, dynamics and management strategies. *Journal of Retailing*, 85(1), 31–41. <https://doi.org/10.1016/j.jretai.2008.11.001>
35. Villa-Turek, E. (2020). Opinion mining in Twitter using VADER and Gensim's latent Dirichlet

- allocation (LDA). Towards Data Science. Retrieved from <https://medium.com/towards-data-science/opinion-mining-in-twitter-using-vader-and-gensims-latent-dirichlect-allocation-lda-a834c2a936>
36. Wang, L. , Law, R., & Guillet, B. D .(2015). Impact of hotel website quality on online booking intentions: eTrust as a mediator. *International Journal of Hospitality Management*, 47, 108–115. <https://doi.org/10.1016/j.ijhm.2015.03.012>
 37. Widiastini, N. M. A., & Prayudi, M. A. (2021). Women’s significant roles in pursuing hotel revenue: Case of Bali, Indonesia. *Journal of Social Sciences and Humanities*, 11(3). Retrieved from <https://ojs2.pnb.ac.id/index.php/SOSHUM/article/view/147/85>
 38. Widiastini, N. M. A., Arsa, I. K. S., Syah, A. M., & Hajrarhmah, D. (2024). How do micro, small, and medium enterprises (MSMEs) in Bali survive the pandemic? A qualitative study in Buleleng, Tabanan, Gianyar, and Denpasar. *International Journal of Professional Business Review*. Retrieved from <https://vtechworks.lib.vt.edu/handle/10919/114890>
 39. Widiastini, N. M. A., Arsa, I. K. S., Prayudi, M. A., & Karta, N. L. P. A. (2025). Strategic collaborations and diversification: Pathways to sustainable growth in Bali’s tourism village and business ecosystems. *Journal Kajian Bali (Journal of Bali Studies)*, 15(1). <https://doi.org/10.24843/JKB.2025.v15.i01.p06>
 40. Yudiaatmaja, F. (2013). *Analysis regresi dengan menggunakan aplikasi computer statistic*. Jakarta: Gramedia Pustaka Utama.
 41. Zeithaml, V.A. (1988). Consumer perceptions of price, quality, and value: A means-end model and synthesis of evidence. *Journal of Marketing*, 52(3), 2–22. <https://doi.org/10.1177/002224298805200302>
 42. Zhao, T. (2025, January 17). Zhao Tonglu: my country's economic operation is stable and making progress, and the total economic volume has reached a new level. *China Economic Network*. URL http://www.ce.cn/xwzx/gnsz/gdxw/202501/17/t20250117_39269895.shtm

APPENDIX

A. Perceptual attribute evaluation dimension system table

First level indicator	Secondary indicators	Evaluation content	Data Source
Room facilities and environment	Completeness and cleanliness of facilities	Bedding comfort, sound insulation, bathroom equipment quality, room cleaning frequency, public area hygiene, bedding replacement frequency, etc.	Online review keywords, review frequency analysis, sentiment score analysis
Space design and aesthetics	Design style and integration of cultural elements	Overall decoration style, light layout, visual element uniformity; brand culture presentation, Zen space, tea culture elements, etc.	Frequency and sentiment analysis of words such as "decoration, environment, design" in reviews; combined with manual identification of typical reviews
Dining experience	Breakfast quality and dining convenience	Richness of dishes, taste satisfaction, reasonable layout of the buffet breakfast area, waiting time in the dining area, waiter response speed, etc.	Summary analysis and sentiment tendency of keywords such as "breakfast, queuing, service" in online reviews

Value-added services and activity experience	Cultural experience and spatial diversity	Meditation, singing bowls, yoga courses, intangible cultural heritage handmade experience and other value-added services with brand culture or physical and mental healing nature; The hotel provides a variety of space settings for solitude, reading, and meditation, such as the "meditation tea room"	Analysis and feedback on review keywords "meditation, activity, quiet, space"
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B. Interactive attribute evaluation dimension system table

First-level indicators	Secondary indicators	Evaluation content	Data Source
Communication efficiency	Response speed and communication fluency	Front desk processing time, service robot task completion efficiency, employee problem solving time, whether communication with customers is clear	Keywords in online reviews: "timely, quick response, speed, communication, smooth" etc.
Emotional connection	Personalized greetings, warmth and care	Proactively caring about customer emotions, quickly understanding customer needs, smiling service, welcome courtesy	Keywords in reviews: "enthusiasm, thoughtfulness, experience, welcome gift, touching" etc.
Service attitude	Service awareness, quality and professionalism	Proper attitude, butler service, personalized service recommendation accuracy, proactive help for customers	Descriptions: "professional, polite, good attitude, help, initiative" etc.
Personalized interaction	Characteristic service behaviors, situational communication experience	Personalized service that meets customer preferences, meditation courses, holiday surprises	Analysis of specific cases: "customization, arrangement, meditation room, surprise, special" etc.
Relationship maintenance	Return customer maintenance, emotional memory creation, service failure repair	Whether to maintain stable service or establish long-term relationships, create unforgettable interactive memories, service compensation processing, complaint response speed processing and resolution	Willing expressions in reviews: "second stay, still satisfied, will choose again, will stay again, impressed, solved, handled" etc.