

Beyond Star Ratings and Scores: Unveiling Guests' "Voices" in AI Hotel Online Reviews via LDA

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Abstract. With the in-depth integration of artificial intelligence (AI) technology and the hotel industry, AI-smart hotels have developed rapidly. However, issues such as weakened emotional connections caused by technological substitution and polarized user reviews have become increasingly prominent. Nevertheless, there is a lack of in-depth analytical research on online user reviews of smart hotels, making it an urgent challenge to accurately grasp user needs. This study employs the Latent Dirichlet Allocation (LDA) topic model to conduct text mining on online reviews of AI-smart hotels. Through steps including data preprocessing, model construction, and optimization, it extracts 8 core topics from the reviews, covering dimensions such as smart facilities, overall evaluation, repurchase intention, and environmental hygiene, which comprehensively reflect users' key concerns. Innovatively, this research distills consumer-focused topics from massive online reviews of AI hotels, addressing the problem of identifying consumers' needs for AI-smart hotels amid complex textual information and filling the gap in relevant theoretical research. Additionally, it provides operational and referential suggestions from three perspectives: AI hotel marketers, AI technology manufacturers, and consumers.

Keywords: AI Hotels; LDA Topic Model; Online Reviews; Smart Facilities; User Needs.

1. Introduction

In recent years, the breakthrough progress of artificial intelligence (AI) technology has deeply integrated with the digital transformation needs of the global hotel industry, giving rise to the AI-smart hotel model centered on intelligent services, unmanned operations, and personalized experiences [1]. The Zhejiang Provincial Action Plan for Innovative Development of Culture and Tourism Market (2025-2027) points out that many provinces and cities in China have incorporated smart hotels into their cultural and tourism innovation strategies. For instance, Zhejiang Province explicitly proposes to achieve full coverage of intelligent transformation for tourist hotels across the province by 2027, with an additional 50 green smart hotels and 30 cultural-Topic smart hotels [2]. The global smart hotel market size exceeded 30 billion USD in 2023, with an annual growth rate of over 15% [3]. The integration of AI technology and hotels not only reduces hotels' labor costs but also meets the rising consumer demand for technological experiences. For example, Alibaba's FlyZoo Hotel has improved the efficiency of check-in procedures through full-scenario facial recognition, AI room butlers (Tmall Genie), and robot service chains [4], which confirms the market's widespread acceptance of "contactless intelligent services."

However, in the process of large-scale implementation of smart hotels, a series of issues have gradually emerged. The introduction of intelligent service technologies, which replace traditional services, weakens the emotional connection between consumers and service providers and increases human-machine interaction time. As a result, some consumers have poor experiences with intelligent services, leading to polarized user feedback. With the popularization of social media and e-commerce, online reviews have gradually become a core information source for interpreting user needs [5]. Online reviews on platforms such as Dianping, Meituan, and Ctrip truly reflect users' opinions and demands. Nevertheless, these platforms are flooded with massive amounts of textual data, posing significant challenges to information extraction and analysis. Therefore, how to accurately identify the key topics of concern to consumers from the vast amount of online reviews of AI hotels has become an urgent issue to be addressed.

Machine learning and text mining technologies offer solutions to this problem; models such as LDA, support vector machines, and decision trees can sort and mine these data. However, due to the complexity of data sources, coupled with the fact that smart hotels themselves are still in the early stages of development, there is a paucity of in-depth analytical studies on online user reviews of AI-smart hotels. Therefore, this study will employ machine learning and text mining technologies to identify user needs and key topics from online reviews of AI-smart hotels. The findings of this research are expected to provide valuable guidance for AI hotel operators, helping them grasp user needs more accurately and thereby optimize service quality.

2. Literature Review

Existing research on AI in the hotel sector can be categorized into two types: one focuses on the application effects of AI tools in hotel text analysis, and the other emphasizes the impact of AI technologies on hotel user behavior and service experiences.

In terms of the application of AI tools in text analysis, scholars have primarily explored the utility and limitations of generative AI in processing hotel user reviews. In the field of hotel hospitality, Hala Sun et al. employed grounded theory and qualitative content analysis for manual coding, comparing the results with ChatGPT-based coding using specific prompts to examine the utility of generative AI (ChatGPT) in qualitative analysis of hotel guests' positive experiences. The findings indicated that the topics and codes generated by ChatGPT largely matched those from human coding, and this capability can enhance data analysis efficiency. However, key elements identified through manual coding (such as guest-to-guest interactions and safety guarantees) were omitted by ChatGPT. Meanwhile, this study established a methodology for using ChatGPT in qualitative analysis [6]. In the field of hotel online review management, Huihui Zhang et al. investigated the differences in effectiveness and influencing factors between generative AI responses and human responses. This study used GPT-3.5 to generate over 32,129 responses and calculated their similarity to human responses. Regression analysis revealed that AI responses with high temperature settings were more effective for positive reviews, while low temperature settings might have negative effects, emphasizing the importance of fit between technology and tasks [7]. In the field of hotel online reviews, Shizhen (Jasper) Jia et al. studied the impact of AI-generated versus human-generated review summaries on customer trust, information processing, and booking intentions. Through three scenario-based experiments, they found that human-generated summaries triggered higher customer trust, thereby enhancing booking intentions. However, when processing negative reviews, there was no significant difference in the impact of the two types of summaries on booking intentions, and trust was not the sole mediating variable. Further analysis showed that information processing effort was a potential mediating factor; particularly when facing negative reviews, customers invested more cognitive resources in reading AI-generated summaries [8].

In terms of the impact of AI technologies on user behavior and service experiences, research primarily revolves around user acceptance, satisfaction, and marketing transformations. In the field of hotel recommendations, GuoQiong Ivanka Huang et al. examined how the inspirational role of generative AI and anxiety caused by a lack of transparency influence users' acceptance of hotel recommendations. The results indicated that generative AI's ability to produce creative content can effectively inspire customers, enhancing their willingness to accept hotel recommendations. However, this inspirational process may be hindered by customer anxiety arising from insufficient transparency [9]. In the context of chain hotels in coastal tourist destinations in western Thailand, Noptanit Chotisarn et al. analyzed the impact of AI-empowered service attributes on customer satisfaction and loyalty. The findings showed that service efficiency and enjoyment significantly affect satisfaction with AI services, and satisfaction strongly influences customer loyalty. In contrast, reliability, perceived intelligence, and aesthetics had no significant impact on satisfaction. The model exhibited strong explanatory power for both satisfaction and loyalty [10]. Huiying Du et al. focused on the field of unmanned smart hotels, investigating consumer acceptance of such establishments. First, they

integrated the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB), finding that attitude, subjective norms, and perceived behavioral control all positively influence usage intention. Second, they further explored the factors affecting perceived safety, revealing that people's beliefs about unmanned smart hotels and safety control guarantees shape perceived safety, which is influenced by factors such as perceived physical risk, privacy concerns, website design, and hotel reputation [11]. In the field of hotel marketing, Jacques Bulchand-Gidumal et al. explored the impact of AI on hospitality and tourism marketing. The results identified ten trends of AI in hotel marketing, clustered into four topics, and elaborated on the potential changes AI may bring to hospitality and tourism marketing [12]. In the fields of tourism, hospitality, and leisure, Chulmo Koo et al. discussed the applications of AI and robotics. They introduced studies included in a related special issue, covering topics such as motivational attribution of service robots and the application of robots in hotels, emphasizing the interdisciplinary nature and significance of research in this field [13].

Most of the aforementioned studies focus on user-generated content such as hotel online reviews, exploring AI applications in hotel scenarios, and extensively utilizing text analysis techniques to investigate user attitudes and behaviors. However, existing methods primarily rely on manual coding or general AI tools for topic extraction, with relatively insufficient application of topic models such as LDA. This leads to inadequate in-depth exploration of the implicit, multi-dimensional demand structures embedded in user reviews. Furthermore, there is a lack of specificity toward the particular scenario of "AI-smart hotels": analyses of users' specific needs in this context (e.g., concrete demands for AI services) are insufficient, and there is a dearth of research on the correlation between technical characteristics and user needs. To address these research limitations, this study employs LDA topic modeling to conduct an in-depth analysis of online reviews of AI-smart hotels, aiming to identify and distill users' core needs and key topics of concern.

3. Research Methodology

This study adopts the Latent Dirichlet Allocation (LDA) topic modeling framework to analyze user review texts in hotel scenarios. Its core objective is to mine the implicit topic structure in textual data through a probabilistic generative model. The fundamental assumption of LDA is that a document is composed of a mixture of multiple topics, where each topic is represented as a probability distribution of words. This method automatically infers the relationships between documents and topics, as well as between topics and words, through an unsupervised learning mechanism. It does not rely on manually annotated training sets, thus adapting well to text analysis tasks across different domains. This study employs a standardized LDA topic modeling process, encompassing data preprocessing, model construction with parameter optimization, and topic interpretation. LDA assumes that documents are generated by a mixture of latent topics, and its joint probability distribution is expressed as [14]:

$$p(\theta, \mathbf{z}, \mathbf{w} | \alpha, \beta) = p(\theta | \alpha) \prod_{n=1}^N p(z_n | \theta) p(w_n | z_n, \beta) \quad (1)$$

$\theta \sim \text{Dirichlet}(\alpha)$ represents the topic distribution of a document, where α controls the sparsity of the distribution; $\varphi_k \sim \text{Dirichlet}(\beta)$ denotes the word distribution of topic k , with β regulating the concentration of words; z_n is the topic label of the n th word, and w_n is the corresponding word.

In the data preprocessing stage, the original review texts are first subjected to standardization. Punctuation marks, special characters, and non-linguistic elements are removed using regular expressions, retaining valid semantic units. A Chinese word segmentation tool is employed in conjunction with a domain-specific dictionary (e.g., compound terms such as "smart guest room" and "voice control") to perform precise word segmentation, ensuring the integrity of domain-specific terminology. Subsequently, a comprehensive stop-word list is applied to filter out meaningless words, and single-character words and numerical characters are eliminated, leaving only valid terms with a length of 2 or more. Finally, data cleaning operations are executed, including handling missing values,

filtering short texts, and deleting duplicate records, resulting in the preprocessed structured text corpus.

In the model construction and optimization phase, the bag-of-words model is adopted to represent text features. First, a document-term frequency matrix is constructed, and TF-IDF weighting transformation is applied to enhance Topic-distinguishing features while suppressing the influence of high-frequency generic words. The determination of the number of topics is calculated by combining perplexity and coherence: perplexity evaluates the model's predictive ability, and coherence score measures the semantic association strength of words within a Topic. By analyzing the change curves of these indicators, the optimal number of topics is selected comprehensively. For model training, sparsity prior parameters are set ($\alpha=0.01$, $\eta=0.01$), and variational Bayesian inference is used for 50 iterations of training to ensure parameter convergence.

Perplexity evaluates the generalization ability of the model [14]:

$$\text{Perplexity} = \exp \left(- \frac{\sum_{d=1}^D \log P(w_d)}{\sum_{d=1}^D N} \right) \quad (2)$$

D represents the number of documents, and N represents the total number of words. A lower value indicates a stronger ability of the model to predict new data.

Coherence use C_v metric [14]:

$$C_v = \frac{1}{K} \sum_{k=1}^K \frac{1}{m(m-1)} \sum_{i < j} \frac{\log \frac{P(w_i, w_j) + \epsilon}{P(w_i)P(w_j)}}{-\log P(w_i, w_j)} \quad (3)$$

w_i, w_j represents the top-m words of the same Topic, and ϵ is the smoothing factor. A higher value indicates better semantic coherence of the Topic.

Variational Bayesian iterative optimization is employed, with the maximization objective of its Evidence Lower Bound (ELBO) as follows [15]:

$$L(q) = E_q[\log p(X, Z)] - E_q[\log q(Z)] \quad (4)$$

X is the observed sequence of comment words, and Z is the latent topic assignment.

In the topic parsing stage, the probability distribution results output by the model are extracted. Each topic is represented by the top 30 keywords and their probability weights, forming a topic feature matrix. The probability weights of keywords are used to create word clouds for visual display, where the font size maps to the importance of words. Meanwhile, the document-topic probability distribution is calculated, and each comment is assigned a topic (the topic with the highest probability is taken as the topic name). The similarity between topics is quantified and displayed using the interactive visualization tool pyLDAvis, which calculates topic distances based on Jensen-Shannon divergence and presents clustering relationships in a two-dimensional space.

In pyLDAvis visualization, the distance between topics p and q is calculated based on Jensen-Shannon divergence:

$$D_{JS}(p, q) = \frac{1}{2} D_{KL} \left(p, \frac{p+q}{2} \right) + \frac{1}{2} D_{KL} \left(q, \frac{p+q}{2} \right) \quad (5)$$

Here, is the Kullback-Leibler divergence:

$$D_{KL}(p, q) = \sum_{i=1}^T p_i \ln \frac{p_i}{q_i} \quad (6)$$

4. Results and Analysis

Based on the aforementioned research methods, this section will present in detail the final topic results extracted after model training, and conduct a detailed interpretation and visual analysis of the core semantic connotations of each topic. The aim is to reveal the core hotel service dimensions concerned by users and their specific performance characteristics.

4.1. Basis for Selecting the Number of Topics

In the process of topic modeling, two core indicators—Perplexity and Coherence—are used to evaluate the performance of models with different numbers of topics. Figure 1 shows the trend of Perplexity changing with the number of topics, and Figure 2 shows the trend of Coherence changing with the number of topics. It can be seen from Figure 1 that the logarithmic perplexity of the model shows a monotonically decreasing trend as the number of topics increases, dropping from -28.05 when there are 2 topics to -30.87 when there are 20 topics, and gradually slowing down starting from the 8th topic. As shown in Figure 2, the Coherence index presents a different changing pattern: it fluctuates and decreases from 0.49 with 2 topics to 0.38 with 20 topics, and increases sharply starting from the 8th topic. Based on the comprehensive analysis of the trends of these two indicators, the modeling scheme with 8 topics is finally selected.

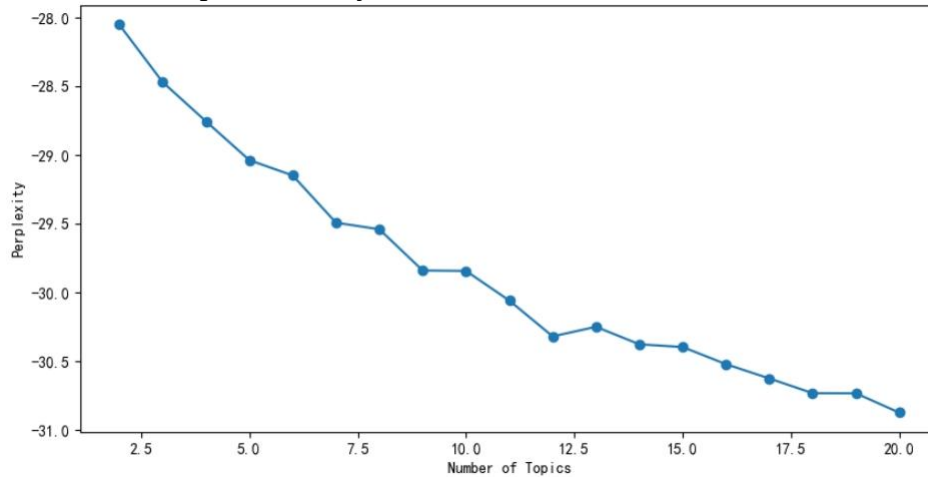


Figure 1 Line Chart of Perplexity Variation with the Number of Topics

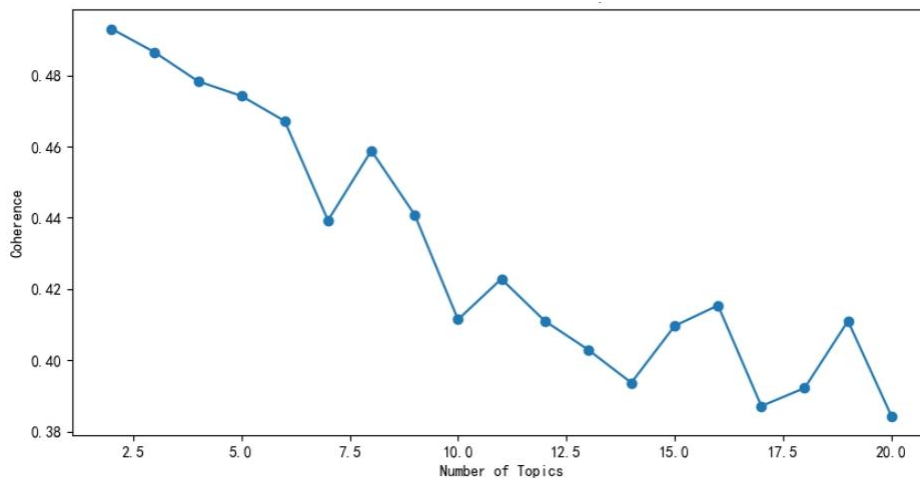


Figure 2 Line Chart of Coherence Variation with the Number of Topics

4.2. Analysis of Topic Contents

After determining that 8 topics constitute the optimal model, an in-depth analysis of each topic's content is conducted. The top 100 keywords of each topic (sorted by weight) are extracted, and

combined with the scenario of AI-smart hotels, the topics are named and their connotations are explain.



Figure 3 Intelligent Facilities and Basic Services (Topic 1)

This Topic focuses on the core scenarios and basic services of AI-smart hotels. As a key identifier, "intelligent" reflects users' attention to the intelligent elements of hotels, indicating that at the basic experience level, intelligent elements (such as self-service check-in devices and smart room controls) have become important components of customers' perception and evaluation. Words like "room," "facilities," "gym," and "parking" reflect evaluations of the hardware environment. Terms such as "free," "check-in," and "front desk" point to service processes and additional benefits. Overall, it presents users' intuitive experiences with the basic configurations and services of smart hotels.



Figure 4 Overall Evaluation and Recommendation Intention (Topic 2)

This Topic strongly expresses customers' high satisfaction and positive recommendation intention. Keywords such as "satisfied," "excellent," and "positive reviews" hold extremely high weights, directly reflecting the overall recognition of AI-smart hotels. "Recommend" and "worthwhile" reflect users' willingness to share. Terms like "business trip" and "accommodation" imply that the scenarios are mainly business trips, indicating the high recognition of smart hotels after meeting business needs, and intelligent services may have indirectly enhanced users' overall experience. This Topic is a core embodiment of customer loyalty and word-of-mouth communication.



Figure 7 Geographic Location and Transportation Convenience (Topic 5)

This Topic explicitly centers on the hotel's geographical location and the transportation convenience it entails. Keywords such as "airport," "subway station," and "transportation" indicate users' attention to the distance between the hotel and major transportation hubs. Terms like "very close" and "advantageous" underscore the importance of convenience, which is particularly critical for smart hotels—intelligent services (e.g., robot guidance, smart navigation) can further amplify the benefits of a favorable location. Notably, "robot" emerges as a key term; when combined with contexts like "airport," it suggests that intelligent robots may have played a role in delivering location-based convenience services (such as item delivery or guidance) or left a distinct impression on customers.



Figure 8 Technological Experience and Regional Characteristics (Topic 6)

This Topic features distinct regional and intelligent characteristics. "Sense of technology" appears as a core characteristic keyword, implying that hotels or reviews under this Topic particularly emphasize their high-tech attributes. Meanwhile, the regional label "Beijing" is prominent, pointing to benchmark smart hotels or distinctive experiences in this specific city. Terms such as "exclusive enjoyment," "facilities," and "cost-effectiveness" describe the premium experience enhanced by the sense of technology, with the overall evaluation leaning positive.

differences between topics, thereby enabling more accurate exploration of user needs and guiding the optimization of hotel services.

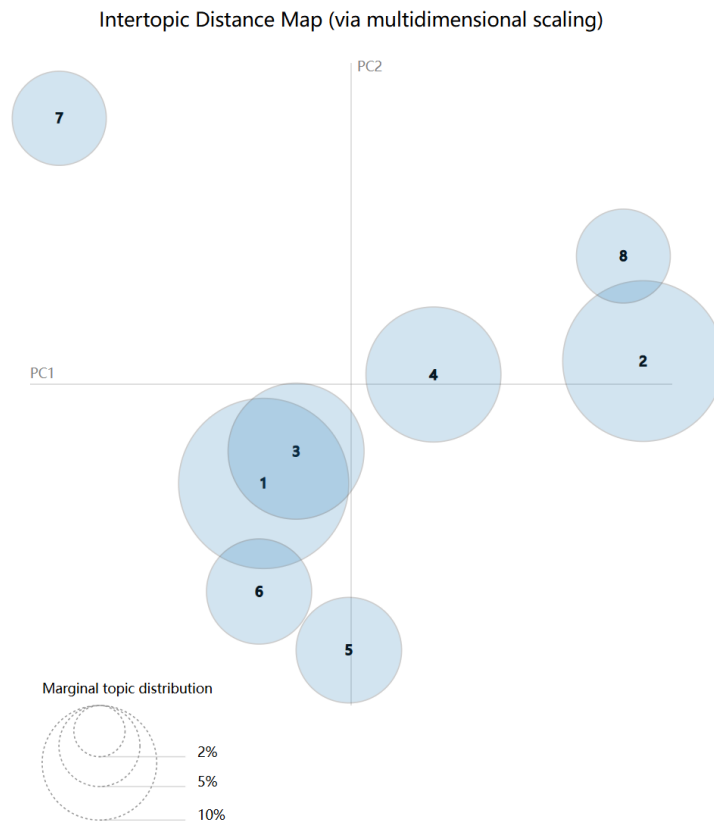


Figure 11 Spatial Distribution of topics (1–8 indicate descending order of proportion)

The topics, ordered by their frequency from highest to lowest, are as follows: Topic 1 (22%), Topic 4 (19.6%), Topic 3 (13.9%), Topic 5 (8.5%), Topic 6 (8.4%), and topics 2, 7, and 8 (each 6.7%).

Table 1 Topic-Vocabulary Characteristics

Topic Number	Topic Name	Top 10 Feature Words by Topic Probability	Corresponding Spatial Number	Frequency Proportion
Topic1	Intelligent Facilities and Basic Services	Hotel, room, free, intelligent, check-in, service, good, front desk, clean, breakfast	1	22%
Topic2	Overall Evaluation and Recommendation Intention	Satisfaction, experience, recommendation, excellent, good, worthwhile, check-in, service, environment, satisfactory	8	6.7%
Topic3	Repurchase Intention and Comfort Perception	Next time, comfortable, breakfast, special, good, hotel, will again, overall, room, like	4	13.9%
Topic4	Environmental Hygiene and Service Evaluation	Good, clean, environment, hygiene, service, facilities, room, tidy, quiet, service attitude	2	19.6%

Topic Number	Topic Name	Top 10 Feature Words by Topic Probability	Corresponding Spatial Number	Frequency Proportion
Topic5	Geographic Location and Transportation Convenience	Airport, good, geographic location, hotel, very close, travel, location, distance, superior	5	8.5%
Topic6	Technological Experience and Regional Characteristics	Beijing, hotel, airport, sense of technology, service, breakfast, clean, environment, exclusive, room	6	8.4%
Topic7	Additional Services and Detailed Feedback	Shuttle service, sound insulation, restaurant, comfortable, taste, room, good, effect, newly renovated, breakfast	7	6.7%
Topic8	Front Desk Service and Personalized Experience	Front desk, upgrade, attitude, service, hotel, room, five-star, enthusiastic, clean, good	3	14.1%

From the perspective of spatial positional relationships, topics 1, 3, 5, 6, and 8 are relatively clustered, forming an "intelligent experience value transmission cluster." This clustering characteristic indicates that user evaluations follow an inherent logic: starting from intelligent basic experiences, progressing to the deepening of distinctive value, and ultimately forming a closed loop of emotional services. This implies that smart hotels need to strengthen the synergy between intelligent facilities and manual services. For example, after guests complete intelligent check-in, the front desk can identify their needs through the system and proactively push personalized services, thereby achieving the integration of intelligent efficiency and humanized services. topics 2 and 4 are spatially adjacent yet relatively independent, reflecting the causal relationship between basic experiences (such as environmental hygiene and service quality) and overall evaluations. Smart hotels must take basic experiences as the foundation and consolidate the cornerstone of user satisfaction. Topic 7 is relatively isolated in position with clear semantic boundaries, focusing primarily on specific aspects such as "detailed feedback." Its evaluation dimensions are significantly different from those of other topics, requiring targeted optimization of these segmented experiences.

From the perspective of Topic proportions, topics 1 and 4 account for the highest proportions, emerging as focal points in user evaluations. Therefore, hotels should strive to enhance the practicality of intelligent facilities and strengthen the synergy between intelligent facilities and services, as this will solidify users' overall evaluations of the hotel. topics 3 and 8, with moderate proportions, serve as key pillars of the user experience. They focus on the emotional value derived from front-desk interactions, which is associated with users' likelihood of reselecting the hotel. Hence, such emotional interactions need to be integrated into intelligent service scenarios to deepen the user experience. topics 2, 5, 6, and 7 cover aspects such as location, distinctive features, and detailed feedback. Collectively, they constitute multiple dimensions from which users evaluate AI-smart hotels and represent key areas of user concern.

From the perspective of the overlapping and distinct characteristics of the topics, topics 1, 6, and 8 exhibit a high degree of overlap, indicating opportunities for "intelligent + human" service innovation. For instance, a human-machine collaborative closed-loop service process could be designed, where after guests complete intelligent check-in, the hotel delivers personalized service

cards tailored to their needs. The partial overlap between topics 2 and 4 suggests that hotels can utilize intelligent tools to quantify basic experiences—for example, generating "intelligent cleaning reports" to enhance the credibility of such foundational experiences. The distinctness of topics 5, 7, etc., from other topics creates space for differentiated innovation. For example, hotels in remote locations can leverage intelligent surrounding services to convert locational disadvantages into advantages, while applying intelligent noise reduction technologies to address detailed issues.

5. Conclusion

Based on the Latent Dirichlet Allocation (LDA) topic modeling method, this study conducted text mining on online reviews of AI-smart hotels, ultimately extracting 8 core topics: intelligent facilities and basic services, overall evaluation and recommendation intention, repurchase tendency and comfort perception, environmental hygiene and service evaluation, geographical location and transportation convenience, technological experience and regional characteristics, additional services and detailed feedback, and front desk services and personalized experience.

The findings of this study hold significant practical value. Hotel marketers can leverage the results to gain insights into users' core concerns and evaluation dimensions, providing a basis for optimizing service configurations and adjusting operational directions, thereby enhancing user experience and market competitiveness. Technology manufacturers can more accurately identify the optimization directions for technology applications and users' key pain points, offering clear guidance for technological iteration and product upgrades. Consumers, on the other hand, can develop a more comprehensive understanding of the value composition of smart hotel services.

Targeted suggestions for different stakeholders are as follows: For AI hotel marketers, there is a need to balance investment in intelligent technologies and manual services. While improving service efficiency, they should strengthen training to enhance employees' ability to establish emotional connections. Emphasis should be placed on improving environmental hygiene and the quality of basic services, with specific improvements made to address detailed issues highlighted in user feedback (e.g., sound insulation, additional services). For AI technology manufacturers, it is necessary to further simplify the operation procedures of smart devices to reduce user barriers—for instance, simplifying the control commands for smart lights to "turn on" and "turn off." Strengthening technological research and development will enable AI systems to more accurately identify user needs and enhance personalized service capabilities, while also prioritizing the protection of user privacy and data security. For consumers, it is recommended that they fully reference online review information when making decisions to comprehensively understand the actual performance of target smart hotels (e.g., responsiveness of smart devices, service details) and select hotels that better align with their needs. After their stay, sharing authentic and specific reviews (e.g., the response speed of smart door locks, cleanliness) will not only help hotels improve their services but also provide valuable references for other consumers.

This study has certain limitations. In terms of samples, it mainly relies on online reviews from domestic Chinese platforms, which cannot fully represent the evaluation of AI-smart hotel users globally, and the geographical representativeness of the samples needs to be improved. Additionally, as an initial study on online reviews of AI-smart hotels, the exploration of the deep correlations and influence mechanisms between topics is insufficient. Future research can expand the sample scope to include online review data from different regions worldwide, further analyze the intrinsic connections between topics, and integrate more research methods to enrich the conclusions, thereby providing more comprehensive guidance for the development of AI-smart hotels.

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