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From negative feedback to actionable insights: a computational analysis of service robot adoption challenges in Chinese hotels

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ABSTRACT
With the rapid rise in labour costs in China's hotel industry, service robots have emerged as a potential solution to enhance service efficiency and reduce operational expenses. However, their adoption rate in Chinese hotels remains low. While prior studies have primarily explored technical performance and costs from a managerial perspective, there is a lack of systematic methodologies examining adoption barriers from the lens of guests' negative emotions. This study employs web-crawling technology to collect 20,900 low-rated reviews from six major Chinese online travel platforms. Using Latent Dirichlet Allocation (LDA) topic modelling combined with computational grounded theory, the authors identified ten key barriers to the adoption of service robots in hotels. Notably, this study introduces "Cultural Misfit", "Frequent Malfunctions", and "Inconvenient Operation" as distinct barriers. It also reveals a cascading effect involving service quality, functional utility, and expectation alignment, highlighting that multidimensional interactions drive technology acceptance. These findings provide theoretical and practical insights for optimising service robot deployment, offering new perspectives to improve service efficiency and user acceptance in China's hotel industry.

KEY WORDS
Latent Dirichlet allocation, service robots, hotel industry, adoption barriers

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Introduction

As labour costs in China continue to rise rapidly (Zuo, 2023), service robots have gained attention in the hotel industry as a potential solution. Research indicates that service robots can replace approx. 30 % of hotel staff labour - equivalent to 1.25 workers - while reducing check-in and checkout times by 30 % and guestroom service response times by 37 % (Zhang et al., 2019; Zhong et al., 2022). Despite their potential to enhance efficiency, adoption rates remain low, with reports highlighting limited uptake in China's hotel sector (Ding et al., 2023). Most studies have

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examined this issue from a managerial perspective, identifying barriers such as slow response speeds (Wang et al., 2023; Chung & Cakmak, 2018) and inefficient human-robot interactions (Tussyadiah & Park, 2018). Additionally, lack of personalisation and emotional engagement (Milohnić & Kapeš, 2024; Tussyadiah & Park, 2018), poor robot design (Milohnić & Kapeš, 2024; Tussyadiah & Park, 2018), inadequate speech recognition (Milohnić & Kapeš, 2024), and unmet guest expectations (Wang et al., 2023) have been noted as critical factors affecting guest acceptance and managerial decisions. These challenges undermine the potential of service robots to improve service quality and replace human labour, making it essential to investigate the barriers hindering their adoption amidst rising labour costs and the need for service optimisation.

However, the literature reveals significant gaps in understanding these adoption barriers, particularly in three areas: data scope, research methodology, and context-specific factors. First, data collection in prior studies often relies on semi-structured interviews with hotel staff (Choi et al., 2019) or surveys (Milohnić & Kapeš, 2024). These methods suffer from small sample sizes and lack generalisability due to variations in robot models (Tuomi et al., 2020), which limits their ability to capture the full spectrum of guest experiences (Ding et al., 2023). Second, methodological limitations include selection bias in thematic analyses due to small samples (Choi et al., 2019), questionable reliability of results (Yörük et al., 2023), and restricted expressiveness in closed-ended surveys (Milohnić & Kapeš, 2024; Rosete et al., 2020). While sentiment analysis has been applied to online reviews (Ceccarelli, 2011), it often fails to uncover the specific reasons for service quality decline (Tuomi et al., 2020). Third, despite China being a key market for service robot applications, its low adoption rate suggests a gap between technical performance and service efficacy (Ding et al., 2023). Scholars note that emerging guest demands for hygiene, safety, and emotional engagement may further impact acceptance (Ceccarelli, 2011); yet, the influence of these factors on guest trust and satisfaction remains underexplored (Tuomi et al., 2020).

Unlike previous studies, this research used web-crawling software to collect 20,900 low-rated reviews of hotel service robots from six major Chinese online travel platforms (Tongcheng, Ctrip, Lvmama, Qunar, Tuniu, and Elong). By applying LDA topic modelling integrated with computational grounded theory, the authors labelled themes and verified their reliability, identifying specific technical and service quality issues. Furthermore, the authors conducted two cross-theme post-hoc analyses - high-frequency word co-occurrence and theme interaction - to explore the complexity of guest feedback in Chinese hotels. The theoretical and practical implications of these findings are discussed in detail below.

This study addresses the following research questions: (1) How can large-scale, cross-platform data collection methods identify key factors affecting guest experiences with service robots across diverse hotel settings? (2) How can improved methodologies reveal the specific impacts of technical and interaction issues on service quality enhancement by service robots? (3) What are the critical technical and service barriers that Chinese hotel guests perceive as limiting service robot adoption?

1. Literature review

1.1. Applications of service robots in the hotel industry

Service robots are intelligent systems designed to perform specific service functions autonomously or semi-autonomously in non-manufacturing environments, aiming to enhance user experience and task efficiency (Kapur & Williams, 2025; Ceglowski & Golub, 2012). Recent studies have quantitatively explored their advantages in the hotel industry, particularly in reducing labour costs and improving operational efficiency. Advances in AI algorithms and declining sensor costs have significantly improved the autonomous navigation capabilities of robots (Lei et al., 2023), driven by developments in Robot Operating Systems (ROS) and Natural Language Processing (NLP) technologies (Rosete et al., 2020). Additionally, service robots can optimise operations by collecting data, such as guest preferences, to enhance service quality (Qi et al., 2024). These technical advantages highlight their potential to address challenges in the hotel sector.

Systematic research has identified various application scenarios for service robots in hotels, including food delivery, luggage handling, front-desk reception, and guest guidance (Choi et al., 2019; Tuomi et al., 2020). Their adaptability varies across hotel types: in luxury hotels, robots enhance guests' perceptions of technological innovation through branding while balancing technology with service experience; in budget hotels, they focus on cost savings (Tuomi et al., 2020; Belanche et al., 2020). These findings underscore the diversity and adaptability of service robot applications across various hotel contexts.

Despite technological advancements, deployment is constrained by market conditions and cultural contexts. In Western markets, service robots are increasingly integrated into luxury hotels and chains, supported by high technology acceptance and robust infrastructure (Yörük et al., 2023). However, even in these regions, adoption rates fall short of expectations, particularly in small and medium-sized hotels, due to cost and maintenance challenges (Stirpe et al., 2020). In contrast, China benefits from strong R&D, manufacturing capabilities, and supply chain advantages, positioning it as a potential leader in robot adoption (Leung et al., 2023). However, low adoption rates suggest that barriers exist related to high expectations of guests for service quality, cultural adaptability, and privacy concerns.

1.2. Evaluation criteria for service robot efficacy in hotels

Evaluating the efficacy of service robots in hotels involves assessing their service levels and guest satisfaction across three dimensions: technical performance, service quality, and user experience.

Technical performance focuses on task execution efficiency, such as whether a delivery robot can complete tasks quickly and accurately. Studies show that efficient task execution significantly enhances guest perceptions of service efficiency (Lestari et al., 2022), while slow response speeds can diminish the overall efficacy. This dimension provides a technical foundation for efficacy evaluation through objective performance metrics.

Service quality is assessed by comparing robot services to human services, emphasising reliability and stability. Research indicates that guests prioritise reliability over emotional engagement (Chiang & Trimi, 2020; Wang et al., 2020). Service robots also demonstrate advantages in improving satisfaction and reducing labour costs (Yang & Chew, 2020). This dimension highlights the practical value of robot services.

User experience evaluates efficacy from a subjective perspective, focusing on guest dissatisfaction due to unmet expectations (Çalişkan & Sevim, 2023). For instance, minor errors in task execution or unnatural interactions can reduce guest recognition of robot functionality (Tung & Au, 2018). Centred on convenience, comfort, and psychological acceptance, this dimension reveals deeper guest needs (Xie & Kim, 2022). By emphasising user perceptions, it offers insights beyond technical metrics, aiding in the identification of areas for improvement and enhancing guest satisfaction (Han et al., 2024).

1.3. Challenges to service robot adoption

Technical performance issues in service robots refer to design or operational failures that hinder their ability to meet expected standards, negatively impacting task execution, service efficacy, and guest experience (Huang et al., 2021). Existing studies categorise these issues into hardware problems (e.g., sensor failures) and software issues (e.g., inadequate algorithm optimisation and limited intelligence) (Hong et al., 2018; Tuomi et al., 2020). Industry data indicate an average failure rate of 15 % in specific scenarios, far exceeding human service levels (Bowen & Morosan, 2018). Slow response speeds (Ceccarelli, 2011; Chung & Cakmak, 2018), high failure rates, and limited intelligence (Choi et al., 2019) directly reduce task accuracy and service quality, affecting efficacy (Chiang & Trimi, 2020). For example, navigation algorithm flaws may cause delivery robots to get lost (García et al., 2023), or speech recognition failures may prevent front-desk robots from processing requests (Milohnić & Kapeš, 2024), leading to service disruptions and guest doubts about reliability.

Additionally, inefficient human-robot interactions and a lack of personalisation are core barriers. Robots often perform poorly in interactions due to limited comprehension or emotional engagement (Garcia et al., 2022), particularly in luxury hotels where empathy is expected, resulting in expectation gaps and resistance (Milohnić & Kapeš, 2024; Wang et al., 2023). Although affective computing technologies (e.g., voice tone analysis) aim to address this (Lajante & Dohm, 2024), their complexity and lack of cross-cultural adaptability limit effectiveness (Rosete et al., 2020). These challenges highlight the need to overcome significant hardware, software, and acceptance barriers to bridge the gap between theoretical benefits and practical outcomes.

Technical improvements should go beyond single-function enhancements, focusing on integrated hardware-software optimisation. For instance, adaptive algorithms can improve robots' responsiveness to dynamic environments (Milohnić & Kapeš, 2024; BenMessaoud et al., 2011). Service improvements should prioritise the precise matching of user needs, such as modular designs for scenario-specific customisation, enhancing service consistency and guest satisfaction (Ye et al., 2022; Tung & Au, 2018). Empirical studies show that optimised systems can significantly improve efficiency and user acceptance in specific tasks (Stirpe et al., 2020; Xie & Kim, 2022).

However, implementing these improvements is constrained by the complexity and applicability of technical development. High costs of integrated optimisation and diverse algorithm adaptation needs may exceed some hotels' capabilities (Goel et al., 2022), while the effectiveness of modular designs in cross-cultural contexts requires further validation (Rasheed et al., 2023). These challenges emphasise the need for a deeper understanding of real-world application contexts. A more systematic approach is necessary to analyse how technical limitations affect service quality (Çalişkan & Sevim, 2023), providing opportunities for future research to explore optimisation pathways, enhance efficacy, and address diverse application needs.

Beyond technical issues, non-technical barriers significantly hinder the adoption of service robots by affecting user acceptance. Resistance often stems from robots' lack of emotional engagement or complex operations, particularly in scenarios requiring personalisation (Rasheed et al., 2023). Studies show that this resistance is often due to unreliable technology, such as speech recognition failures or unintuitive interfaces, eroding trust in convenience and functionality (Tussyadiah & Park, 2018; BenMessaoud et al., 2011). Privacy concerns further exacerbate acceptance challenges, with guests expressing unease about data collection (e.g., camera surveillance) due to inadequate privacy safeguards in design (Leung et al., 2023; Rasmussen et al., 2024). For Chinese guests, cultural dimensions of technology adaptation pose significant barriers. Limitations in understanding local languages and contexts (e.g., difficulties with dialect recognition) reduce interaction efficacy (Leung et al., 2023; Ye et al., 2022), while heightened expectations for hygiene and safety amplify demands for reliability (Lee et al., 2023). Moreover, the appearance and perceived intelligence of robots influence psychological acceptance; designs lacking friendliness or intelligence may diminish perceived service quality (Çalişkan & Sevim, 2023). In guest-facing scenarios (e.g., handling requests or complaints), non-technical issues further impede adoption. Robots often struggle with complex requests or complaints due to limited comprehension and a lack of emotional support, failing to address guest dissatisfaction effectively. Such limitations reduce perceptions of service attitude, impacting satisfaction and acceptance (Yörük et al., 2023; Huang et al., 2021; Zuo, 2023).

Addressing non-technical barriers requires focusing on user experience and cultural adaptability. For example, affective computing can enhance robots' emotional engagement (Lajante & Dohm, 2024), while privacy-preserving designs can build trust (Heuer et al., 2019). For the Chinese market, improving dialect recognition and contextual understanding can meet cultural adaptation needs (Ye et al., 2022). Additionally, refining robot appearance to enhance friendliness and perceived intelligence can improve psychological acceptance (Çalişkan & Sevim, 2023). These strategies improve user experience and trust, thereby significantly enhancing service efficacy and acceptance, and providing practical guidance for the adoption of service robots in hotels.

1.4. Research gaps

Although service robots are applied in various hotel scenarios to complement human services, significant research gaps remain, limiting a comprehensive understanding of the relationship between technical performance issues and service efficacy, which hinders their adoption. These gaps are evident in three areas: data scope limitations, methodological shortcomings, and insufficient exploration of context-specific factors.

First, existing studies often rely on small-scale interviews and surveys, with limited sample sizes and a lack of generalisability due to variations in robot models (Ceccarelli, 2011; Rosete et al., 2020; Tuomi et al., 2020), failing to capture the diversity of guest experiences. Moreover, research from a staff perspective struggles to reflect the true sentiments of guests (Ivanov et al., 2020), thereby limiting insights into the user experience.

Second, methodological limitations include subjective bias in thematic analyses (Choi et al., 2019; Yörük et al., 2023) and failure to uncover specific reasons for service quality decline in sentiment analyses (Ceccarelli, 2011; Tuomi et al., 2020). Closed-ended surveys restrict participants' ability to express personalised sentiments, thereby reducing explanatory power (Milohnić & Kapeš, 2024; Rosete et al., 2020). These methodological shortcomings hinder systematic analysis of how technical and interaction issues impact service quality.

Third, despite China's rapid growth in service robot applications, its low adoption rate remains underexplored (Leung et al., 2023). Most studies focus on managerial perspectives, examining technical performance issues like process optimisation and implementation costs (Ding et al., 2023; Rosete et al., 2020), with limited systematic analysis of guests' subjective perceptions. While some studies mention inefficient interactions, a lack of personalisation, and privacy concerns (Ceccarelli, 2011; Tuomi et al., 2020), they fail to deeply explore how cultural misfit affects guest experience (Choi et al., 2020), how inconvenient operation reduces service quality (Liu et al., 2019), or how slow responses and a lack of emotional engagement impact experience and satisfaction (Chen et al., 2025). Additionally, the specific impact of privacy concerns on the guest experience and acceptance lacks systematic analysis (Chang et al., 2022). These contextual gaps limit a comprehensive understanding of adoption barriers in the Chinese market.

2. Research methods

This study aims to empirically analyse technical and service barriers to service robot adoption from the perspective of a guest. To achieve this, the authors developed a theoretical framework based on the literature, collected user reviews through web-crawling, applied LDA topic modelling to identify key barriers, and validated the findings through qualitative analysis, comparing them with existing studies to confirm technical and service issues. Fig. 1 illustrates the technical framework, covering theoretical foundations, empirical analysis processes, and expected policy implications, from data collection to topic modelling and improvement recommendations, laying the groundwork for a subsequent analysis.

2.1. Data collection

This study used the web-crawling software Gooseeker to collect user reviews related to service robots in Chinese hotels from six major online travel platforms (Tongcheng, Ctrip, Lvmama, Qunar, Tuniu, and Elong) between January 2021 and December 2024. These reviews covered various robot types, including delivery and cleaning robots (Appendix A). These platforms, akin to TripAdvisor, generate substantial daily review data across diverse hotel types - budget, mid-range, and luxury - allowing users to share experiences, post reviews, and rate services.

On a 5-point rating scale, reviews below 3 points typically reflect negative sentiments (Guo et al., 2017), better capturing service deficiencies, and were thus selected as the primary data source (Zheng et al., 2021). The authors initially gathered approximately 837,500 raw reviews from hotels nationwide, spanning budget to luxury categories. To ensure data quality, the authors excluded reviews with fewer than five Chinese characters or lacking specific descriptions (e.g., "good", "bad", "boring"), resulting in a final sample of 20,900 negative reviews with scores below 3 points.

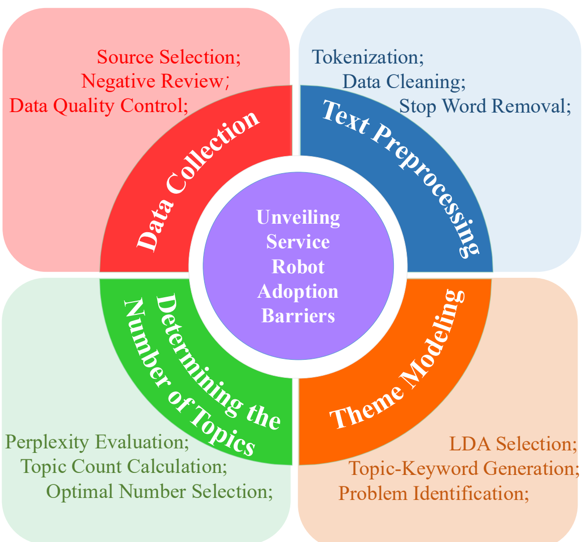


Fig. 1. Integrated framework for unveiling barriers to the adoption of service robots

2.2. Text preprocessing

Text preprocessing followed established methods (Guo et al., 2017; Wang et al., 2019; Taecharungroj & Mathayomchan, 2019) to prepare clean data for topic modelling. First, the authors used the Jieba tool in Python, widely applied for Chinese text processing, to segment the review texts. Second, during data cleaning, the authors removed common but meaningless words (e.g., "can", "okay") using a custom dictionary and excluded low-frequency words that were difficult to converge or interpret, refining the extracted features. Third, the authors eliminated irrelevant stop words (e.g., "and", "is") using a standard stop-word list from Sichuan University's AI Lab.

2.3. Topic modelling

The authors employed topic modelling, an unsupervised learning technique, to automatically identify themes in large-scale text data by grouping documents based on themes for further analysis. It assumes that each document contains multiple themes, with each theme represented by a probability distribution of words (Blei, 2012). In this study, topic modelling was used to uncover the primary issues in low-rated reviews, reflecting guests' core dissatisfactions with service robots. Compared to sentiment analysis, topic modelling better identifies specific reasons for dissatisfaction and overlooked details (Fang & Zhan, 2015; Zhang et al., 2022).

Common topic modelling methods include Latent Semantic Indexing (LSI), Latent Dirichlet Allocation (LDA), Hierarchical Dirichlet Process (HDP), and Probabilistic Latent Semantic Analysis (PLSA). Prior studies show that LDA, with its hierarchical Bayesian probabilistic model, outperforms other methods in large-scale data mining (Wang et al., 2019; Taecharungroj & Mathayomchan, 2019). Thus, the authors selected LDA for our analysis. The LDA model generation process is depicted in Fig. 2, where ϕ denotes the keyword distribution, and its Dirichlet distribution parameter is β; θ denotes the topic distribution, and α is its Dirichlet distribution parameter. z denotes the topic generated by the model, w represents the final keyword generated by the model, S is the word count in the document, and D is the number of documents.

The LDA model generation process mainly involves the following steps:

1) Sampling the "Topic-keyword distribution ϕ "for each topic from the Dirichlet distribution with the parameter β

2) Sampling the "document-topic distribution θ "for each document from the Dirichlet distribution with the parameter α

3) Sampling 1 subject z from θ.

4) Adopt 1 keyword w from ϕ.

2.4. Determining the number of topics

Selecting an appropriate number of topics is critical (Hagen, 2018). Too many topics may lead to uninterpretable results, while too few may reduce dimensional accuracy (Nikolenko et al., 2016). To minimise human intervention and identify the optimal number of topics, we used the perplexity score as an evaluation metric (Blei, 2012). A lower perplexity

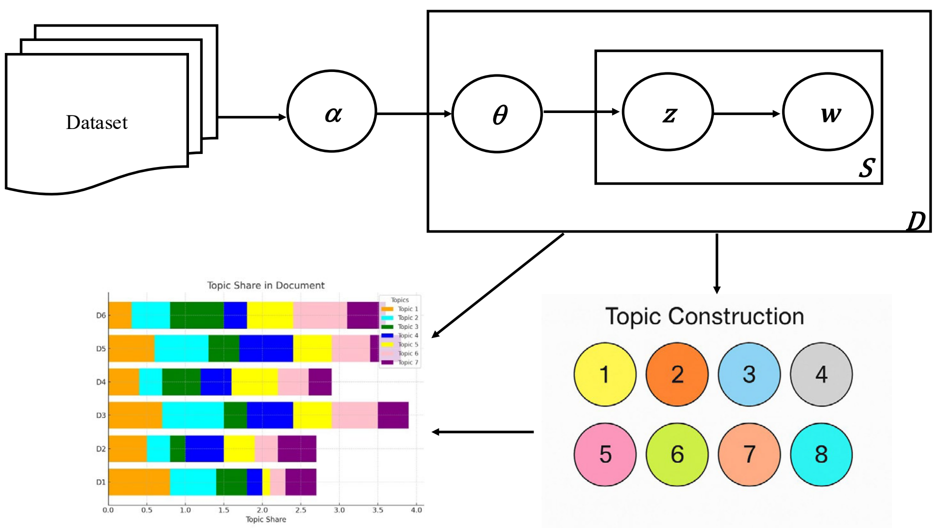


Fig. 2. Structure of the LDA model

score indicates less uncertainty in the model, reflecting better performance and more accurate corpus representation. This method's effectiveness has been validated in prior studies (Zhang et al., 2022). The perplexity score is calculated as follows:

$$P_e = \mathrm{e}\frac{-\Sigma \lg p(w)}{N_l}$$

where is the probability of occurrence of each word w, which equals the sum of the product of the probability values of each topic in the text and the probability value of the vocabulary in the topic; is the total number of words in the text. Through this calculation, we determined 10 as the optimal number of topics, as shown in Fig. 3.

3. Research results

3.1. Qualitative analysis

Using the LDA topic modelling method, the authors identified ten themes and listed the top ten high-frequency words for each. The word weights, word clouds for the ten themes, and negative comment counts are detailed in Table 1. The association between theme distribution and related words is shown in Fig. 4.

The qualitative analysis involved two key steps: coding to assign labels to each theme and reliability testing. For coding, the authors applied the computational grounded theory method (Zhang et al., 2022) and opted for manual coding to address potential issues with machine coding, such as handling slang and internet language. Two trained coders, who are experienced in social media and user reviews, participated in the analysis. They first reviewed the top ten high-frequency words for each theme in Table 1, then examined the top ten high-probability reviews and ten random reviews per theme (Appendix B), independently naming each theme and finalising labels through discussion. For example, Theme 4, with the most negative reviews, focused on robots' lack of flexibility, as seen in comments like "I asked for half a day, and the robot just repeated the same sentence, completely unable to solve my issue" and "During checkout, the robot rigidly told me to find a human, which was too troublesome". Drawing on prior research (Zuo, 2023), the authors categorised this barrier as a service issue due to robots' inability to handle non-standardised demands and labelled it "Lack of Flexibility".

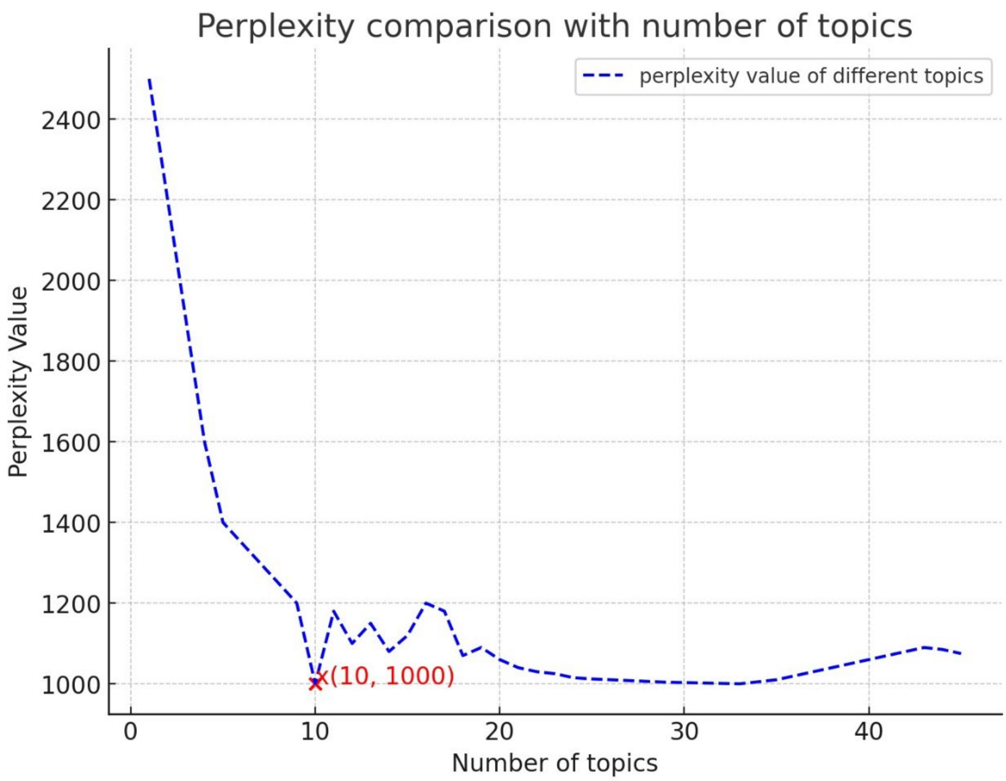


Fig. 3. Perplexity assessment across varying topic numbers

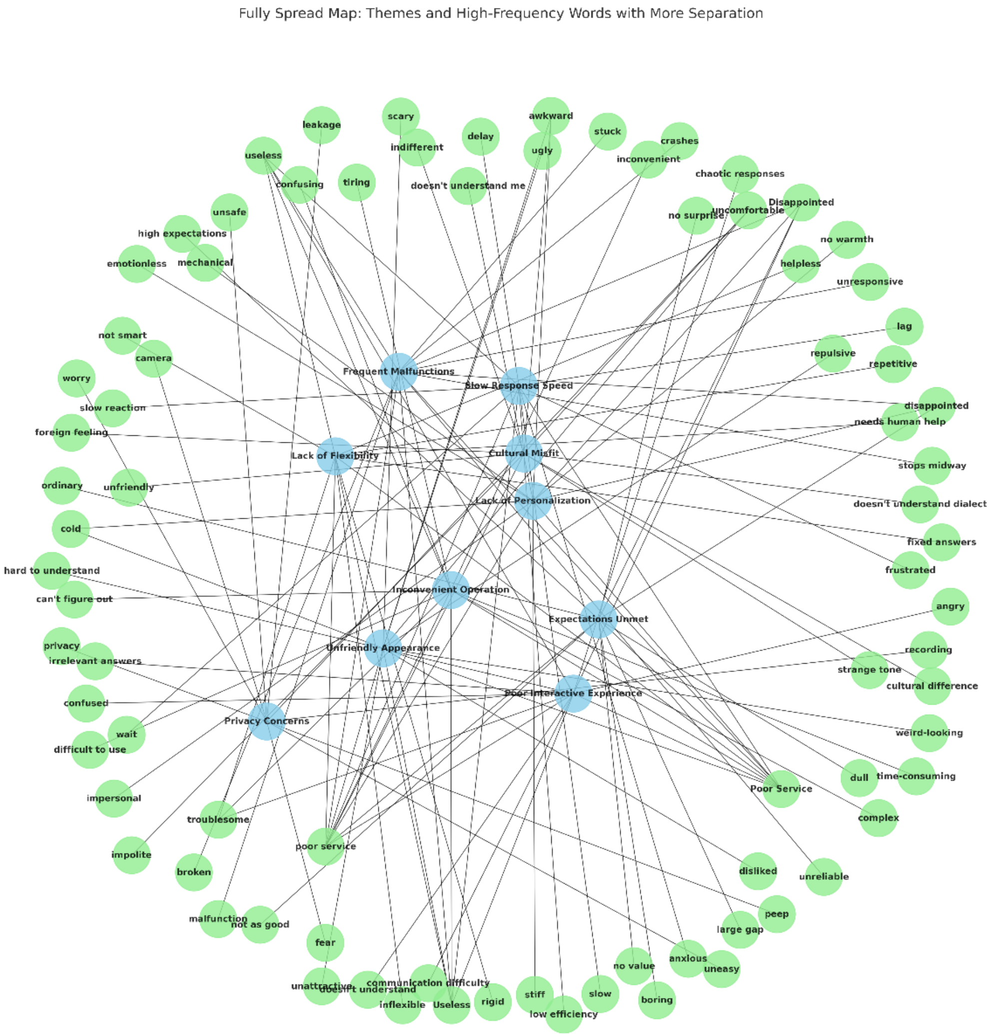
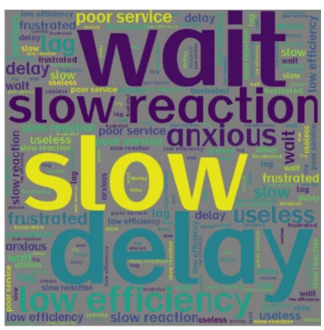
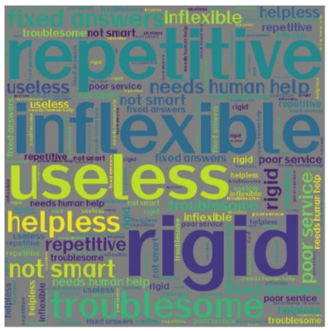
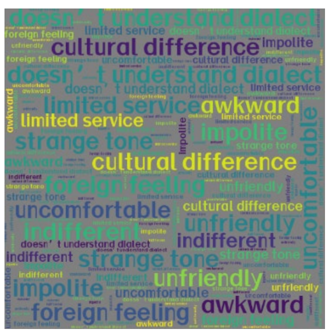
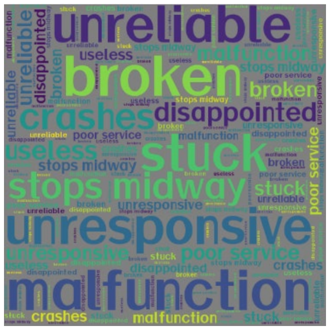
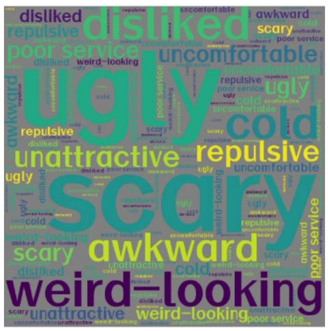
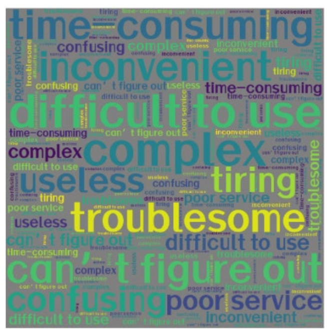


Fig. 4. Theme distribution

Tab. 1. Themes, high-frequency words, and negative comment counts

No.	Label	Top ten high-frequency words	Word cloud	Negative comment count
1	Slow Response Speed	slow (0.092), wait (0.070), delay (0.061), slow reaction (0.048), low efficiency (0.034), anxious (0.026), useless (0.021), lag (0.018), poor service (0.015), frustrated (0.012)		2,530

No.	Label	Top ten high-frequency words	Word cloud	Negative comment count
2	Lack of Personalisation	cold (0.067), emotionless (0.058), mechanical (0.042), doesn't understand me (0.036), stiff (0.031), disappointed (0.027), no warmth (0.023), awkward (0.019), impersonal (0.016), poor service (0.013)		2,668
3	Privacy Concerns	privacy (0.080), fear (0.062), recording (0.053), camera (0.040), unsafe (0.033), leakage (0.028), peep (0.024), worry (0.020), uncomfortable (0.017), uneasy (0.014)		2,300
4	Lack of Flexibility	rigid (0.071), repetitive (0.050), inflexible (0.041), useless (0.035), troublesome (0.030), helpless (0.025), fixed answers (0.021), not smart (0.018), needs human help (0.015), poor service (0.012)		2,852
5	Cultural Misfit	doesn't understand dialect (0.057), strange tone (0.048), impolite (0.040), foreign feeling (0.034), unfriendly (0.029), cultural difference (0.025), uncomfortable (0.021), awkward (0.018), indifferent (0.015), limited service (0.012)		1,932

No.	Label	Top ten high-frequency words	Word cloud	Negative comment count
6	Frequent Malfunctions	malfunction (0.084), broken (0.065), unresponsive (0.052), stuck (0.039), unreliable (0.032), stops midway (0.027), crashes (0.023), disappointed (0.019), useless (0.016), poor service (0.013)		2,254
7	Poor Interactive Experience	doesn’t understand (0.051), irrelevant answers (0.044), chaotic responses (0.037), hard to understand (0.032), communication difficulty (0.028), confused (0.024), angry (0.020), useless (0.017), troublesome (0.014), poor service (0.011)		2,047
8	Unfriendly Appearance	ugly (0.060), scary (0.050), weird-looking (0.041), disliked (0.035), cold (0.030), awkward (0.026), unattractive (0.022), repulsive (0.019), uncomfortable (0.016), poor service (0.013)		1,748
9	Inconvenient Operation	difficult to use (0.065), complex (0.055), can’t figure out (0.046), time-consuming (0.039), troublesome (0.033), inconvenient (0.028), confusing (0.024), tiring (0.020), useless (0.017), poor service (0.014)		1,863

No.	Label	Top ten high-frequency words	Word cloud	Negative comment count
10	Unmet Expectations	no surprise (0.075), high expectations (0.057), disappointed (0.048), not as good (0.041), ordinary (0.035), boring (0.030), no value (0.026), large gap (0.022), dull (0.018), poor service (0.015)		1,624

Tab. 2. Inter-rater consistency test results

Label	LDA-Rater A	LDA-Rater B	Rater A-Rater B
	Kappa (Interpretation)	Kappa (Interpretation)	Kappa (Interpretation)
Slow Response Speed	0.485 (Moderate)	0.451 (Moderate)	0.792 (Substantial)
Lack of Personalisation	0.472 (Moderate)	0.436 (Moderate)	0.803 (Almost Perfect)
Privacy Concerns	0.583 (Moderate)	0.547 (Moderate)	0.874 (Almost Perfect)
Lack of Flexibility	0.449 (Moderate)	0.413 (Moderate)	0.685 (Substantial)
Cultural Misfit	0.395 (Fair)	0.362 (Fair)	0.614 (Substantial)
Frequent Malfunctions	0.504 (Moderate)	0.478 (Moderate)	0.729 (Substantial)
Poor Interactive Experience	0.428 (Moderate)	0.394 (Fair)	0.657 (Substantial)
Unfriendly Appearance	0.367 (Fair)	0.341 (Fair)	0.523 (Moderate)
Inconvenient Operation	0.453 (Moderate)	0.417 (Moderate)	0.691 (Substantial)
Unmet Expectations	0.238 (Fair)	0.219 (Fair)	0.405 (Moderate)

Note: "LDA" refers to the theme with the highest probability match for each comment. Kappa values are Cohen's (1960) Kappa coefficients, interpreted as: < 0.00 (No Agreement), 0.00-0.20 (Slight), 0.21-0.40 (Fair), 0.41-0.60 (Moderate), 0.61-0.80 (Substantial), 0.81-1.00 (Almost Perfect) (Richard & Koch, 1977).

To ensure the reliability of the results, the authors randomly selected 200 reviews for independent labelling by two researchers, following established guidelines (Hagen, 2018; Zhang et al., 2022). The researchers were unaware of the LDA classifications and each other's labels. The authors used Cohen's Kappa coefficient (Cohen, 1960) to assess inter-rater and LDA consistency. As shown in Table 2, consistency between LDA and Raters A and B ranged from fair to moderate (0.219-0.583), while consistency between Raters A and B was higher, ranging from moderate to almost perfect (0.405-0.874). This discrepancy may stem from reviews containing multiple themes, while the authors restricted each review to a single label, leading to disagreements between LDA and human coding on complex reviews. Nevertheless, the Kappa coefficients in Table 2 indicate reasonable reliability of LDA in theme classification (Cohen, 1960), particularly with high inter-rater consistency, validating its effectiveness in handling large-scale reviews. This supports the authors' approach to analysing the impact of technical issues on service quality through improved methods, highlighting the benefits of combining human validation with automated classification.

3.2. Validation of results

Following Hagen (2018), topic modelling results should align with prior literature findings. The authors compared the LDA-identified themes with existing studies, as shown in Table 3. Seven of the ten themes partially overlapped with previous research, though not identically. Specifically, themes like slow response speed, a lack of personalisation, privacy concerns, poor interactive experience, unfriendly appearance, and unmet expectations showed similarities with prior findings.

Topic modelling combines the strengths of quantitative and inductive qualitative analysis (Schmiedel et al., 2018), with LDA excelling in data collection and processing. LDA proved highly effective and comprehensive in analysing negative barriers to service robot adoption in Chinese hotels. As shown in Table 3, beyond validating existing findings, this study identified "Cultural Misfit", "Frequent Malfunctions", and "Inconvenient Operation" (Themes 5, 6, and 9) as novel barriers not previously addressed in the literature.

3.3. Cross-theme post-hoc analysis results

This study further explored the complexity of guest feedback on service robots in Chinese hotels through two post-hoc analyses: high-frequency word co-occurrence and theme interaction. The authors identified the cross-theme distribution of high-frequency words, "Poor Service", "Useless", and "Disappointed", and the interaction among "Cultural Misfit", "Frequent Malfunctions", and "Inconvenient Operation". The results of each analysis are presented below.

The high-frequency words "Poor Service", "Useless", and "Disappointed" appeared across multiple themes. Cross-theme analysis revealed that 3.85 % of reviews mentioned these words simultaneously. "Poor Service" spanned eight themes - Slow Response Speed, Lack of Personalisation, Lack of Flexibility, Frequent Malfunctions, Poor Interactive Experience, Unfriendly Appearance, Inconvenient Operation, and Unmet Expectations - appearing in comments like "It took so long to deliver, I waited forever", "It got stuck, so unreliable", "Cold and emotionless, no human touch", and "So hard to use". "Useless" appeared in five themes - Slow Response Speed, Lack of Flexibility, Frequent Malfunctions, Poor Interactive Experience, and Inconvenient Operation - seen in comments like "So inefficient, useless" (Slow Response Speed), "Can't solve problems, useless" (Lack of Flexibility), and "Took forever, useless" (Inconvenient Operation). "Disappointed" was present in three themes - Lack of Personalisation, Frequent Malfunctions, and Unmet Expectations - reflected in comments like "Cold and emotionless, too disappointed" (Lack of Personalisation), "It got stuck, too disappointed" (Frequent Malfunctions), and "Hyped up but so disappointing" (Unmet Expectations).

Cross-theme analysis showed that 4.01 % of reviews (approximately 875) involved multiple themes, such as "It couldn't understand my dialect and got stuck, so hard to use", reflecting interactions among Cultural Misfit, Frequent Malfunctions, and Inconvenient Operation. The co-occurrence rate between Cultural Misfit and Inconvenient Operation was 2.5 %, and between Frequent Malfunctions and Inconvenient Operation, it was 3.0 %, indicating that operational inefficiency is central to these interactions. Specifically, Cultural Misfit, due to dialect recognition failures, led to language adaptation issues,

Tab. 3. Comparison between the themes obtained by the LDA method and those obtained by other methods

Topic	(Wang et al., 2023)	(Milohnić & Jelena Kapeš, 2024)	(Chung & Cakmak, 2018)	(Tussyadiah & Park, 2018)	(Ceccarelli, 2011)
Topic 1. Slow Response Speed	N/A	Slow response speed affects customer satisfaction	Slow response speed impacts user acceptance of service robots	N/A	N/A
Topic 2. Lack of Personalisation	Lack of emotional connection and warmth	N/A	Lack of personalised interaction affects guest acceptance	Lack of human-like interaction and warmth	N/A
Topic 3. Privacy Concerns	Privacy risks associated with service robots (Shizhen (Jasper) Jia et al., 2024)	N/A	N/A	N/A	N/A
Topic 4. Lack of Flexibility	Poor speech recognition capability	N/A	Lack of flexibility affects usability	N/A	Low efficiency in human-robot interaction
Topic 5. Cultural Misfit	N/A	N/A	N/A	N/A	N/A
Topic 6. Frequent Malfunctions	N/A	N/A	N/A	N/A	N/A
Topic 7. Poor Interactive Experience	N/A	N/A	Poor interactive experience affects customer acceptance	N/A	N/A
Topic 8. Unfriendly Appearance	Unattractive robot appearance	N/A	Robot appearance design affects guest acceptance	N/A	N/A
Topic 9. Inconvenient Operation	N/A	N/A	N/A	N/A	N/A
Topic 10. Unmet Expectations	Importance of expectation management in technology acceptance (Zia and Alotaibi, 2024)	N/A	N/A	N/A	N/A

Note: "N/A" indicates that the topic was not addressed in the corresponding literature.

making operations difficult as users struggled with mismatched interfaces and repeated attempts at different commands. Frequent Malfunctions, such as system freezes, exacerbated this, with operational interruptions (e.g., uncompleted tasks) eroding trust. This interaction was particularly pronounced during peak times, when guest expectations for quick service were frustrated by operational inefficiencies and frequent failures.

4. Discussion of the results

By analysing 20,900 negative reviews, this study identified ten barriers to service robot adoption in the hotel industry from a guest perspective. These findings align with Collins (2020), who argued that users' intrinsic feelings toward technology significantly influence acceptance behaviour. Additionally, Bandura's (1986) social cognitive theory suggests that subjective expectations and experiences shape technology acceptance. This study further indicates that guests' experiential needs extend beyond privacy and technical failures, reflecting broader cultural and service design impacts, differing from Kim et al.'s (2021) findings in Thai hotels. Moreover, we introduce "Cultural Misfit", "Frequent Malfunctions", and "Inconvenient Operation" (Themes 5, 6, and 9) as novel challenges, posing new considerations for service robot promotion and development. While Nurul Nabila Said et al. (2023) suggest Chinese users have high tolerance for technical issues, our findings show that cultural adaptability and operational inconvenience significantly reduce acceptance in specific scenarios, profoundly impacting the adoption process in the hotel industry.

4.1. Basic theoretical discussion

Using LDA topic modelling on 20,900 negative reviews from Chinese hotel guests, this study identified ten barriers, seven of which - Slow Response Speed, Lack of Personalisation, Privacy Concerns, Lack of Flexibility, Poor Interactive Experience, Unfriendly Appearance, and Unmet Expectations - align with common issues in prior literature. Below, the authors analysed these themes, integrating theoretical frameworks and representative reviews to highlight their specific manifestations in Chinese hotel contexts.

Slow Response Speed. As one of the most frequent barriers, this theme reflects significant shortcomings in task execution efficiency. For example, a guest noted, "This robot took forever to deliver items; I waited ages at my door", and another stated, "I asked it to fetch something, but it didn't move for ten minutes". While Cao et al. (2023) suggested that technological advancements have improved robot service speed in standardised settings, the analysis by this research authors of 2,530 related reviews found that approx. 75 % (around 1,900) focused on delays in real-time services. This contradicts Cao et al.'s optimistic view, supporting Gupta et al. (2020) on navigation flaws in dynamic settings, indicating the limited applicability of general efficiency improvements in complex hotel environments (e.g., crowded corridors and elevator delays). This delay significantly impacts Chinese guests' expectations for immediacy, as explained by Davis's (1989) Technology Acceptance Model (TAM), which posits that acceptance depends on perceived usefulness. Slow Response Speed directly undermines robots' utility as real-time service tools, with comments like "It's so slow, I'd rather get it myself" reflecting strong dissatisfaction. Further analysis suggests this issue is exacerbated during peak demand periods in hotels.

Lack of Personalisation. This theme highlights a significant lack of emotional interaction, as seen in comments like, "It's so cold, no human touch at all, so disappointed", and "It answers like a machine, no warmth". While Ranieri and Romero (2016) claimed that robots have some human-like features, such as simulating emotions through voice tones, this research analysed 2,668 reviews and found that 68 % (around 1,815) focused on the absence of emotional connection (e.g., "no warmth", "like a machine, not a person"). Such results contradict Cao et al. (2023) and deepen Vallverdú and Trovato's (2016) view that a lack of personalisation is particularly pronounced in high-emotion service settings. This barrier diminishes robots' emotional utility in hotels, reflecting Chinese guests' high expectations for warmth and personalisation, as supported by Ying et al. (2020), who note that Chinese hotel guests prioritise warmth and personalisation over mere technical performance.

Privacy Concerns. This theme reflects guests' distrust in robots' privacy safeguards, with comments like "I feel like it's recording my room information, so uneasy" and "I'm not comfortable, but I was too lazy to get it myself". Prior studies (Jia et al., 2024) have explored privacy risks, and findings of this research align with the privacy paradox (Barnes, 2006). Specifically, while 55 % of 2,300 reviews (around 1,265) expressed concerns about privacy breaches (e.g., "I'm afraid my room info will be leaked"), 20 % (around 460) also indicated continued use driven by convenience, consistent with the privacy paradox's trade-off between concerns and utility. Over 60 % of related comments (around 1,380) focused on psychological resistance (e.g., "I feel my privacy is being invaded", "I always feel unsafe"), rather than technical flaws, suggesting that technical solutions fail to address trust barriers. This psychological resistance can be understood through trust theory (Mayer et al., 1995), which states that trust depends on perceived ability, benevolence, and integrity, while the lack of transparent data handling by robots erodes guest trust.

Lack of Flexibility. This theme indicates robots' inability to handle diverse demands, as seen in comments like "It just repeats the same answer, so useless" and "It's too rigid for last-minute changes". It aligns with TAM's perceived usefulness dimension (Davis, 1989), where guests devalue robots' utility due to their inflexibility, which also affects perceived ease of use. However, it contradicts Buerkle et al. (2023), who suggested that robots have high flexibility, likely because their study focused on industrial multi-tasking and not hotel guests' real-time, personalised needs. Of 2,852 related reviews, 70 % (around 1,998) focused on functional failures in real-time services, supporting Brandstötter et al.'s (2022) findings regarding inadequate scenario adaptability. Tsushima et al. (2025) suggested that this barrier may be improved with the integration of advanced language models, such as ChatGPT, DeepSeek, and Grok.

Poor Interactive Experience. This theme centres on robots' deficiencies in language comprehension and communication, with guests lamenting, "I asked about checkout time, and it gave a chaotic response, totally incomprehensible" or "I explained for ages, but it still didn't understand, so frustrating". This directly ties to TAM's perceived ease of use (Davis, 1989), where inefficient interactions diminish perceived usability. Romero-Gonzalez et al. (2020) emphasised the importance of speech interaction for acceptance, a finding our study corroborates, validating the critical role of language comprehension in hotel services. However, this contradicts Ren et al. (2024), who claim language adaptability has significantly improved. In the dataset of this research, 65 % of the 2,047 related reviews (around 1,330) highlighted failures in real-time communication, indicating that the issue extends beyond mere speech recognition accuracy to a broader lack of adaptation to guests' linguistic habits in hotel settings. This deepens Rasoul Zahedifar et al.'s (2025) research, exposing the limitations of general language adaptability in dynamic hotel environments, such as handling multilingual requests or colloquial expressions. This finding also diverges from Jeong et al. (2024), possibly because their study focused on controlled lab settings or standardised language tests, rather than the diverse, immediate demands of hotel guests.

Unfriendly Appearance. Robot design appearance significantly shapes acceptance, as this theme reveals through comments like "This robot looks so ugly, it feels awkward" and "It looks weird, I don't feel comfortable using it". This supports the aesthetic usability effect (Tractinsky et al., 2000), which posits that attractive designs enhance perceived usability and satisfaction. Of 1,748 related reviews, 60 % (around 1,049) centred on psychological rejection, deepening Saeki and Ueda's (2024) discussion on design psychology and revealing Chinese guests' expectations for aesthetics and comfort beyond functionality. This barrier reduces robots' emotional utility, reflecting Chinese guests' psychological need for familiarity and affinity, possibly tied to a cultural emphasis on harmonious aesthetics and social comfort, as Sadangharn (2022) suggests.

Unmet Expectations. This theme, comprising 1,624 reviews (7.8 % of the total), reflects a significant gap between robot promotion and actual experience, with guests noting, "It was hyped up, but it's no different from regular service" and "It's supposed to be smart, but it can't do anything well". Of these reviews, 70 % (around 1,137) focused on disappointment with intelligent services, supporting Zia and Alotaibi (2024) on the importance of expectation management, and extending Guo et al.'s (2024) expectation theory by showing that Chinese guests' high expectations for efficient, personalised intelligent services were unmet. This contradicts Wu and Huo (2023), who claim robots generally meet user needs.

4.2. Discussion of key findings

This study introduces "Cultural Misfit", "Frequent Malfunctions", and "Inconvenient Operation" as significant barriers to service robot adoption in Chinese hotels, previously underexplored or not independently identified. Unlike prior studies focusing on general technology acceptance (e.g., privacy, efficiency), this research, through contextual analysis and large-scale data validation, highlights unique impacts of these barriers in real-time hotel service settings, offering a fresh perspective on adoption complexities.

Cultural Misfit. Identified as a structural barrier rooted in technical limitations, this theme surfaces in comments like "It couldn't recognise my Sichuan dialect and lacked polite responses", and "It answered coldly, with no emotional connection, like a foreigner". While Choi et al. (2020) mentioned cultural differences affecting acceptance, they did not treat it as a distinct barrier. Tuomi et al. (2020) focused on functionality in Western markets, overlooking China's diverse dialects and politeness norms. Of 1,932 reviews, 62 % (around 1,198) focused on language adaptation and politeness issues, aligning with Ganesh's (1980) cultural dimension theory, where Chinese collectivist culture expects emotional connection and localisation, unmet by robots, leading to cultural alienation.

Frequent Malfunctions. This theme, identified as a structural barrier, quantifies the impact on Chinese guests' real-time service expectations, emphasising the need for reliability optimisation tailored to hotel conditions. A typical comment reads, "It got stuck halfway delivering a towel, so unreliable". While Tuomi et al. (2020) discussed general technical failures, they did not focus on real-time hotel demands. Xu et al. (2023) optimistically suggested that hardware improvements have resolved frequent failures, but 68 % of 2,254 related reviews (around 1,533) highlighted real-time failures - "stuck in the corridor" or "delivery interrupted" - supporting Senthamaraim et al.'s (2024) findings regarding the need for environmental adaptability.

Inconvenient Operation. This theme is another structural barrier that reflects the impact of interface complexity on non-expert users, with comments like "So hard to use, I tried for ten minutes to get water and gave up" and "Too many buttons, I couldn't figure it out, so frustrating". Liu et al. (2019) suggested simplifying interaction designs but did not identify it as a distinct barrier. Pepi Stavropoulou et al. (2020) proposed user training, but 64 % of 1,863 reviews (around 1,192) focused on inefficient experiences - "Took forever, useless" or "Too complex, I gave up" - highlighting high expectations for convenience among Chinese guests. Gutsche et al. (2025) predict user-friendliness as key to adoption, resonating with the findings of this research.

4.3. Cross-theme analysis

The high-frequency words "Poor Service", "Useless", and "Disappointed", extracted via LDA, represent service quality, functional utility, and expectation alignment issues, respectively. Their cross-theme overlap reveals a cascading effect of adoption barriers. While prior studies identified these issues independently (Gupta et al., 2020; Buerkle et al., 2023; Wu & Huo, 2023), this study introduces their progressive linkage, where a single flaw triggers a chain reaction amplifying dissatisfaction. A typical review states, "The hotel's service robot was terrible! I asked for a bottle of water, waited 20 minutes - it was so slow, and it spoke so coldly, no human touch. I'd rather get it myself; it felt useless. The hotel hyped it as a 'smart assistant,' but it was so disappointing! I won't use it again". This effect erodes trust, significantly reducing acceptance, with some guests stating, "I won't use robots again". It highlights Chinese guests' high standards for immediacy, emotional connection, and promotional consistency, suggesting acceptance is driven by multidimensional factors.

Conversely, the interaction among Cultural Misfit, Frequent Malfunctions, and Inconvenient Operation reveals the complexity of user experience in adoption. Prior studies treated these as separate barriers (Gupta et al., 2020; Buerkle et al., 2023), overlooking their interactions. This study fills the gap, showing that single-dimensional technical improvements (e.g., enhancing hardware reliability) are insufficient. Robot design must simultaneously improve multimodal speech recognition (for cultural adaptation), environment-adaptive hardware (e.g., anti-jamming sensors), and simplified interfaces (e.g., one-button operations) to meet the needs of Chinese user. This supports TAM's multidimensional drivers (Davis, 1989), where interactions reduce perceived ease of use (due to complexity and failures) and usefulness (due to cultural misfit), further suppressing acceptance through diminished user attitudes and intentions.

Conclusions

Understanding service robot adoption barriers is crucial for hotel practitioners to optimise deployment and enhance guest experience. However, guest-centric methodologies are lacking for a systematic examination of these barriers through negative emotions. This study analyses 20,900 negative reviews from six major Chinese online travel platforms using LDA topic modelling and computational grounded theory. It confirms technical barriers like Slow

Response Speed and Lack of Flexibility, user experience issues like Lack of Personalisation, Poor Interactive Experience, and Unfriendly Appearance, and significant impacts of Privacy Concerns and Unmet Expectations on service efficiency and acceptance. Furthermore, it introduces Cultural Misfit, Frequent Malfunctions, and Inconvenient Operation as key barriers in China. The study also reveals interaction effects among cultural adaptation, reliability, and usability, alongside a cascading effect of service quality, functional utility, and expectation alignment, forming a vicious cycle that significantly reduces acceptance. It emphasises the need for systematic optimisation of multidimensional interactions and cascading effects to meet the high standards of Chinese hotel contexts, providing theoretical support for future research on the multidimensional drivers of technology acceptance.

Theoretical contributions

This study makes several theoretical contributions. First, it overcomes the limitations of traditional research through superior data collection methods. Unlike prior studies relying on small-scale interviews and surveys with limited sample sizes and generalisability (Ceccarelli, 2011; Rosete et al., 2020; Tuomi et al., 2020), this study used web-crawling to collect 20,900 negative reviews from six major Chinese online travel platforms, providing a robust guest-centric approach to understanding adoption barriers. Second, traditional thematic analyses are prone to subjective bias (Yörük et al., 2023) and fail to uncover specific reasons for service quality decline (Nurul Nabila Said et al., 2023). This study used LDA integrated with computational grounded theory to identify ten barriers to service robot adoption from negative reviews. Third, by focusing on the unique expectations of Chinese hotel guests, this study addresses a gap in prior research, which often examines technical performance and costs from a managerial perspective (Rosete et al., 2020; Leung et al., 2023), neglecting a systematic analysis of guests' subjective perceptions. We introduce "Cultural Misfit", "Frequent Malfunctions", and "Inconvenient Operation" as distinct barriers and reveal their practical-expectation cascading effect with service quality, functional utility, and expectation alignment through cross-theme interactions. Specifically, while prior studies (Tuomi et al., 2020; Xu et al., 2023) focused on independent impacts of technical failures, ignoring interactions with cultural or operational factors, and Leung et al. (2023) overlooked cultural dimensions in Chinese contexts, this study quantifies these interactions. It reveals a cascading cycle of trust-efficiency-culture in dynamic hotel settings, where expectations for quick, personalised services are disrupted by Cultural Misfit, worsened by Inconvenient Operation, and collapse due to Frequent Malfunctions. This suggests that adoption barriers stem from complex couplings, emphasising the need for an ecological approach to optimise reliability and adaptability to meet Chinese hotel standards. Additionally, the cross-theme overlap of "Poor Service", "Useless", and "Disappointed" forms a linked cycle, where technical limitations trigger functional constraints, exacerbating dissatisfaction due to unmet expectations, providing a theoretical basis for contextual optimisation.

Practical implications

Based on these findings, the authors propose the following recommendations to optimise service robot deployment, enhancing service quality and guest satisfaction. For technical issues, such as response delays and Frequent Malfunctions, hotels should enhance navigation algorithms with real-time path optimisation and deploy anti-jamming sensors in complex environments to improve efficiency and reliability, addressing delivery delays and task interruptions. The newly identified Inconvenient Operation barrier requires simplifying interaction interfaces to reduce usage difficulty and frustration. Human-robot interaction challenges, including Lack of Personalisation, Poor Interactive Experience, and Lack of Flexibility, necessitate integrated improvements. Incorporating affective interaction features and large language models can mitigate coldness and chaotic responses while enhancing adaptability to diverse demands. The newly identified Cultural Misfit barrier demands tailored adaptations, such as multi-dialect recognition and local etiquette protocols, to bridge language and cultural gaps. Additionally, unfriendly appearances can be addressed by designing culturally aesthetic forms to enhance emotional acceptance. To tackle Unmet Expectations and Privacy Concerns, hotels should establish continuous feedback mechanisms to align marketing with performance and implement transparent data policies to alleviate psychological resistance. Moreover, the cross-theme interaction of Cultural Misfit, Frequent Malfunctions, and Inconvenient Operation requires simultaneous improvements in language adaptation and interface simplicity to mitigate cultural barriers exacerbating operational inefficiencies, alongside enhanced hardware reliability to reduce trust erosion from failures. Similarly, the cascading effect of "Poor Service", "Useless", and "Disappointed" necessitates holistic improvements in response efficiency, emotional interaction, and expectation alignment to break the cycle from efficiency deficits to trust crises. Furthermore, addressing cross-theme effects requires comprehensive optimisation. Simultaneously enhancing reliability, usability, and cultural adaptability can disrupt the cycle of widespread dissatisfaction from single failures. Additionally, establishing an integrated ecosystem of staff and robots, with staff trained to support during peak times or failures, ensures service continuity, meeting guests' high expectations for immediacy, warmth, and consistency.

Limitations and future research

Despite providing comprehensive insights into service robot adoption barriers through large-scale web-crawling and LDA topic modelling, this study has limitations. First, its focus on negative reviews from Chinese hotel guests may not fully capture positive experiences or perspectives from non-Chinese markets, limiting generalisability. Additionally, data from six major online travel platforms exclude offline feedback or niche platforms, potentially missing some user voices. Second, while LDA effectively identifies key barriers, it relies on explicit textual expressions, failing to capture implicit emotions or non-verbal factors, possibly underestimating their impact on service quality. Future research can address these limitations by expanding the data scope to multilingual markets or offline interviews to compare acceptance across cultural contexts. Additionally, integrating visual analysis or emotion detection technologies (e.g., facial expression recognition) can complement text analysis, revealing non-verbal impacts on guest experience. Finally, longitudinal experiments can validate the dynamic effects of technical improvements (e.g., dialect recognition) on trust and satisfaction, providing precise practical guidance for service robot optimisation.

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Data availability statement

The data used to support the findings of this study are included within the article.

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Appendices

Appendix A. Types of hotel service robots

Type	Function description	Image
Hotel Concierge Robot	Guides guests to rooms, suitable for large hotels. Features map navigation, elevator calling, and smooth operation to enhance the check-in experience.	
Delivery Robot	Equipped with drawers or compartments to deliver items like toothbrushes, towels, slippers, and meals, ensuring privacy.	
Carpet Cleaning Robot	Automatically cleans hotel carpets, reducing manual cleaning workload and improving hygiene efficiency with path planning and vacuuming functions.	
Assistive Robot	Supports guests with mobility issues (e.g., elderly or disabled), providing mobility assistance or item transport to enhance convenience.	

Appendix B. Top 10 high-probability and random reviews for each topic

Label	Example of comments
Topic 1. Slow Response Speed	
Top 10 High-Probability Reviews	This robot was so slow in delivering items; I waited half a day at my door. Its response to my question was painfully slow, driving me crazy. Waiting for the robot during checkout was a complete waste of time. The service efficiency is so low, nowhere near as fast as human staff. The delay was ridiculous; I waited 20 minutes for breakfast. It's so frustrating to use this robot when I'm in a hurry. It lagged several times and didn't even deliver the towel. It's slower than a turtle; I'd rather go to the front desk myself. The service was so poor, I wanted to complain about the wait. Useless, it took twice as long as a human to deliver something.
Random 10 Related Reviews:	I saw the robot stuck in the corridor; I waited 10 minutes for it to move. I asked for directions, and it kept repeating "please wait", which annoyed me. It took longer to deliver water than for me to buy it downstairs — unbelievable. The efficiency is absurdly low; my breakfast was cold by the time it arrived. I found the answer myself while waiting for its response. It got stuck when I was rushing to check out, ruining my mood. Slower than a snail — how can the hotel even use this? The slow service drove me nuts; I won't use it again. I ordered a cup of coffee and fell asleep waiting for it. It took half an hour to crawl to my room — ridiculous.

Topic 2. Lack of Personalisation	
Top 10 High-Probability Reviews	The robot is so cold, with no human touch at all. Asking it a question feels like talking to a machine — completely emotionless. Its mechanical responses left me so disappointed. It doesn't understand me; the service feels so stiff. There's no warmth at all, not as good as human service. It was so awkward, like talking to myself. The lack of human touch made me very uncomfortable. Its cold tone gave no sense of interaction. The service was terrible, far too mechanical. So disappointing; the robot isn't friendly at all.
Random 10 Related Reviews	I asked if it could hurry, and it just repeated "please wait" — so cold. Its emotionless responses made me feel so isolated. I complained about the room, but it felt like talking to a wall. The stiff tone made me not want to use it again. Asking a simple question was so awkward. There's no warm interaction; it felt like staying in a factory. Human staff would at least smile; this robot had nothing. Its cold attitude made me a bit angry. The lack of human touch doesn't suit a hotel setting. The mechanical service made me miss human front desks.
Topic 3. Privacy Concerns	
Top 10 High-Probability Reviews	This robot has a camera; I'm afraid of being secretly recorded. There's no privacy protection at all — who knows what it's recording? I'm worried it might be recording audio; it feels so unsafe. Seeing it staring at me made me very uncomfortable. I don't dare use it; I'm afraid my personal information might get leaked. It gives such a strong sense of being watched; I turned it off immediately. Safety concerns make me hesitant to use it. The camera is always on — it's so creepy. I don't feel secure; I always think I'm being monitored. No matter how good the service is, I won't use it — too little privacy.
Random 10 Related Reviews	It took a photo while delivering something; I quickly moved away. The recording feature made me afraid to speak freely. The hotel said it's fine, but I'm still worried about data leaks. The unsafe feeling kept me locking my door the whole time. I saw it had a camera, so I pushed it into a corner. The possibility of being watched made me unable to sleep at night. I felt uncomfortable — who knows where those videos go? I'm scared it might transmit my voice somewhere. I don't dare use it; who can guarantee it's not recording? Privacy issues made me prefer going to the front desk myself.
Topic 4. Lack of Flexibility	
Top 10 High-Probability Reviews	The robot is so rigid; it only says fixed phrases. It just keeps repeating the same response — useless for any question. It can't adapt at all; it couldn't solve my problem. So troublesome; I ended up having to find a human. I felt helpless; it only said, "Please contact the front desk".

	Its fixed answers made me feel so foolish. It's not smart; it freezes on slightly complex requests. The service is terrible — way too inflexible. Useless; it got confused the moment I changed my request. Getting human help was faster than using it.
Random 10 Related Reviews	I wanted to change the water delivery time, but it just said no. I asked how to turn off the lights, and it repeated itself three times — useless. It can't adapt; I asked about breakfast options, and it froze. So troublesome; I ended up getting the item myself. I felt so helpless; the robot was utterly clueless. Its fixed responses made me think it's just a decoration. It's not smart; it even got directions wrong. The service is too rigid, not user-friendly at all. Useless; anything slightly complex, and it tells me to find a human. I wanted to adjust the checkout time, and it just told me to go to the front desk.
Topic 5. Cultural Misfit	
Top 10 High-Probability Reviews	The robot doesn't understand dialects; it couldn't comprehend what I said. Its tone is so strange, not polite at all. It doesn't feel friendly, so different from how locals speak. It has such a foreign vibe; I'm not used to it. The cultural gap made me feel so awkward. It doesn't understand local customs — too cold. The service is poor; its tone isn't friendly at all. Its impolite responses made me very angry. The cold attitude doesn't feel like local service. So awkward; talking to it felt so strange.
Random 10 Related Reviews	I spoke in my Sichuan dialect, and the robot couldn't understand — so disappointing. Its tone was odd, like a foreigner; the service was terrible. Not friendly at all; it felt like talking to an alien. I'm not used to its way of responding — too stiff. The cultural gap was huge; it didn't understand my local question. It lacks politeness; it responded so coldly to everything. The service is terrible, with no local flavour at all. Its foreign vibe made me not want to use it again. The cold responses made me uncomfortable. It was awkward; I gave up after chatting with it for two sentences.
Topic 6. Frequent Malfunctions	
Top 10 High-Probability Reviews	The robot kept malfunctioning; it stopped halfway while delivering something. It broke down twice — too unreliable. It didn't move at all when I asked it to deliver water. It got stuck several times; the service had to rely on humans to fix it. It stopped midway, and I got so annoyed waiting. It crashed twice; the experience was terrible. So disappointing; it always has issues. Useless; it broke down on the way while delivering something. The service is poor; the malfunction rate is outrageously high. So unreliable; it breaks every time I use it.

Random 10 Related Reviews	It got stuck in the hallway while delivering a towel; no one fixed it for ages. After it broke down, I had to go to the front desk myself to get the item. It didn't move several times; the hotel even said it was normal. It got stuck, and I had to push it to get it moving — so ridiculous. It stopped in the elevator midway; the service was completely disrupted. After crashing, its screen went black — really scary. So disappointing; it broke down halfway through delivering water. Useless; it has so many issues, I don't dare call it anymore. The service was terrible; it broke down, and no one cared. So unreliable; it stopped working right after I used it.
Topic 7. Poor Interactive Experience	
Top 10 High-Probability Reviews	It didn't understand anything I asked; its responses were chaotic. It answered irrelevantly; I asked one thing, and it replied with something else. Its responses were so chaotic; even asking for directions, it got it wrong. It couldn't understand my words; communication was too difficult. It was so confusing; talking to it felt like solving a riddle. I got angry; it kept answering my questions incorrectly. Useless; it couldn't explain anything clearly. So exhausting; I talked to it for ages with no result. The service is poor; the interactive experience was awful. Communication was so difficult, I wanted to smash it.
Random 10 Related Reviews	I asked where breakfast was, and it told me to ask the front desk — so frustrating. It answered irrelevantly; I asked about turning off the lights, and it said the weather was nice. Its chaotic responses left me completely lost; it's so dumb. It couldn't understand Mandarin; I had to repeat myself three times with no result. Its confusing responses made me give up entirely. I got angry; it messed up even a simple question. Useless; talking to it was like talking to a brick wall. So exhausting; I explained for ages, and it still asked me to repeat. The service is terrible; the interaction was a complete mess. Communication was tough; I couldn't even get the WiFi password from it.
topic8：Unfriendly Appearance	
Top 10 High-Probability Reviews	The robot looks so ugly; I didn't feel good seeing it. It's scary; seeing it at night felt like encountering a monster. Its weird appearance made me not want to approach it. I didn't like its look — too cold. It felt awkward; its appearance isn't likeable at all. It's not attractive; I had no interest in using it. I felt a strong sense of rejection; I got annoyed just looking at it. It's uncomfortable; its appearance is too strange. The service is poor, and it looks so ugly, too. Its cold design made me not want to use it.
Random 10 Related Reviews	It's so ugly; I didn't even want to look at it while it was delivering something. It's scary; I almost got frightened by its shadow at night. Its weird appearance made me feel the hotel was low-class. I didn't like it; it looked like a big metal block. It felt so awkward; I just pushed it away. It's not attractive at all; it doesn't look cute in the slightest. I rejected its appearance; it's too unfriendly. It's uncomfortable; I wanted to stay away from it when I saw it.

	No matter how good the service is, its ugly look can't be saved. Its cold appearance gave me no good impression.
Topic 9. Inconvenient Operation	
Top 10 High-Probability Reviews	The robot is too hard to use; I couldn't figure it out. It's ridiculously complicated; I couldn't understand how to operate it. It wastes time; ordering something took forever to figure out. So troublesome; I'd rather go get it myself. It's inconvenient and really exhausting to use. I couldn't figure out its buttons; it's too complicated. Useless; operating it was so difficult. The service is poor; it's too hard to get started with. It's exhausting; I don't want to touch it again after using it once. I couldn't figure it out, so I had to ask for help in the end.
Random 10 Related Reviews	It's ridiculously hard to use; I tried ordering water and struggled for ten minutes. It's so complicated, I just gave up. It wastes time; ordering breakfast took longer than making it myself. So troublesome; the screen was even hard to press. It's inconvenient; elderly people wouldn't be able to use it at all. I couldn't figure out how to turn it on — so dumb. Useless; I operated it for ages with no response. The service is terrible; it's exhausting to use. It's exhausting; I pressed buttons for ages, and it barely moved. I couldn't figure it out; asking it anything was pointless.
Topic 10. Unmet Expectations	
Top 10 High-Probability Reviews	There's no surprise; using it felt no different from regular service. I had high expectations, but I was so disappointed. It's not as good as human service; it doesn't feel advanced at all. It's very ordinary, nothing special. It's boring; I got tired of it after using it twice. It has no value; my expectations were all for nothing. There's a huge gap; the promotion was better than the reality. It's dull; it's not as cool as I imagined. The service is poor; I thought it would be very smart. So disappointing; it's too average.
Random 10 Related Reviews	No surprise; I thought it would be a high-tech experience. I had high expectations, but it's just a decoration. It's not as good as humans; human service is more thoughtful. It's so ordinary; I got excited for nothing. It's boring; using it isn't fun at all. It has no value; it's flashy but not practical. There's a huge gap; the advertisement was too exaggerated. It's dull; I'd rather they didn't have a robot. The service is average; my expectations fell flat. So disappointing; I thought it would be convenient.