Service Improvement Analysis Based on User Feedback Evaluations

--Taking Shared Motorcycle User Feedback Data as an Example

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Abstract. With the rise of new environmentally friendly travel modes, shared motorcycles are favored by more and more citizens, but they also often have many problems such as indiscriminate parking, inaccessibility, operational errors and so on, Therefore, the quality of the service needs to be improved. In the study, taking the feedback from shared motorcycle users in City C, a city in China, as the focus, we integrate TF-IDF and LDA topic model for text analysis. The research results show that the problems reflected by consumers are mostly focused on the use of vehicles, positioning accuracy, cost reasonableness, system operation, and other aspects. Given the above problems, suggestions with practical value are proposed to product suppliers and operators from the perspectives of product quality, system optimization, and placement points.

Keywords: shared motorcycle, LDA, TF-IDF, service improvement

1 Introduction

Since the national 13th Five-Year Plan put forward the sharing economy for the first time in 2016, the scale of the sharing economy market has been rising year by year in China. The transaction scale of the sharing economy market in 2022 was about 3,832 billion yuan, a year-on-year growth of about 3.9%. In terms of traveling, nearly 4 million shared motorcycles were launched nationwide in 2021, with a revenue of 9.36 billion yuan, which is expected to exceed 20 billion yuan in 2025. In May 2021, the first batch of 50,000 newly licensed shared motorcycles was launched in City C, a city in Hunan Province in China. The operation of shared motorcycles has eased urban traffic pressure, but it has also led to many problems such as illegal parking, vehicle damage, and user distrust, posing a greater challenge to urban traffic management.

At present, domestic evaluation studies on the service quality of shared motorcycles focus on service efficiency, innovative design, and the performance of the vehicles themselves. Foreign countries mainly consider the service quality of public bicycles.

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Mingning Ma [1] takes Meituan shared motorcycle as an example to explore the formation mechanism of user stickiness based on three factors: system, users and use environment. Ying Wang [2] constructed a structural equation model on the user evaluation data of shared motorcycles in Lhasa city and found that the two aspects of overall planning and user safety have the greatest impact on user satisfaction. Chahine [3] conducted a comparative experiment on the services of shared bicycles and shared motorcycles during the epidemic, and found that the frequency of commuting trips increased after COVID-19 and users of the two have different characteristics. Xiang Yan et al [4] found that "e-scooter + Transit" bundle pricing can effectively promote "Mobility-N" trips. After organizing the existing literature, it is found that few scholars have conducted service quality improvement studies on e-scooters from the perspective of user feedback. However, user feedback is the most intuitive and real evaluation based on users' own experience, which is indispensable and valuable data for service quality improvement research.

User Generated Content (UGC), i.e., original user content. In the rise of content community e-commerce today, many consumers will refer to the feedback evaluations of those who have already purchased goods before purchasing them, which also indicates that user-generated content is an important factor influencing consumers' purchasing decisions [5]. Hengbo Du et al [6] constructed an LDA topic model for Chinese book review data on Amazon.com to explore the effect of Chinese book export. Tianyi Li et al [7] proposed a mining method for the value elements of paintings based on BERT-LDA and K-means clustering and verified the index system through Random Forest and other algorithms in response to the lack of a standard value assessment index system in the field of paintings. Shouwei Zhang et al [8] analyzed the collected report texts with the help of KH Coder software and LDA topic model and summarized seven holistic media images. Zewen Hu et al [9] took a robot learning research paper as an example and used LDA and Word2vec for theme modeling and theme evolution analysis.

This study focuses on the user feedback data of shared motorcycles, introduces TF-IDF and LDA algorithms, mines user needs and real problems occurring during the use of the product and conducts research and analysis. Finally, we put forward corresponding service improvement suggestions to the product manufacturers and operators, improving the user experience and assisting the development of the country's green economy and sharing economy industry.

2 Data Source and Research Methodology

2.1 Data Source

The research data comes from the feedback information of shared motorcycle users collected by a shared motorcycle operation company in Wuhan and a total of 32,381 pieces of user feedback data were obtained from February 2021 to November 2021 in City C, including user feedback time, gender, age, riding time, latitude and longitude of start and end location, riding cost, feedback information, etc., of which the user's self-administered feedback information is selected as the research object.

2.2 Research Methods

2.2.1 TF-IDF

Term Frequency-Inverse Document Frequency (TF-IDF) comprehensively judges the importance or representativeness of a single keyword by calculating its Term Frequency (TF) and Inverse Text Frequency (IDF) [10].TF-IDF believes that when a keyword has a high TF and a low IDF, it is more representative in a particular document, which is favorable to retaining more important but less frequent keywords.

TF is the word frequency, which indicates the frequency of occurrence of a word in a document, and its calculation formula is as follows.

$$tf_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}} \tag{1}$$

In the formula, $n_{i,j}$ means the number of times the words appear in the document, and $\sum_k n_{k,j}$ means the total number of words in the document, which is the frequency of the words appearing.

IDF is the inverse document frequency, which is a measure of the weight of a word, and its calculation formula is as follows.

$$idf_i = \log \frac{|D|}{1 + |j : t_i \in d_j|} \tag{2}$$

In the formula, $|D|$ denotes the total number of documents in the corpus and $|j : t_i \in d_j|$ denotes the number of documents containing the word.

TF-IDF is obtained by multiplying two values, and its calculation formula is as follows.

$$TF - IDF = tf \cdot idf \tag{3}$$

2.2.2 LDA Topic Model

Latent Dirichlet Allocation, LDA, is an unsupervised machine learning document topic generation model based on Bayesian distribution, which contains a three-layer structure of words, topics, and documents, and considers that each topic is represented by a different distribution of words and each document is represented by a different distribution of topics, and the topics and the words are both represented by polynomial probability distributions in the form [9]. The mathematical definition of LDA algorithm is as follows.

$$P(W, Z, \theta, \phi; \alpha, \beta) = \prod_{i=1}^{M} P(\theta_j; \alpha) \prod_{i=1}^{K} P(\phi; \beta) \prod_{t=1}^{N} P(Z_{j,t} | \theta_j) P(W_{j,t} | \phi z_{j,t}) \tag{4}$$

In the formula, α and β define the Dirichlet distribution, θ and ϕ define the multinomial distribution, Z is the topic vector containing all words in the corpus, W is the vector containing all words in all documents, M is the number of documents, K is the number of topics and N is the number of words.

Since its proposal, LDA has been widely used in text mining, information retrieval, sentiment analysis and other fields. Sheng Chen et al [11] introduced LDA model, sentiment analysis, social network analysis method and T-TOE analysis model based on the public comment text with the topic of ChatGPT in Reddit platform to explore the influence and impact brought by generative artificial intelligence technology. Hengbo Du et al [6] constructed an LDA topic model for Chinese book review data on Amazon.com in the U.S. to dig deeper into overseas readers' evaluations of books exported from China. Ali et al [12] constructed a black-box model, LDA-GA-SVM, for the detection of hepatocellular carcinoma (HCC), and the results showed that the prediction accuracy of HCC had been improved. X. Liu et al [13] proposed an intelligent topic model, PQDR-LDA, to analyze user disease consultation text and doctor response text on online medical consultation platforms to explore the management strategy of online medical consultation platforms.

After organizing the existing studies, it is found that the LDA model can accurately extract topics from a large number of texts, and its topic extraction results have a higher degree of differentiation compared with traditional word frequency clustering statistics and other methods [14, 15].

2.3 Research Design

After cleaning the data, filtering out deactivated words, and identifying relevant words in the original corpus based on feedback from shared motorcycle users in City C, the text undergoes TF-IDF weighting analysis. Subsequently, an LDA theme model is constructed, and the optimal number of themes for the model is determined using topic coherence indexes. Themes are then identified based on the distribution of topic-words from the classification results. Finally, the data mining results of user feedback information are synthesized to propose suggestions for improving shared motorcycle services.

3 Research Program

3.1 TF-IDF Analysis

TF-IDF weighting analysis was performed on the documents to identify the importance of each keyword, increasing the weight of words that appear less frequently but are more important and decreasing the weight of words that appear more frequently but are not related to the study, to highlight the document topic and help optimize the subsequent LDA modeling topic classification results. As shown in Table 1, the top 10 keywords in each document in terms of weight average are as follows, which were translated from Chinese into English.

Table 1. Weighted averages (partial)

NO.	Keywords	Weight
1	Unreasonable charges	0.888
2	Chain	0.822
3	Brake failure	0.815
4	Charging error	0.786
5	Positioning error	0.785
6	Unable to drive normally	0.766
7	Continue riding	0.764
8	Misjudged return station	0.759
9	Time-consuming	0.753
10	Inaccurate positioning	0.750

3.2 Optimal Number of Topics Determination

In the LDA topic modeling process, the optimal number of topics K value is a key factor affecting the quality of topic clustering. The selection of this number of topics can usually be evaluated by using the Topic-Conference score, which indicates better topic clustering when the topic consistency index is higher.

The number of topics is set in the interval of 5 to 15, and the optimal number of topics is selected by plotting the curve of the coherence score under different numbers of topics for comparison. The analysis results are shown in Figure 1: when the number of themes is 11, the score of topic-coherence score is higher, so the number of topics is set to 11.

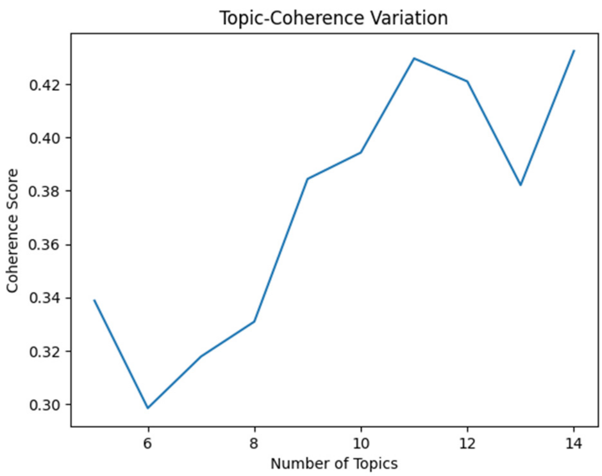

Fig. 1. Topic-Coherence Score Curve

3.3 LDA Model Training

Based on the topic-coherence score results, the LDA model is trained on the text data with an optimal number of themes set to 11. The number of text iterations is 30. The top 10 words with the highest probability in each theme are recorded to characterize the topic meanings. The final topic clustering results are presented in Table 2 (The words were translated from Chinese into English.).

Table 2. LDA Theme Classification Results

Topic	Content
1	returned (0.311), deducted (0.116), at the return station (0.076), one dollar (0.037), find (0.032), indiscriminate deductions (0.030), verified (0.027), park (0.027), unreasonable (0.015), overcharged (0.015)
2	helmet (0.217), can't start (0.094), use (0.082), didn't ride (0.070), lock (0.035), at the time (0.024), take a picture (0.022), billing (0.019), can't open (0.018), wear (0.015)
3	no (0.177), press a wrong button (0.066), ride (0.060), motorcycle (0.057), return (0.056), charge (0.053), deduct (0.034), success (0.034), misjudgment (0.026), failure (0.020)
4	return station (0.106), overcharge (0.069), out (0.062), over (0.055), fee (0.036), outside (0.036), problem (0.036), no power (0.030), open (0.029), kilometer (0.028)
5	can't ride (0.375), can't (0.065), someone else (0.032), unlocked (0.032), ride (0.029), go (0.025), in place (0.022), forgot to return the bike (0.020), no (0.019), ride (0.018)
6	return station (0.444), unable to return vehicle (0.086), inside (0.054), not there (0.036), said (0.034), time (0.025), not there (0.021), nearby (0.013), half a day (0.012), good (0.010)
7	vehicle (0.183), cost (0.079), location (0.049), unable (0.037), caused (0.034), time (0.030), exceeded (0.027), refresh (0.021), piece (0.020), used (0.019)
8	motorcycle (0.259), ride (0.134), can't (0.051), turned on (0.034), stopped (0.031), malfunctioned (0.022), started (0.021), next to (0.015), no power (0.013), power (0.013)
9	stop (0.185), no power (0.096), car (0.059), vehicle malfunction (0.049), return point miscalculation (0.034), seconds (0.033), can't stop with cars around (0.032), would have (0.028), doesn't work (0.024), bad (0.023)
10	returning a car (0.120), parking (0.119), inaccurate location (0.047), place (0.047), arrival (0.039), location (0.027), place (0.027), direct (0.026), didn't (0.023), first time (0.020)
11	return (0.185), dispatch fee (0.173), money (0.071), collect (0.063), point (0.039), more deductions (0.024), expensive (0.023), bill (0.018), small program (0.018), yet (0.017)

4 Analysis of Results

4.1 Theme Recognition Analysis

Based on the training results of the LDA model, combined with the vocabulary expression of each topic and the understanding analysis of the original corpus, thematic identification was conducted on the classification results. And the distribution of "topic-word" was obtained, revealing that the issues highlighted in user feedback mainly focus on abnormalities in bike returns, helmet unlocking, errors in app operation, irregularities in bike usage, location discrepancies, cost anomalies, etc. The 11 topics were grouped into five categories: returning issues, quality issues, positioning issues, cost issues and operation issues (Table 3).

Table 3. Major Topic Category (M-Topic)

M-Topic	Topic Category	Topic Composition
1	Returning Issues	Topic 1: Slow car return leads to overtime charges Topic 6: Unable to return the car at the return point.
2	Quality Issues	Topic 2: Helmets cannot be unlocked properly Topic 4: Overcharging due to vehicle breakdown outside the return point Topic 5: Vehicles can't be ridden Topic 8: Vehicle without electricity Topic 9: Power failure while traveling
3	Positioning Issues	Topic 7: Positioning can not be refreshed, resulting in overcharging
4	Cost Issues	Topic 11: Overcharging dispatching fee at the return point
5	Operation Issues	Topic 3: Mistakenly pressing the return button of the app.

- M-Topic 1: Returning Issues, such as "Slow motorcycle return speed", "Misjudgment of return station", "Unable to return motorcycle", etc. Whether it is convenient to return a vehicle is an important part of the evaluation of satisfaction with the use of shared vehicles. However, due to the inaccuracy of Bluetooth connection at the point of return and the cumbersome steps of returning, the phenomenon of failure to return a motorcycle occurs repeatedly, and users have to try to turn off the lock or go to a new point of return several times, which greatly reduces the sense of satisfaction.
- M-Topic 2: Quality Issues, such as "helmet verification failure", "helmet broken", "vehicle can't move", "out of battery", "power failure in the middle of traveling" and so on. The ability of bikes to function properly is the primary factor determining whether consumers choose shared electric bikes as their mode of transportation. However, issues such as bike malfunctions, power outages mid-ride, and helmets malfunctioning frequently occur, which inevitably affect the consumers' sense of experience, generating a bad brand image in their minds and diminishing consumer desire for such products.

- M-Topic 3: Positioning Issues, such as "positioning unable to refreshed", "positioning is not allowed" and so on. An accurate positioning system can help users record their travel paths, calculate the distance traveled and generate a reasonable charging strategy, as well as help operators accurately understand the geographic distribution of vehicles to protect users' driving safety. However, if it is impossible to accurately locate the vehicle, it will cause great trouble for consumers and operators, affecting the user's traveling experience and failing to protect the safety of users and vehicles.
- M-Topic 4: Cost Issues, such as "overcharging", "excessive dispatch fees", "too expensive", etc. Cost is a critical factor for users to assess the cost-effectiveness of consumption, but during usage, instances such as bikes being unable to be used yet still being charged, or additional dispatching fees being charged at return points, significantly reduce users' willingness to consume again.
- M-Topic 5: Operational Issues, such as "mistakenly pressing the return button". Some users said that they would accidentally press the "return button" when stopping temporarily during a ride, resulting in the forced termination of the trip and bringing unnecessary trouble to the ride. This phenomenon is attributed to consumers' rusty operation of small programs, and operators can appropriately educate users on the basic operation of small programs to help them complete their trips.

4.2 Visual Analysis

The pyLDAvis model was used to visualize the theme clustering results (Figure 2). The left figure shows the bubble map showing the heat of each topic, the larger the bubble, the higher the frequency of the theme. The distance between the bubbles reflects the degree of difference between the topics: the closer the distance, the more similar the meaning of the two themes. If the bubbles overlap, it means that the two topics may have the same characteristic words. And the right words are the keywords for each topic, which were translated from Chinese into English.

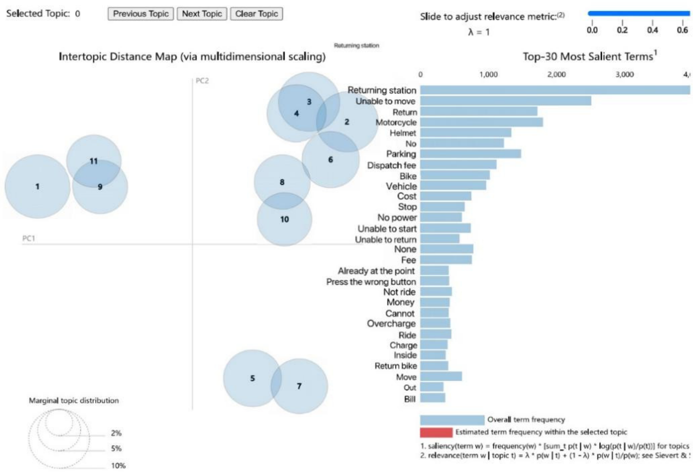

Fig. 2. LDA Thematic Clustering Visualization

From the results of the visual analysis, we can see that user feedback evaluations are mainly distributed in the areas of vehicle return points, inability to ride, helmets, scheduling fees, etc. Most of the problems are concentrated in the first quadrant, which is related to the quality of vehicles and helmets. And most of them reflect the problems of vehicles not being able to start, helmets failing to be verified, and not being able to return the vehicle normally, which is one of the most common problems encountered by users in the process of using the vehicle, and is also the main hand in the future service improvement program of the shared motorcycle.

5 Conclusions and Recommendations

As an emerging mode of urban transportation and travel, shared motorcycles provide convenience for citizens, but also bring challenges to urban transportation governance. This study focuses on the feedback evaluations of shared motorcycle service in City C and analyzes it by using TF-IDF and LDA models, summarizing that the problems of users' feedback mainly focus on the inconvenience of returning bicycles, inaccessibility of vehicles (or helmets), inaccuracy of positioning, unreasonable costs, and errors in the operation of APP, etc. Finally, given the outcomes of the study, we provide some further suggestions for the improvement of shared motorcycle operation, aiming to provide some constructive development ideas for both shared electric bike operators and urban planners.

1. Optimize the return system to improve parking efficiency. First of all, operators need to understand the peak riding hours and geographic areas of the public, scientifically plan the parking spots of shared motorcycles, and optimize the intelligent recommendation system of the parking spot, so as to recommend more suitable parking areas for users according to their real-time location and the parking situation of the surrounding parking spots. Secondly, improve the sensitivity of the "electronic fence" and vehicle positioning system to help users regulate their own return behavior. Furthermore, strengthen the user education and reward and punishment mechanism, establish a credit system, let users understand the correct way of returning vehicles and its importance, and establish a reward and punishment mechanism through points, coupons and other forms to improve the user's awareness of standardized parking.
2. Strengthen the overhaul mechanism to ensure safety during travel. First of all, vehicle manufacturers should evaluate the durability and corrosion resistance of production materials prior to mass production, and choose better quality and cost-effective materials for production. Secondly, the operation department needs to enhance vehicle quality monitoring and testing mechanism, regularly conduct comprehensive performance tests on shared motorcycles, and strengthen the inspection of key components of the vehicles, so as to ensure that all the vehicles on the market meet the safety standards. In addition, vehicle and helmet manufacturers should optimize the vehicle design based on users' needs and behavioral habits, and develop new products with higher quality, safer and more convenient.

3. Update positioning technology to reduce operational risks. Firstly, optimize and upgrade or introduce advanced positioning technology to improve the accuracy and response speed of positioning, and add base stations in urban areas to assist positioning and improve the positioning ability in areas with poor GPS signals such as tall buildings or indoor areas. Secondly, analyze the topography, buildings and roads in the city through GIS to optimize the positioning algorithm and reduce the positioning error. Furthermore, we set up a ground verification team to regularly inspect the consistency between the actual position of the vehicle and the position displayed by the system, and correct the deviation in time.
4. Transparent charging policy and optimized marketing tools. First of all, operators need to publicize riding prices to ensure transparency and inform consumers about fee calculation, and dynamically adjust the service price according to market research results. Secondly, operators should clarify fee-charging standards for abnormal behaviors such as vehicle damage, loss, and exceeding normal usage time. Furthermore, they should formulate reasonable preferential strategies, give welfare gift packages to newly registered users and users with high usage frequency, and strengthen commercial cooperation with local merchants and scenic spots to attract users in the form of coupons and joint promotions.
5. Upgrade the software system and simplify the interaction process. Developers should first simplify the registration process for new users to enhance user efficiency. Second, design an intuitive user interface and clear operating instructions to ensure that users can easily find key functions such as maps, vehicle information, and payment. Further, optimize the map positioning and intelligent recommendation system to help users accurately find the location of nearby vehicles and provide walking navigation to the vehicle location to improve user convenience. At the same time, operators need to ensure that the app responds on time and loads quickly, reducing the occurrence of program waiting or lagging and improving the user's sense of service experience.

The success of shared motorcycles does not only depend on the advanced technology but also on whether it can be integrated into the bloodline of the city and become part of people's daily lives. We expect that shared motorcycles will play a more important role in the future urban transportation system, providing urban residents with a more convenient, efficient and greener way to travel.

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