Article

The Evaluation of User Satisfaction and Prospects Analysis of Shared Bicycle Services

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Abstract: Since their introduction, shared bicycle services have rapidly expanded across Chinese cities and have become a key component of urban micro-mobility. By 2025, with the integration of AI-powered dispatch systems, smart parking, and green transport policies, shared bicycles are increasingly embedded within smart city frameworks. This study investigates user satisfaction and its influencing factors to support service optimization and sustainable development. A stratified three-stage unequal probability sampling method was used to survey 1,080 residents in urban and suburban areas of Beijing. Data analysis incorporated descriptive statistics, logistic regression, principal component analysis, fuzzy comprehensive evaluation, and text mining. Results indicate strong market penetration of shared bicycles, with dynamic pricing, deposit systems, and smart parking emerging as key user concerns. Age, occupation, and income remain significant determinants of usage frequency. While users express high satisfaction with app functionality and bicycle hardware, cost-effectiveness and safety continue to affect overall experience. Sentiment analysis reveals increasing expectations for environmentally friendly and intelligent mobility solutions. Based on the findings, the study recommends flexible pricing models, safety enhancements, and targeted service strategies to expand user engagement and support the evolution of shared mobility in urban China.

Keywords: shared bicycles; user satisfaction; urban mobility; fuzzy evaluation; text mining

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1. Introduction

Since the emergence of shared bicycles in China, the concept of "green, convenient, and low-carbon" travel has rapidly gained attention from both users and the capital market. With the continuous advancement of mobile internet, GPS positioning, big data, and smart lock technologies, shared bicycle systems have gradually shifted toward dockless operation and scan-to-ride functionality, significantly improving the efficiency of short-distance urban travel. By 2025, shared bicycles have become an integral part of many cities' public transportation systems and play a critical role in solving the "last-mile" travel problem, driven by the development of intelligent transportation and refined urban governance[1-8].

Research on shared bicycles, both domestically and internationally, has primarily focused on user behavior, business models, impacts on transportation systems, and regulatory policies. In Western countries, such as the United States, projects like Citi Bike in New York operate under government-led models with strict regulatory frameworks[9]. In contrast, China's market has evolved from enterprise-led, capital-driven expansion to a phase of gradual regulatory refinement[10-12]. Platforms such as Meituan Bike and Qingju (HelloBike) have rapidly scaled their operations and built large user bases supported by technological innovation[13-19].

In recent years, academic focus has gradually shifted from macro-level market development to micro-level user satisfaction and behavioral analysis[20]. Existing literature indicates that socio-demographic factors such as age, occupation, and income significantly influence shared bicycle usage frequency and satisfaction[21]. At the same time, cost, safety, and parking issues remain major obstacles to improved user experience. With the growing application of text mining and sentiment analysis techniques, researchers are increasingly able to extract valuable insights from user reviews, providing data-driven support for optimizing product design and enhancing service quality[22-25].

In summary, the shared bicycle industry in 2025 is undergoing a critical transition from large-scale expansion to service optimization and differentiated operations. There is an urgent need to better understand user satisfaction, identify potential user groups, and upgrade operational strategies to build a more sustainable, efficient, and user-centered development model[26-28]. This study combines questionnaire surveys with text data analysis to systematically explore shared bicycle users' behavioral characteristics and satisfaction evaluation, aiming to provide scientific recommendations for service improvement[29-31].

2. datas and Methods

2.1. Data Collection Procedure

To obtain comprehensive and reliable data on user satisfaction and behavior regarding shared bicycle services in 2025, a multi-stage stratified probability sampling design was implemented in Beijing. The primary objective was to ensure representativeness across different urban zones and population segments while maintaining operational feasibility.

2.1.1. Survey Objectives

The main goals of the survey included:

- Collecting demographic data (gender, age, occupation, income) to characterize current users;
- Identifying factors influencing both the use and frequency of shared bicycle usage;
- Investigating reasons behind non-usage among potential users;
- Assessing user satisfaction with various aspects of the service (e.g., vehicle quality, user experience);
- Providing data-driven recommendations for service improvement.

2.1.2. Sampling Design

A stratified three-stage unequal probability sampling method was used:

Stage 1: Stratified Sampling of Administrative Districts. Beijing was stratified into central urban areas and suburban zones. According to population data, 5 districts were selected from the central urban layer and 3 from the suburban layer using PPS (Probability Proportional to Size) sampling based on 2025 estimated population data.

Stage 2: Sampling of Subdistricts. Within each selected district, subdistricts were chosen using proportional stratified random sampling. A total of 40 subdistricts were selected—30 from urban districts and 10 from suburban districts.

Stage 3: Sampling of Residents. Systematic sampling was conducted within selected subdistricts. Investigators intercepted pedestrians near shared bicycle hotspots and invited one respondent every five minutes to complete a questionnaire. If declined, the next available person was approached. Sampling points rotated every two hours to improve coverage.

2.1.3. Sampling Design

The sample frame included:

- Primary units: Administrative districts within Beijing
- Secondary units: Subdistricts within selected districts
- Tertiary units: Residents in proximity to shared bicycle deployment zones

2.1.4. Survey Instrument Design

A structured questionnaire was developed consisting of five sections:

- Demographics (e.g., age, gender, education, occupation, income)
- Usage behavior among current users
- Satisfaction evaluation of shared bicycle features
- Non-user analysis, identifying reasons for non-usage
- User suggestions and improvement feedback

2.1.5. Pilot Testing

Prior to the formal survey, a pilot study was conducted with 80 questionnaires distributed (2 per subdistrict). A total of 76 valid responses were collected. Reliability and validity tests were performed on the pilot data. Based on the results, modifications were made to improve question clarity and structural logic.

2.1.6. Sample Size Estimation

Using the pilot data with an estimated shared bicycle usage rate $P = 0.55$, and setting a 95% confidence level with a 4% margin of error, the optimal sample size was calculated as:

$$n = \frac{N \cdot t^2 \cdot p(1-p)}{(N-1) \cdot d^2 + t^2 \cdot p(1-p)} \approx 594 \tag{1}$$

Assuming a design effect (deff) of 1.8 due to multi-stage sampling, the adjusted sample size was 1,069. To account for a projected 12% invalid response rate, the final target sample was set at 1,215 respondents.

2.1.7. Final Survey Implementation

A total of 1,220 questionnaires were distributed, and 1,080 valid responses were collected, resulting in an effective response rate of **88.52%**. For subdistricts exceeding the optimal sample size, data truncation was applied; for those under-sampled, follow-up distribution ensured quota fulfillment.

2.2. Data verification

We employed three analytical methods to validate the survey data: reliability analysis, validity analysis, and randomness (run) test to ensure internal consistency and data quality.

2.2.1. Reliability Analysis

Reliability includes internal and external consistency. For the satisfaction-related survey items, 14 items were divided into four components based on thematic grouping: satisfaction with bicycle appearance and components, user experience, app usability, and pricing. We used Cronbach's α coefficient to assess the internal consistency within each component. The results are shown below:

Table 1. Reliability Test Results.

Dimension	Cronbach's α	No. of Items	Reliability Evaluation
Bicycle appearance & components	0.993	6	Very good
User experience	0.976	2	Very good
App usability	0.976	3	Very good
Pricing	0.967	3	Very good

2.2.2. Validity Analysis

Validity analysis includes **content validity** and **construct validity**. Following standard item analysis procedures, we calculated the correlation coefficient between each item and its corresponding dimension's total score to test content validity. For construct validity, correlation analysis between dimensions was conducted.

Table 2. Validity Analysis.

Dimension	Appearance Satisfaction	User Experience	App Satisfaction	Pricing Satisfaction
Correlation Coefficient	0.993**	0.998**	0.986**	0.979**
Significance (p-value)	0.000	0.000	0.000	0.000

$p < 0.05$ indicates strong correlation between individual items and their dimensions, verifying appropriate content and structural validity.

3. Results and Analysis

3.1. Analysis of Factors Influencing Shared Bicycle Usage Based on a Binary Choice Model

In the previous section, descriptive statistical methods were used to analyze the characteristics of shared bicycle users. However, whether or not an individual uses shared bicycles is typically the result of multiple influencing factors. Therefore, it is necessary to construct an econometric model to comprehensively examine these factors. This section utilizes a binary choice model to quantitatively analyze the influence of variables such as gender, age, education, occupation, monthly income, and monthly public transportation expenditure on the likelihood of using shared bicycles, in order to identify significant traits of shared bicycle users.

3.1.1. Model Selection

The binary choice model is designed to explain individual decision-making when faced with two mutually exclusive alternatives. Since the variable of interest—whether an individual uses shared bicycles—is binary in nature, the binary logistic regression model (Logit model) is employed in this analysis.

3.2. Model Construction

The dependent variable y_i represents whether individual iii has used shared bicycles. If the response is "yes", then $y_i = 1$; otherwise $y_i = 0$.

Many survey responses involve categorical data. For instance, monthly public transportation expenditure is divided into five intervals. If encoded as 5, 4, 3, 2, 1 and used directly in the model, it would imply that the intervals are equidistant and have a uniform influence on the dependent variable—an assumption that is overly simplistic and unrealistic. Similarly, unordered categorical variables like occupation have no inherent numerical hierarchy, making it inappropriate to assign them a single regression coefficient. Therefore, we adopt the statistically standard practice of using **dummy variables** for categorical predictors, and then simplify the model based on significance testing.

Table 3. Variable Definitions in the Binary Choice Model.

Variable Name	Symbol	Definition
Gender	—	Categorical
Age	—	Dummy variables, with "61 and above" as the reference group
Education	—	Dummy variables, with "Primary school or below" as baseline
Occupation	—	Dummy variables, with "Retiree" as the baseline
Monthly Income	—	Dummy variables, with "20,000 CNY and above" as the baseline
Public Transit Expenditure	—	Dummy variables, with "≥300 CNY/month" as the baseline
Shared Bicycle Usage (Dep. Var.)	y	$y = \begin{cases} 1 & \text{Yes} \\ 0 & \text{No} \end{cases}$

3.3. Analysis of User Characteristics via the Model

To facilitate data entry, the last option in each category was generally set as the reference group, unless it was labeled "Other" or had fewer than 30 selections—in which case the penultimate option was chosen as the baseline.

A binary Logit model was constructed by including all relevant variables. Backward stepwise elimination was applied to remove non-significant predictors, with a significance level set at 0.1. After multiple iterations, the final regression output is as follows:

Table 4. Final Regression Results.

Variable	Coefficient	Std. Error	Wald Statistic	p-value
age_26–35	2.229	0.790	7.971	0.005
clerk	0.403	0.244	2.956	0.084
Cost_below50	-0.625	0.313	3.984	0.046
Income_10000–20000	0.548	0.347	2.723	0.099

The model yielded a **likelihood ratio chi-square (χ^2) statistic of 23.185**, with a p-value of 0.000, which is significantly lower than the 0.1 threshold. This indicates good overall explanatory power of the model.

3.4. Interpretation of Model Results

Age: The reference group for age is "61 and above". The positive and significant coefficient for the 26–35 age group indicates that individuals in this range are more likely to use shared bicycles. This may relate to the commuting needs of working professionals and the younger generation's openness to new technologies. People in this age group often use shared bicycles to cover short distances between public transport stations and workplaces, making them a major user segment.

Occupation: "With "retiree" as the baseline category, the positive coefficient for **clerk** indicates that office workers are significantly more likely to use shared bicycles at the 10% significance level. This is plausible, as shared bicycles offer a convenient means of transportation for commuting between public transit and workplaces, especially when pressed for time.

Monthly Public Transit Expenditure: Compared to users spending ≥300 CNY/month on transit, individuals spending less than 50 CNY show a significantly negative coefficient. This suggests that users with higher public transit spending are more likely to also use shared bicycles, likely due to more frequent travel and a greater need for efficient last-mile connectivity.

Monthly Income: Income significantly influences shared bicycle usage. Compared to those earning ≥20,000 CNY/month, individuals earning between 10,000 and 20,000 CNY are more likely to use shared bicycles (positive coefficient, $p < 0.1$). This income bracket often includes younger professionals or mid-level staff who rely more on cost-effective transportation. For those earning less than 10,000 CNY/month, the coefficient was not statistically significant—possibly due to sensitivity toward deposit costs, making them more likely to choose lower-cost alternatives.

In general, shared bicycle usage is higher among middle- and lower-income groups, indicating that affordability and convenience remain core advantages driving adoption.

3.2. Analysis of Shared Bicycle Usage Frequency Based on a Multinomial Logistic Model

The frequency with which users engage in shared bicycle usage is influenced by various factors. To analyze this comprehensively, a multinomial logistic regression model was constructed to examine the effects of gender, age, education level, occupation, monthly income, and monthly public transport expenditure. The objective is to identify significant characteristics associated with user groups based on usage frequency.

3.2.1. Model Selection

Since usage frequency is a categorical variable with multiple levels, a multinomial choice model is appropriate. Among multinomial discrete choice models, the Probit model requires multivariate normal distribution assumptions, limiting its practical use. The Logit model, based on the logistic distribution, is more commonly applied due to its analytical tractability and computational efficiency.

3.2.2. Model Construction

The dependent variable 'Y' represents frequency of shared bicycle usage, categorized as follows: 1 = At least once a month, 2 = 1–3 times per week, 3 = 4–6 times per week, and 4 = Once or more daily. Independent variables include categorical data such as age and occupation, for which dummy variables were used to avoid assumptions of equal interval scaling. The reference category was typically set as the last option in each variable group unless it was labeled 'Other' or had fewer than 30 observations, in which case the penultimate option was used.

Table 5. Final Regression Results.

Variable Name	Symbol	Definition
Usage Frequency	Y	1 = Monthly+, 2 = Weekly 1–3, 3 = Weekly 4–6, 4 = Daily
Gender	gender	1 = Male, 0 = Female
Age	age_*	Dummy variables, base: 61+
Education	graduate, college, etc.	Dummy variables, base: Primary or below
Occupation	Student, Clerk, etc.	Dummy variables, base: Retiree
Income	Income_*	Dummy variables, base: 20000+ CNY
Public Transit Cost	Cost_*	Dummy variables, base: 300+ CNY/month
Acceptable Deposit	deposit_*	Dummy variables, base: Above 300 CNY
Acceptable Price	Price_*	Dummy variables, base: Above 2 CNY/hour
Unlock Method	Wechat, APP	Dummy variables, base: both used

3.2.3. Regression Model and Results

After including all necessary variables, the following multinomial logistic regression model was constructed. Non-significant variables were excluded based on likelihood ratio tests using a significance threshold of 0.05. The final model results are summarized below.

Table 6. Multinomial Logistic Regression Results.

Variable	Estimate	Std. Error	Wald / p-value
Income_5000–10000	2.173	.744	8.542 / .003
Income_10000–20000	1.504	.754	3.976 / .046
deposit_below100	-5.011	2.006	6.244 / .012
deposit_100–200	-5.105	2.035	6.294 / .012
deposit_200–300	-4.074	2.023	4.055 / .044
APP	1.889	.552	11.707 / .001
Income_5000–10000	2.173	.744	8.542 / .003
Income_10000–20000	1.504	.754	3.976 / .046
deposit_below100	-5.011	2.006	6.244 / .012
deposit_100–200	-5.105	2.035	6.294 / .012
deposit_200–300	-4.074	2.023	4.055 / .044
APP	1.889	.552	11.707 / .001

The likelihood ratio chi-square statistic of the model was 68.341 ($p < 0.05$), indicating strong overall model significance.

3.2.4. Interpretation of Results

Income: Higher income is associated with lower frequency of shared bicycle usage. At the 5% significance level, users with incomes between 5,000–10,000 CNY and 10,000–20,000 CNY are more likely to use shared bicycles more frequently than those earning 20,000+ CNY. These groups often include younger professionals without private transportation who rely on affordable mobility options for daily commuting.

Deposit Acceptance: A higher tolerance for deposit amounts is associated with higher usage frequency. Users accepting deposits below 300 CNY are significantly less likely to be high-frequency users compared to those accepting deposits over 300 CNY.

Unlock Method: Users who only use the dedicated app to unlock bicycles are more likely to use them frequently, compared to those who use both WeChat and the app. App-exclusive users likely represent long-term or loyal users who frequently engage with the service.

5. Conclusions

Based on a comprehensive analysis of survey data, binary and multinomial logistic regression models, fuzzy comprehensive evaluation, and text mining techniques, this study yields the following key conclusions regarding shared bicycle usage behavior and user satisfaction:

Shared bicycle services enjoy high market awareness, but conversion from awareness to usage remains limited. Survey results indicate that 96% of respondents have heard of shared bicycles, but only 54% have used them. This demonstrates a strong foundation of user awareness, yet also reveals the need for strategies to enhance the transition from awareness to adoption. Both users and non-users prioritize **deposit price** as a primary concern, while **convenience features** such as navigation and real-time traffic updates are also highly valued. Improving these two aspects is likely to enhance user engagement.

The characteristics of potential users are clearly defined. Through binary logistic regression analysis, it is evident that age (particularly 26–35 years), occupation (company clerks), public transit spending, and monthly income (10,000–20,000 CNY) significantly influence the likelihood of shared bicycle usage. These attributes define a user group that is more inclined to adopt shared bicycles and should be the focus of targeted service optimization and promotional strategies.

User satisfaction with hardware is high, but cost satisfaction remains relatively low. According to fuzzy comprehensive evaluation results, the satisfaction score for bicycle hardware reached **80.36**, while convenience scored **76.79**, and cost satisfaction was lower at **70.37**. Among cost-related concerns, **deposit pricing** was weighted most heavily. These findings indicate that while users are generally pleased with the physical quality of shared bicycles, pricing—particularly deposits—remains a key issue limiting satisfaction.

Overall evaluations are positive, though improvement opportunities remain. Text mining results based on data from ASO100, Baidu News, and survey feedback reveal that **70% of users express a positive attitude**, in line with the fuzzy evaluation results. However, terms such as "lower rental cost," "more available bikes," and "adjustable seat" frequently appear in user suggestions, signaling important areas for service enhancement to further improve user experience.

Cost and safety are the main barriers for potential users. Principal component analysis targeting high-potential user groups (such as young professionals and frequent public transport users) shows that **cost and safety concerns** are the dominant reasons for non-usage. Specifically, company employees and public transport users with moderate monthly expenditures refrain from using shared bicycles mainly due to pricing and security issues. Addressing these concerns—by lowering deposits and enhancing ride safety—could significantly expand the user base and improve market penetration.

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