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Mapping Quality of Service and Quality of Experience to Public Bike Systems – An Empirical Case of New Taipei YouBike

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ABSTRACT

Customer service and riding experience are crucial for the success of public transportation systems. This study utilises operational data from a public bike program to develop a quality of service (QoS) model, which involves constructing a dataset of available bikes and docks at each station recorded every five minutes over 55 days across 1,379 rental stations. We developed performance indices and created spatiotemporal visualisations for operational assistance. Additionally, we investigated Google Maps reviews posted by bike users using natural language processing and deep learning techniques to develop a quality of experience (QoE) model. The QoE model analysed 4,256 text reviews and 4,164 image reviews, categorised into intent sentiment, text content and image content. Classification models were developed for detailed opinion analysis. A case study focusing on New Taipei's YouBike system highlights bike shortages as the most significant challenge, particularly at smaller stations. The QoS model identified bike shortages correlated with negative user perspectives in the QoE model, indicating a connection between objective operational data and subjective cyclist opinions. This QoS-QoE joint model provides an integrated approach to assessing service quality and riding experience for public bike operators and city transportation authorities.

KEYWORDS

public bike system; quality of service; quality of experience; sentiment analysis; deep learning; bike-sharing.

1. INTRODUCTION

The "last mile" concept originally emerged from the telecommunications sector, highlighting strategies to address challenges associated with terminal devices such as wiring issues, migration and deregistration. When applied to passenger transportation, it addresses transporting individuals from transit stations to their final destinations. Various strategies have been employed to meet this challenge, such as well-designed pedestrian walkways, quality public bikes and bike lanes, frequent shuttle buses, and sufficient park-and-ride facilities. Public bikes, also known as bike-sharing, have become a prevalent option in numerous urban areas around the globe, with over 2,000 programs in operation and 217 under planning as of June 2024 [1]. Public bike systems are generally established in urban environments, allowing city dwellers to rent bicycles for short-distance travel. This service significantly reduces traffic congestion, cuts down on noise and air pollution, and promotes fitness, tourism and recreational pursuits. It aligns with the trend toward adopting low-carbon transportation options, reflecting the broader societal movement toward enhancing the quality of life.

The functionality of public bike systems, which allow bikes to be rented from one location and returned to another, commonly raises concerns about possible bike or dock shortages in the rental stations. These issues arise due to the substantial disparities in temporal demand and supply [2, 3], especially during peak hours around major trip generation spots. It eventually diminishes public bike service's reliability and user acceptance [4]. Consequently, gaining a comprehensive understanding of the availability of bikes and docks at each station becomes paramount in navigating the challenges posed by the demand-supply imbalance inherent in public bike systems. Historically, research into the user experience or perceptions of public bike systems heavily relied on questionnaire surveys as the primary method for data collection [5-7]. These surveys, conducted in multiple iterations, were crucial for evaluating changes in rider satisfaction over time. Corresponding analysis tools and methods have been developed to complement questionnaire surveys as a result of the increasing availability of diverse data in recent years.

This study introduces a joint model to assess a public bike system's operational performance and user experiences. Operational performance is precisely gauged by analysing extensive data concerning the availability of bikes and docking stations to reveal the system's functionality. Conversely, user experience measurements delve into analysing social media commentary regarding public bikes, which provides insights into user satisfaction levels. The joint model elucidates the public bike system's reliability by examining the temporal evolution of both operational performance and user experience over time. New Taipei City was chosen as the case study because it runs one of Taiwan's largest bike-sharing programs, YouBike, in a major metropolitan area. As of August 2024, New Taipei YouBike had 2.88 million monthly ridership and 1,352 stations; its popularity has led to operational and service issues, making it an ideal case study location. It offers operators and transportation authorities a data-driven foundation to enhance public bike systems, thereby improving urban mobility solutions. This paper is organised as follows: Section 2 reviews the relevant literature, Section 3 outlines the problem formulation and case study, Section 4 maps the joint model of operational performance and user experience, and Section 5 concludes with the findings and implications for future research.

2. LITERATURE REVIEW

Previous studies have examined the travel behaviours of riders and the specific characteristics of public bike trips. For instance, research conducted in Ningbo, China, identified that bike-sharing usage and satisfaction degree presented a strongly positive correlation and were affected by gender, household bicycle ownership, household income, trip model, travel time, station location and users' perception [7]. In Chicago, an analysis of bike trip data revealed distinct temporal patterns: usage peaks are notably observed in the morning and afternoon on weekdays, with a reduced peak around noon; conversely, weekend usage typically spans from 10 A.M. to 8 P.M., demonstrating a different pattern from weekdays [8]. Further studies on New York's CitiBike identified that bike-sharing modifies urban transport dynamics, exceptionally accommodating many short trips during morning and evening rush hours. Factors such as weather conditions, urban schemes, air pollution and seasonal variations affect demand, highlighting challenges like bike rebalancing and station density [9, 10]. A recent study assessing Hungarian cities' readiness for electric bike-sharing revealed 25 factors influencing the deployment, including infrastructure, existing transportation options, demographics, climate, safety and regulations [11]. Another comprehensive review identified weather, built environment, public transportation integration, station-level characteristics, socio-demographics and temporal factors as critical determinants of bike-sharing demand [12]. These insights signal the complexity of public bike demand patterns, present operational challenges and underscore the importance of tailored data-driven approaches in public bike management.

Meanwhile, the U.S. Federal Transit Administration emphasises the discrepancies between service operators' perceptions and users' expectations regarding user needs. Such discrepancies can create difficulties in delivering high-quality service and potentially influence users' perceptions of the service's reliability, communication, reputation, safety and timeliness [13]. Similarly, the International Telecommunication Union differentiates service measurements into two distinct types: quality of service (QoS) and quality of experience (QoE) [14]. QoS refers to the technical aspects of the service that impact its overall performance, including metrics such as the frequency of data loss and the extent of any delays. Conversely, QoE focuses on the satisfaction or dissatisfaction users experience with the service, influenced by factors such as their background, current mood and preconceived expectations. The mean opinion score is often utilised to estimate user perceptions of service performance, as individual satisfaction levels may differ markedly. The principles of QoS and QoE could be integrated into the performance assessment framework of public bike systems in this study.

Conventionally, researchers have used questionnaire surveys to uncover QoS and QoE based on users' subjective opinions. Various questionnaires have been designed to assess rider satisfaction with the public bike program YouBike in Taipei, Taiwan. One questionnaire categorised responses into three dimensions: (software) service quality, (hardware) bike quality and pricing structures; the service quality dimension significantly influenced YouBike riders' satisfaction [5]. Another questionnaire identified the reasons for using YouBike and satisfaction levels concerning bike conditions, rental process, station accessibility, bike availability and customer service; findings indicated that the public bike system was perceived as affordable and convenient for short-distance travel with high rider satisfaction [15]. In Korea, a questionnaire analysis of the Seoul Public Bike system revealed that factors such as occupation type, accessibility, convenience, bike manageability and fare levels significantly influenced overall user satisfaction [16]. Additionally, a web-based satisfaction survey conducted among BikeMi customers in Milan, Italy, revealed that satisfaction is impacted by specific factors such as the mechanics of the bikes, the pick-up and drop-off system and the apps used to manage the service; less concern was noted regarding broader aspects of the service [17]. Likewise, a two-phase questionnaire survey conducted in Madrid, Spain, to assess BiciMAD's user satisfaction showed that station occupancy, bike availability and totem functioning are key service attributes that significantly enhance satisfaction and system reliability [18].

Due to technological advancements, rental transaction data and periodic counts of available bikes and vacant docks at each station are systematically stored in the system's backend. A substantial amount of data is accessible to the public, providing a means to objectively assess QoS and the precise needs for bike deployment. By utilising real-time or historical operational data, statistical models can incorporate various indicators such as the load factor, concurrent usage, compactness ratio, bike shortage risk, dock shortage risk, average waiting time for available bikes or vacant docks, etc. [2-4, 19]. These indicators measure individual stations and the system's QoS by identifying temporal service variability. In many global cities' public bike systems, for example, weekdays present double-peaked patterns corresponding to commuter rush hours, while weekends typically experience a single, more prolonged peak, indicative of leisurely or non-commuter use [3]. Data collected from 377 Bicing stations in Barcelona, Spain, showed that individual stations exhibited distinct daily and weekly patterns reflecting local demographic and geographic influences [4]. In Montreal, Canada, the BIXI bike stations located in high-density areas with mixed land uses and near public transit facilities experienced higher usage, suggesting the potential for bike-sharing integration with public transport to enhance the effectiveness of both services [2]. In Taipei, Taiwan, transaction data from YouBike and Mass Rapid Transit (MRT) trips were analysed to assess how public bikes enhance MRT's first- and last-mile accessibility. The analysis identified service gaps and areas with unbalanced YouBike availability, offering valuable insights for service improvements [20].

Moreover, social media has emerged as a novel avenue for QoE assessment, particularly when conventional methods such as questionnaire surveys encounter certain limitations. Social media data, encompassing the latest text and image opinions, helps capture user perspectives and implicit information in a more dynamic and real-time manner. Social media analysis frequently employs deep learning techniques, a subset of machine learning. These techniques use multi-layered networks that represent data as vectors, capturing features for object identification and classification tasks. Some models, like recurrent neural networks, are suited for natural language processing [21], while others, like convolutional neural networks, excel in image recognition [22]. As a vital application of deep learning techniques, opinion mining could manage sentiment classification, target identification and opinion summarisation based on data from social media platforms. Transportation studies have increasingly focused on social media opinion mining in fields such as bike-sharing [23], urban railways [24, 25] and freeway electronic toll collection [26]. For instance, an analysis of approximately 12,000 tweets related to global bike-sharing highlighted benefits such as convenience, strong performance and sustainability; in contrast, criticisms centred on issues of inequity, rental and safety concerns, criticism of authorities and regulations, and poor performance, particularly among dockless bike-sharing start-ups in Asia that used lower-quality bikes [23]. In Taipei, Taiwan, web reviews and deep learning were used to analyse the connection between image and text opinions on MRT service, uncovering a broad range of public attention to the MRT's cleanliness, efficiency, customer service, station accessibility, fare costs and security measures [24]. In Shenzhen, China, analysis of social media data, mainly focusing on points of interest (POIs) check-ins, identified POIs around MRT stations, spatial distribution, temporal dynamics and correlation between social media check-ins and MRT use [25].

In brief, the literature review has established that while objective operational data can elucidate the QoS of public bike systems, subjective user opinion data like social media insights provides another aspect of understanding the QoE. The rise of big data analytics has significantly enhanced quantitative data science, social media mining techniques and natural language processing (NLP), providing sophisticated tools for analysing both structured and unstructured data. However, despite the availability of various data sources, integrating objective and subjective data to evaluate public bike systems comprehensively remains scarce. A case study on New York CitiBike attempted to construct a framework by synthesising social media data with operational metrics [27]; nevertheless, its data period from 2014 to 2018 posed uncontrolled internal variables (e.g. the expanding scope of CitiBike) and external variables (e.g. the growth of subway infrastructure and the proliferation of ridesharing services like Uber and Lyft) in a changing urban scheme. Such limitation complicates the identification of critical factors that influence CitiBike's performance and user satisfaction. Given these considerations, this research is paramount as it seeks to develop an approach to assessing public bike systems' QoS and QoE, facilitating informed decisions that could enhance user satisfaction and system performance.

3. PROBLEM FORMULATION AND CASE STUDY

This paper proposes a dual-quality model to assess the operation of a public bike system, using New Taipei City YouBike as the empirical case. The framework contains (1) QoS model building that involves bike station rental collection, structured data pre-processing and performance index calculation; (2) QoE model building and training that involves bike riders' opinion data collection, unstructured data pre-processing and opinion classification; (3) contrasting the QoS and QoE model.

3.1 Data resource

The Public Transport Data eXchange (PTX), an open data platform administered by the Ministry of Transportation and Communications in Taiwan, facilitates the collection of structured bike station rental data for the QoS model. To acquire bike riders' opinions on specific sites more precisely, Google Map Reviews were ultimately chosen over other social media platforms as the unstructured data for QoE. The bike station rental data spans from 15 March to 8 May 2022, during which 1,379 New Taipei YouBike stations were operating. A larger dataset is required to develop an accurate QoE model using deep learning techniques, which leads to collecting opinion data over an extended period from 1 January 2016 to 8 May 2022. Variations during this period were minimal (e.g. the same operator, unchanged fare structure and stable population). Once the QoE model was developed, it was mapped to QoS data from the same period (15 March to 8 May 2022) to ensure relevant findings.

3.2 The QoS model

The QoS model of the public bike system can be classified into three mutually exclusive statuses: bike shortage, dock shortage and reliability. These statuses can be presented as the systemwide, spatial and temporal dimensions.

QoS index definition

The systemwide public bike status is defined as the Bike Shortage Index (B), Dock Shortage Index (D) and Reliability Index (R), with subscript i for specific stations or j for specific time epochs. The lower the B and D, or the greater the R, the more reliable the operation. The sum of the three indices is 1, and each index ranges between 0 and 1. The formulae are as follows:

$$B = \frac{\sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{k=1}^{q} b_{ijk}}{nmq};\ b_{ijk} = \begin{cases}1, \bar{a}_{ijk} < s_b\\ 0, \text{otherwise}\end{cases} \tag{1}$$

$$B_i = \frac{\sum_{j=1}^{m}\sum_{k=1}^{q} b_{ijk}}{mq} \tag{2}$$

$$B_j = \frac{\sum_{i=1}^{n}\sum_{k=1}^{q} b_{ijk}}{nq} \tag{3}$$

$$D = \frac{\sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{k=1}^{q} d_{ijk}}{nmq};\ d_{ijk} = \begin{cases}1, \tilde{a}_{ijk} < s_d\\ 0, \text{otherwise}\end{cases} \tag{4}$$

$$D_i = \frac{\sum_{j=1}^{m}\sum_{k=1}^{q} d_{ijk}}{mq} \tag{5}$$

$$D_j = \frac{\sum_{i=1}^{n}\sum_{k=1}^{q} d_{ijk}}{nq} \tag{6}$$

$$R = 1 - B - D \tag{7}$$

$$R_i = 1 - B_i - D_i \tag{8}$$

$$R_j = 1 - B_j - D_j \tag{9}$$

where n is the number of rental stations, m is the number of daily periods (let each period be 5 min, resulting in 288 periods in a 24-hour day), q is the number of days, b_{ijk} is a binary state of bike shortage (1 for available bikes $\bar{a}_{ijk}$ less than threshold s_b, otherwise 0) for station i at period j on day k, d_{ijk} is a binary state of dock shortage (1 for available docks $\tilde{a}_{ijk}$ less than threshold s_d, otherwise 0), $B_i(B_j)$ is the spatial (temporal) index of the bike shortage risk index B, $D_i(D_j)$ is the spatial (temporal) index of the dock shortage risk index D, and $R_i(R_j)$ is the spatial (temporal) index of the system reliability index R.

The public bike and dock shortage could influence users' mode choices. We use the standard deviation of the shortage time length (in min) to illustrate the operational fluctuations by station. They are defined as the Bike Fluctuation Index (BF_i) and Dock Fluctuation Index (DF_i). The lower the BF_i and DF_i, the less fluctuation the station i. Provided that each period j is 5 min, the formulae are as follows:

$$BF_i = \sqrt{\frac{\sum_{k=1}^{q}(\sum_{j=1}^{m} b_{ijk} - mB_i)^2}{q-1}} \times 5 \tag{10}$$

$$DF_i = \sqrt{\frac{\sum_{k=1}^{q}(\sum_{j=1}^{m} d_{ijk} - mD_i)^2}{q-1}} \times 5 \tag{11}$$

QoS index outcomes

Based on the surrounding attributes, bike stations are categorised into four locations close to transit stations (primarily MRT stations), schools, recreational areas and others. If a bike station location has two or more attributes, the priority order for location classification is transit stations, schools and recreational areas. *Table 1* shows the QoS performance outcomes by day, surrounding and station size. One thing in common is that bike shortage (index B) is much more critical than dock shortage (index D). On the one hand, it presents the popularity of YouBike, yet another hidden factor that leads to the bike shortage: that is when constructing the YouBike system, the builder (who later became the operator) set a bike-to-dock ratio of less than 1 to avoid over-occupying docks. The ratio may vary across different programs, and it is as low as 0.5 for Taipei YouBike, resulting in frequent bike shortages. Mitigating bike shortages may depend on setting a higher bike-to-dock ratio or enhancing bike redistribution.

The weekday YouBike service is slightly less reliable than the weekend. It reflects an ordinary situation in many other urban areas: more bike-sharing trips are generated for weekday rigid commuting demands than on weekends for leisure purposes. As for the station location, those close to transit stations have the lowest service reliability; this was also found in other research [17]. The following numbers explain the reason. On average, one Taipei MRT station serves around 30 thousand inbound and outbound passengers daily, while over 85% of the YouBike stations have no more than 40 docks. During the peak hours, passengers to and from an MRT station can reach hundreds, if not thousands, making bike and dock shortages not uncommon. It is also echoed in the third category of *Table 1*. The small YouBike stations have much lower reliability than the medium and large stations.

Table 1 – The systemwide shortage and reliability indices by three categories

Category (no. of stations)	*B*	*D*	*R*
Day			
Weekdays (1,379)	0.22	0.02	0.76
Weekends (1,379)	0.20	0.02	0.78
Surroundings			
Transit stations (206)	0.25	0.02	0.73
Schools (390)	0.21	0.03	0.76
Recreational area (430)	0.20	0.03	0.77
Others (353)	0.21	0.03	0.76
Station size			
Small (400)	0.33	0.05	0.62
Medium (401)	0.28	0.02	0.70
Large (578)	0.09	0.00	0.91

Figure 1 illustrates the relationship between the station size (number of docks) and reliability. Let the 90th percentile of reliability in each station size group (under 9, 10-14, 15-19, 20-24, …, above 55 docks) be the red frontier dots. The frontier dots can be well explained by a natural logarithm function with a coefficient of determination over 0.8. If a station has 30 (40) docks, its reliability index is likely 0.75 (0.85) and above. However, the data do not entirely support the notion that larger YouBike stations are always better. Given a constrained government budget for public bike development, transportation authorities must compromise either more small stations for broader service coverage or fewer large stations for higher service reliability. Medium-sized YouBike stations are, therefore, practically preferred to small stations, and large stations are considered only around major trip generation spots.

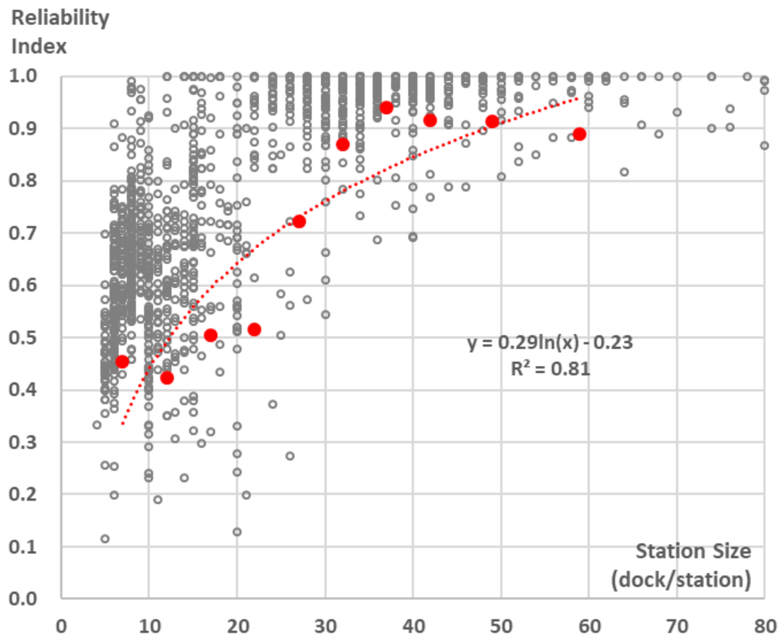
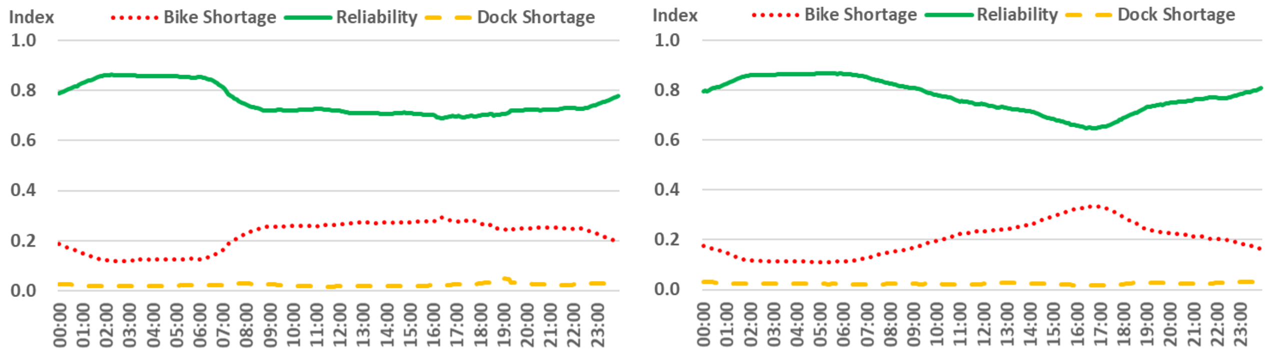


Figure 1 – The scatter plot of the station size and spatial reliability index

Figure 2 presents the operational status from a temporal dimension. The line chart indicates that the operator completes bike allocation by 6:30 to accommodate daytime usage demands, achieving the highest reliability of 0.9 throughout the day. The difference between weekdays and weekends lies primarily in the bike shortage index. On weekdays, the bike shortage index remained 0.25 or higher from 8:00 until 22:00. On weekends, the bike shortage index forms a noticeable afternoon peak of slightly over 0.3 from 15:00 to 17:30. After deducting the dock shortage index, the reliability index at once dropped to as low as 0.65 in the afternoon. In other words, weekday YouBike service consistently encountered high rental demand during daytime school hours and daytime-to-evening working hours of the urban secondary and tertiary industries, while weekday YouBike service was critical only in the late afternoon due to the unavailability of bikes.



(a) *(b)*

Figure 2 – The temporal shortage and reliability indices: a) weekdays; b) weekends

As for the fluctuation indices, the bike shortage appears to fluctuate more sharply than the dock shortage. The median of BF_i within each station category varies from 83 to 263 minutes, indicating stations had low B_i on certain days and high B_i on other days rather than a stable daily B_i throughout the study period. In contrast, the median of DF_i within each station category varies from 1 to 93 minutes. A lower fluctuation index suggests how predictable the service is. Large YouBike stations offer more capacity to accommodate bike returns and checkouts; therefore, they tend to have lower bike and dock shortage fluctuations than smaller stations on weekdays or weekends. Those close to transit stations or schools also performed slightly lower fluctuations. When a rental station fluctuates due to frequent bike or dock shortages, people will rely more on the program's app for real-time information than their daily riding experience to ensure travel reliability.

Table 2 – The median of the fluctuation indices by category

Category		BF_i **(min)**	DF_i **(min)**
Weekdays	Transit stations	182	30
	Schools	191	34
	Recreational areas	203	34
	Others	213	48
	Small	255	93
	Medium	259	48
	Large	113	7
Weekends	Transit stations	190	26
	Schools	181	25
	Recreational areas	204	26
	Others	209	29
	Small	263	91
	Medium	263	36
	Large	83	1

3.3 The QoE model

The QoE model is based on the opinion mining technique. It adopts YouBike riders' opinions (reviews) left on Google Maps, including the posted texts and images exemplified in *Figure 3*. Each opinion is labelled in the dataset and classified into three categories: intent sentiment, text content and image content, per the guidelines proposed by prior research that integrates texts and images [27]. Such classifications help the operator better realise YouBike QoE in various aspects, as shown in *Table 3*. Intent sentiment identifies customers' feelings (sentiment polarity) towards riding experiences. For instance, if someone complained about a broken bike, the operator would see this negative opinion through the sentiment polarity. Intent sentiment is divided into five levels: very negative, negative, neutral, positive and very positive. The analysis revealed that YouBike received predominantly (very) positive opinions (65%), which outnumbered neutral (7%) and (very) negative opinions (27%).

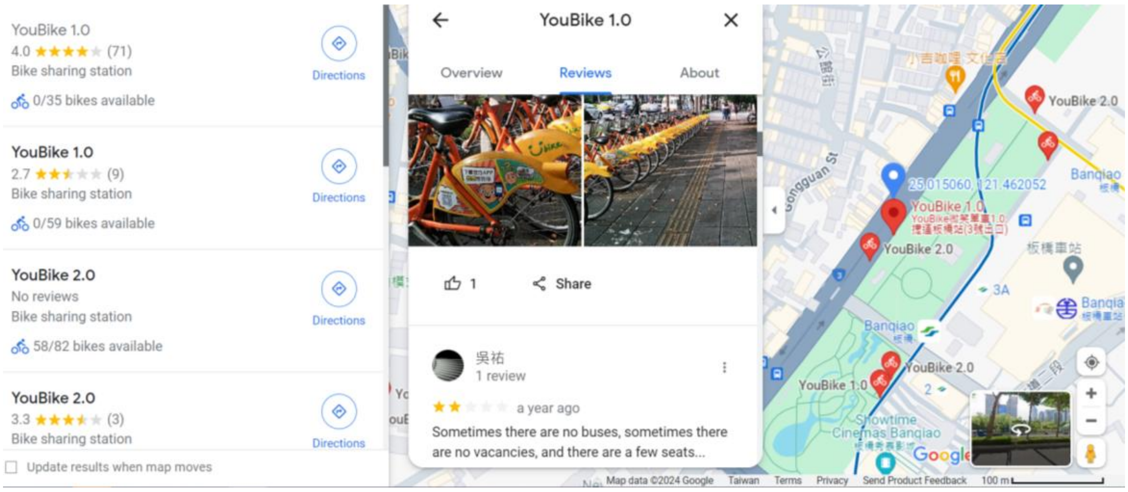


Figure 3 – The QOE data source

Text content divides the descriptive target of opinions into bike and dock availability, membership and ticketing, station locations and surroundings, bike conditions and others. Many users cared about bike and dock availability (35%), station locations and surroundings (41%). For example, certain YouBike users noted such issues as remote locations from major trip generation spots, disorganised surroundings or inconspicuous stations. Image content reveals the image topics as four types: bike and dock availability, kiosks and ticketing panels, station locations and surroundings and bike conditions. Bike and dock availability again tops (64%), followed by the bike condition issues (21%). Service availability is no doubt fundamental to QoE. In addition, bikes must be in perfect working order to ensure a comfortable and safe ride. Therefore, these two categories were frequently mentioned in the image content.

Table 3 – Dataset opinion counts by category

Category	Label	Count	%
Intent sentiment	Very negative	414	10
	Negative	734	17
	Neutral	311	7
	Positive	1,508	35
	Very positive	1,289	30
Text content	Bike and dock availability	1,498	35
	Membership and ticketing	322	8
	Station location and surroundings	1,757	41
	Bike condition	370	9
	Others	309	7
Image content	Bike and dock availability	2,670	64
	Kiosk and ticketing sensor	333	8
	Station location and surroundings	300	7
	Bike condition	861	21

Dataset pre-processing

Our raw data contained 4,256 Chinese text opinions and 4,164 image opinions as the input for model training and testing. The text opinions were first converted into word vectors (features) for further analysis. Before that, the text underwent segmentation using a popular software, Jieba [28]. As the language structure of Chinese wording is very different from English, Jieba is explicitly developed to divide Chinese sentences into meaningful wordings. Given that most opinions are about YouBike, a transportation-word supplement dictionary was fed into Jieba, adding the proper nouns related to YouBike operation and local slang.

The supplement dictionary could enhance appropriate segmentation and better judgement. For example, "YouBike" may be wrongly split into You/Bike without the dictionary. Additionally, YouBike is recognised as Ubike and Smiley-Bike, which shortens You to U for upturned lips and smiles. The supplement dictionary prevents the model from mistakenly interpreting riders with smiley faces in the sentiment analysis. In local slang, YouBike is also known as "Double Little Yellow" (a reference to its colour), similar to the taxi nickname "Little Yellow" for its yellow appearance.

After text segmentation, the segmented word list removed common words for better model training. These common words, also known as stopwords, consist primarily of prepositions and conjunctions. The Word2Vec Skip-gram modal was used to extract text features because it has better training results on rare words [29], making it suitable for this dataset. The Word2Vec Skip-gram model converts words into vectors and trains a neural network to predict nearby words in a sentence based on a target word. As for the image opinions, they were compressed into an RGB format with the size of 224×224 to save computational resources and then converted into a NumPy array. Each array has three dimensions: image height, width and RGB channel, bringing out the image representation needed for the QoE model.

Model structure and training

A neural network model was built to identify the three opinion categories of YouBike QoE through a deep-learning method. The modelling process involves the utilisation of Python, Tensorflow and Keras. As shown in *Figure 4*, the pre-processed images and texts serve as the input of the visual and textual models that would later generate the classification results for the intent sentiment, text content and image content analysis.

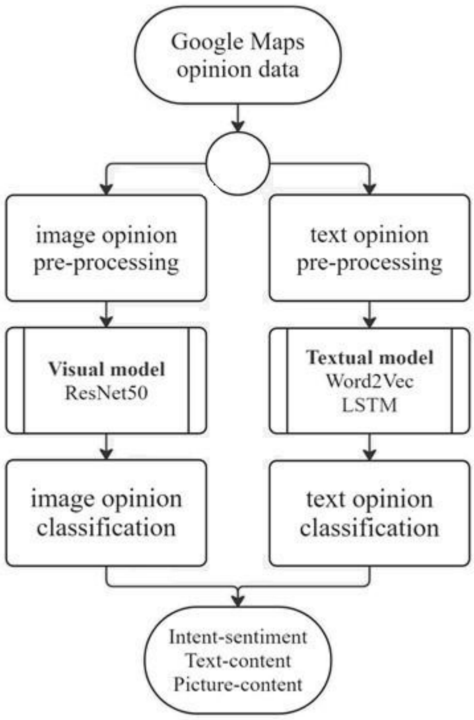


Figure 4 – The QoE model-building process

The textual model takes those words from Word2Vec and conducts encoding via long short-term memory (LSTM) [30]. Specifically, the pre-processed text is first passed to the input layer. Subsequently, feature extraction is performed through the embedding layer. The extracted features then become the input of the LSTM network layer for training. A dropout layer is included to prevent overfitting with Softmax as the activation function. Finally, the model outputs data via the fully connected dense layer. The parameter settings in the training process are as follows: batch size be 32, epochs be 150 and optimiser be Adam, as shown in *Figure 5*.

embedding_input	input:	[(None, None)]
InputLayer	output:	[(None, None)]
embedding	input:	(None, None)
Embedding	output:	(None, None, 250)
lstm	input:	(None, None, 250)
LSTM	output:	(None, 64)
dropout	input:	(None, 64)
Dropout	output:	(None, 64)
dense	input:	(None, 64)
Dense	output:	(None, 5)

Figure 5 – The QoE text model structure

In contrast, the visual model takes the pre-processed image representation and then undergoes the pre-trained ResNet50 model [31] that accordingly consists of convolution layers, pooling layers, batch normalisation, activation function layers, fully connected layers, shortcut connections and pre-activation design. The ResNet50 model is a 50-layer residual network designed for image recognition tasks, maintaining high accuracy even in deep networks. It is trained with the following parameter settings: batch size be 8, epochs be 50, image size be 224×224, loss function be sparse categorical cross-entropy and optimiser be Adam. The visual model structure is illustrated in *Table 4*.

Table 4 – The QoE visual model structure

Layer	Filter size	ResNet 50-layer
Input	224×224	
conv1	112×112	7×7, 64, stride 2
conv2_x	56×56	3×3 max pool, stride 2 $\begin{bmatrix} 1\times 1, 64 \\ 3\times 3, 64 \\ 1\times 1, 265 \end{bmatrix} \times 3$
conv3_x	28×28	$\begin{bmatrix} 1\times 1, 128 \\ 3\times 3, 128 \\ 1\times 1, 512 \end{bmatrix} \times 4$
conv4_x	14×14	$\begin{bmatrix} 1\times 1, 256 \\ 3\times 3, 256 \\ 1\times 1, 1024 \end{bmatrix} \times 6$
conv5_x	7×7	$\begin{bmatrix} 1\times 1, 512 \\ 3\times 3, 512 \\ 1\times 1, 2048 \end{bmatrix} \times 3$
Output	1×1	average pool

Note: conv1-5 refer to the convolutional layers in ResNet50.

The dataset comprises 4,256 text opinions and 4,164 image opinions. It is split into 80% for training and 20% for testing by the Python library Scikit-learn. This division ensures a robust evaluation of the model's performance by providing ample data for training while reserving a significant portion for unbiased testing. *Table 5* shows two typical measures of model performance: accuracy and F1 score. Accuracy is intuitive, representing the ratio of correctly predicted observations to the total observations. It offers a straightforward measure of the model's overall correctness. The F1 score, on the other hand, is more nuanced. It is the harmonic mean of precision and recall, making it particularly useful for datasets with imbalanced classes. It measures the ratio of correctly predicted positive observations to the total predicted positives, thereby balancing the precision (how many selected items are relevant) and recall (how many relevant items are selected). The intent sentiment shows the best classification prediction performance across both measures, indicating that the model effectively identifies user sentiments from the dataset. The second best is the image content, where the model performs moderately. The accuracy and F1 score for text content classification indicate underperformance in precision. Possible reasons include the limited size of opinion data and the complexity of Chinese text. The classification precision could improve significantly with a larger dataset and the development of advanced Chinese language models.

Table 5 – Classification accuracy and F1 score

Category	Accuracy	F1 score
Intent sentiment	90%	0.90
Text content	48%	0.39
Image content	65%	0.58

The confusion matrices for intent sentiment, text content and image content are detailed in *Tables 6* through *8* for further exploration. Each intent sentiment label exhibits a prediction accuracy exceeding 0.85, showing the model's robustness in sentiment classification. Regarding the text content labels, the bike and dock availability (BDA) and the station location and surroundings (SLS) have a moderate accuracy of approximately 0.6, suggesting that there is room for improvement on another three labels: the membership and ticketing (MT), the bike condition (BC) and others. Among the image content labels, the kiosk and ticketing sensor (KTS), BDA and BC demonstrate moderate accuracy; only the SLS underperforms, pointing to potential areas where the model could be refined.

Table 6 – Confusion matrix of intent sentiment

Predicted / **Actual**	**Very negative**	**Negative**	**Neural**	**Positive**	**Very positive**
Very negative	72 (0.92)				
Negative		125 (0.89)			
Neural			51 (0.86)		
Positive				269 (0.91)	
Very positive					251 (0.90)

Table 7 – Confusion matrix of text content

Predicted / **Actual**	**BDA**	**MT**	**SLS**	**BC**	**Others**
BDA	84 (0.60)				
MT		4 (0.07)			
SLS			176 (0.59)		
BC				41 (0.15)	
Others					1 (0.01)

Note: BDA for bike and dock availability; MT for membership and ticketing; SLS for station location and surroundings; BC for bike condition.

Table 8 – Confusion matrix of image content

Predicted / Actual	BDA	KTS	SLS	BC
BDA	374 (0.71)			
KTS		50 (0.75)		
SLS			6 (0.10)	
BC				98 (0.57)

Note: See Table 7 for BDA, SLS and BC; KTS for kiosk and ticketing sensor.

Since text and image classifications involve pattern detection, increasing data volume could enhance prediction accuracy. It is particularly evident in labels such as BDA, SLS and BC, where additional data could better generalise the model. Some user comments addressed multiple issues simultaneously, leading to a possible decrease in the training accuracy of specific labels. This complexity in user feedback highlights the challenges in achieving high accuracy across all categories and underscores the importance of comprehensive data collection and model refinement.

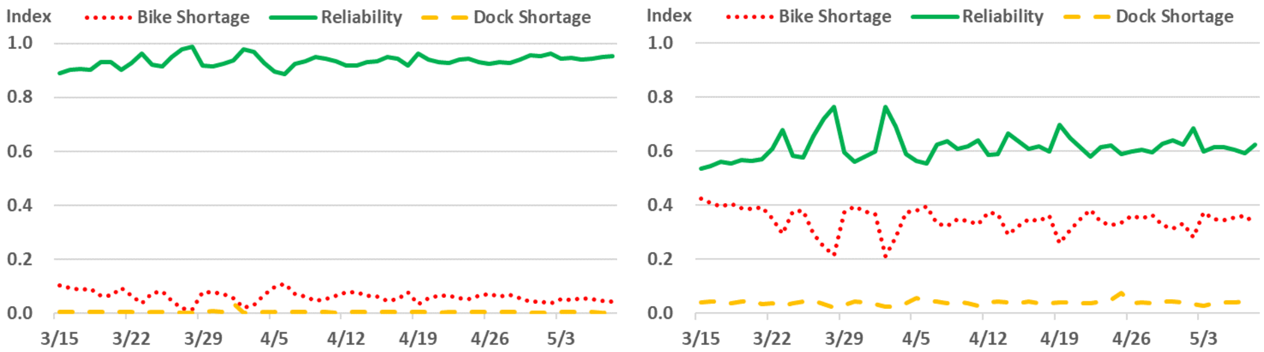
4. MAPPING QOS & QOE

Based on the prior QoS analysis, larger YouBike stations presented fewer bike or dock shortages and lower fluctuations, corresponding to better operational reliability. The QoE analysis further highlighted YouBike riders' shared concerns about bike and dock availability, reinforcing the importance of these factors in user experience and satisfaction. Both the QoS and QoE analyses unanimously indicate that station sizes versus bike and dock availability are critical areas for advanced discussions.

During the study period, the New Taipei City Government was transitioning YouBike from the first generation (1.0) to the second generation (2.0) system for better urban mobility. The 2.0 hardware upgrades included bike design, multiple fare payment methods, system power supply and app-based information provision to replace one kiosk by each station. Theoretically, introducing new features and enhancements in YouBike 2.0 would improve user experience. Nevertheless, station size serves as a notable game changer that differentiates the two generations. The 2.0 system, constrained by a fixed budget for the YouBike expansion project, aims to increase public bike ridership by more stations while maintaining approximately the same number of bikes and docks citywide as the 1.0 system. Therefore, the 2.0 strategy focuses on establishing smaller stations (less than half the average size of YouBike 1.0) to provide broader service area coverage. In contrast, the 1.0 system initially focused on fewer but larger stations, mainly located in the more populated downtown areas, to cater to higher bike rental demand in those regions.

This alteration in the station deployment strategy has resulted in mixed outcomes, bringing benefits and drawbacks simultaneously. With the implementation of more (2.0) accessible stations around the city, YouBike ridership dramatically increased by 21% in September 2023, compared with the same month in 2022. This increase in ridership demonstrates the effectiveness of the new strategy in attracting more users to the system. However, the significant rise in ridership was accompanied by more severe systematic bike and dock shortages in the 2.0 system compared to the 1.0 system.

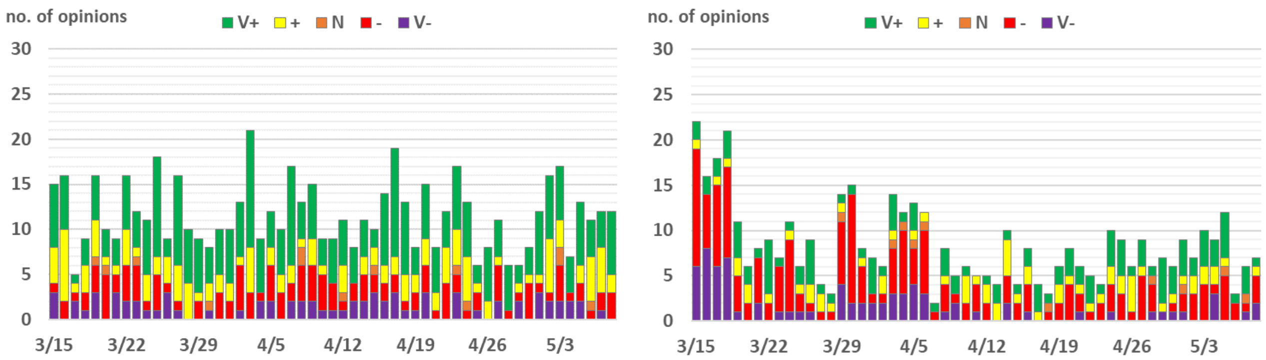
Figure 6 illustrates the daily QoS indices of the two systems. Given an average size of 39 docks per YouBike station, the reliability of the 1.0 system could be maintained at over 0.88 throughout the study period, with a bike shortage index under 0.1 and nearly no dock shortage. This high reliability indicates that users of the 1.0 system experienced fewer disruptions in their biking experience. In contrast, the 2.0 station size ranged from 4 to 40 docks with an average of 11, much smaller than the 1.0 system. It significantly reduced the reliability to around 0.6 or less on many days. This decrease in reliability was primarily due to the substantial rise in the average bike shortage index of 0.35 and the dock shortage index of 0.05. These indices highlight the operational challenges faced by the 2.0 system in maintaining an adequate supply of bikes and available docks to meet the increased demand, thereby negatively impacting the overall user experience. Fortunately, the city government plans to phase out the 1.0 system by 2024. The original locations could make more room for bigger 2.0 stations.



(a) *(b)*

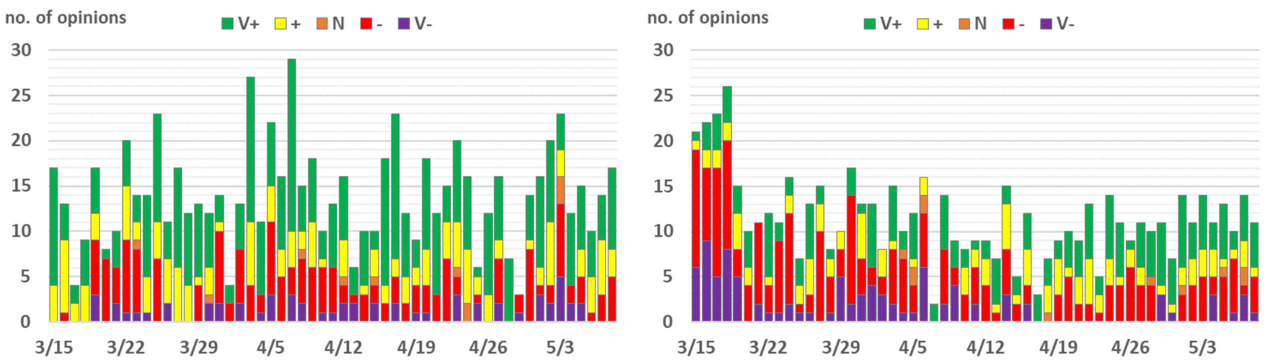
Figure 6 – The temporal shortage and reliability indices: a) the 1.0 system; b) the 2.0 system

Likewise, QoE analysis also found a more severe issue regarding bike and dock availability (BDA) in the 2.0 system than in the 1.0. As shown in *Figures 7* and *8*, there are more fluctuations in the number of opinions, with some days showing higher counts, especially around late March and early April. The text and image opinions consistently indicate that the 1.0 system had fewer (very) negative opinions compared with the 2.0 system. This trend suggests that users were more satisfied with the availability of bikes and docks in the 1.0 system. The number of YouBike users' daily internet BDA opinions varied notably during the study period, with an average of 17 (9) text opinions and 21 (13) image opinions for the 1.0 (2.0) system. This variation indicates differing user experiences and perceptions between the two systems.



(a) *(b)*

Figure 7 – Daily number of BDA textual opinions: a) the 1.0 system; b) the 2.0 system
Note: V- for very negative; - for negative; N for neural; + for positive; V+ for very positive.



(a) *(b)*

Figure 8 – Daily number of BDA image opinions: a) the 1.0 system; b) the 2.0 system
Note: See Figure 7.

Around 29% of the total BDA text and image opinions were (very) negative in the 1.0 system, while up to 38% were (very) negative in the 2.0 system. Nonetheless, the overall (very) positive opinions remained the majority, accounting for 55% and 46% in the 1.0 and 2.0 systems, respectively. Such data suggest that despite significant issues with the 2.0 system, users still found positive aspects in their experience. To some extent, QoE's intent sentiment and QoS's reliability index are interrelated, as other research also indicates that station occupancy and bike availability are key service attributes to enhance satisfaction [17]. The interrelation implies that the system's operational reliability directly affects user satisfaction and perception, highlighting the importance of maintaining high operational standards and efficient bike redistribution to ensure positive user experiences.

Figure 9 scatterplots the daily number of BDA opinions and the corresponding reliability index throughout the study period to map QoS and QoE. The scatterplot is instrumental in visualising the correlation between operational reliability and user feedback. The reliability index outcomes of the 1.0 system were more stable, primarily within a narrow scope of 0.9 to 1, as shown in the upper half of *Figure 9*. The 1.0 system was consistently reliable and less prone to operational issues. This stability means that the 1.0 system was not sensitive to the variation of the (very) negative opinions, indicating a lesser impact of operational fluctuations on user satisfaction. Regardless of the text or image opinions, no linear or other discernible relationship was found between QoS and QoE of the 1.0 system, suggesting that the high reliability mitigated negative user perceptions.

In contrast, the reliability index outcomes of the 2.0 system spread from 0.5 to 0.8, as shown in the lower half of *Figure 9*; this demonstrates more variability and operational inconsistencies in the 2.0 system. It turned out that a lower reliability index would generate more pieces of (very) negative opinions, particularly text opinions. The correlation coefficient between the 2.0 system's reliability and (very) negative text opinions was -0.47, while the correlation with (very) negative image opinions was -0.33, indicating a noticeable linear relationship and users' dissatisfaction with the availability of bikes and docks. It underscores the direct impact of operational reliability on user satisfaction and highlights the necessity for maintaining a high-reliability index. The operator should focus on maintaining the reliability index at a high level to ensure premium QoE, which means fewer disruptions and a more consistent user experience. Ensuring high reliability involves optimising bike and dock availability, improving redistribution strategies and perhaps reevaluating the station size strategy to balance coverage and reliability.

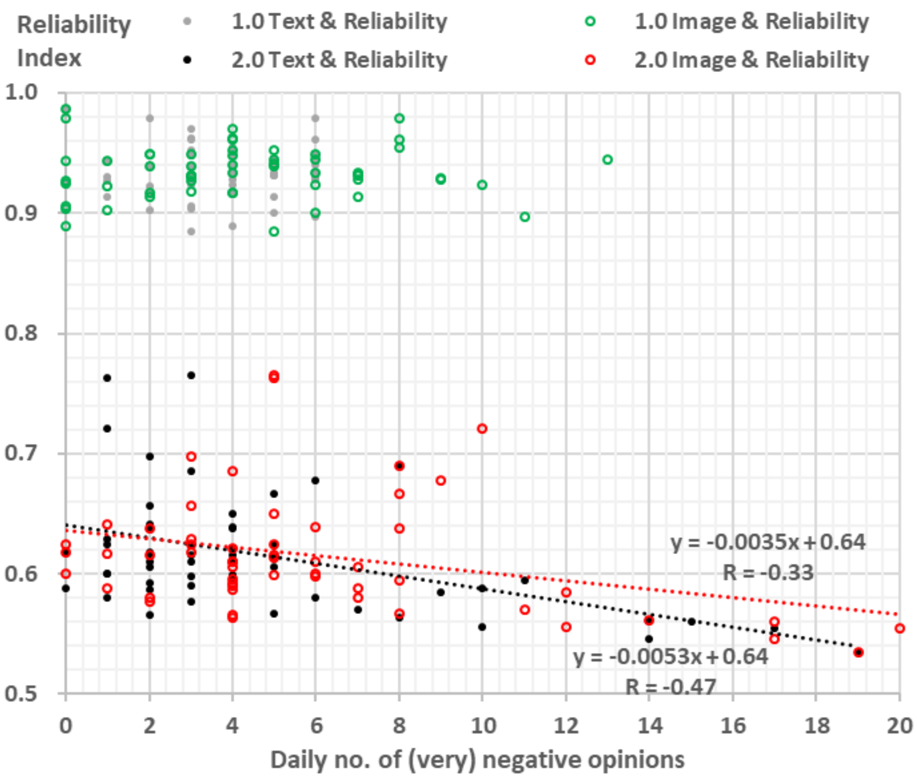


Figure 9 – Daily number of (very) negative opinions concerning the corresponding reliability index

5. DISCUSSIONS AND CONCLUSIONS

As of June 2024, over 1,500 public bike systems worldwide were closed, cancelled, hibernated or suspended out of 2,062 operational systems [1]. Sustaining bike-sharing programs has proven to be more challenging than many anticipated. Although public bike operators can access comprehensive QoS data from their operations divisions and detailed QoE data from their customer service divisions, these data sources are often evaluated separately rather than through a unified analysis, which limits the depth of insights that can be gained. This study introduces a new approach to assessing public bike systems. Operators and transportation authorities can benefit from integrating both QoS and QoE data.

By integrating QoS and QoE data, operators can more thoroughly capture system performance and user satisfaction, thereby enhancing service delivery and responsiveness. In this study, the transportation authority made QoS data publicly available, but due to a lack of access to QoE data, Google Maps reviews were used as a proxy for customer feedback. This highlights a broader issue: while QoS data are often publicly available, QoE data, which reflect user experiences, are generally withheld due to privacy concerns. Transportation authorities should encourage public bike operators to release de-identified, privacy-safe QoE data to enhance transparency and foster stakeholder collaboration; doing so would enable external researchers and analysts to assist in evaluating and continuously improving transportation systems.

The case study of New Taipei shows that QoS indices varied based on factors such as the time of day, weekdays versus weekends, station surroundings and station sizes. In general, peak demand tends to last longer on weekdays than on weekends, while smaller stations and those near transit hubs often experience more severe bike or dock shortages. The QoE analysis corroborated the QoS findings, revealing that bike and dock availability are the primary concerns for YouBike users. When the QoS model indicates lower reliability, the QoE model tends to uncover more negative opinions regarding bike and dock availability. Hardware quality (e.g. well-maintained bikes) is also crucial for rider safety and customer satisfaction. Many public bike systems worldwide have failed due to insufficient maintenance. Fortunately, this has not been a significant issue for YouBike, as its operator benefits from full support from its parent company, Giant Group, a leading global bicycle manufacturer.

Although New Taipei has distinct demographic, socio-economic and geographical attributes that may limit the direct applicability of the findings to cities with different characteristics, the methods and findings from this research offer a foundation for broader application in various urban contexts. To validate the proposed models, the QoS analysis used objective operational data from New Taipei's YouBike system over 55 days to assess service performance. This analysis reveals a generalisable trend observed in many cities: as bike-sharing popularity increases, so does the likelihood of bike and dock shortages, especially during peak usage periods. Conversely, the QoE analysis relied on subjective data from Google Maps reviews to assess user satisfaction with the riding experience. It specifically identified the impact of bike and dock shortages on user satisfaction, demonstrating how user feedback was integrated with operational performance metrics. Classification accuracy, F1 scores and confusion matrices confirmed the model's effectiveness. Therefore, while the specific results may vary depending on factors such as urban density, transportation infrastructure and climate, the approach used in this study is versatile and can be adapted to other cities to gain similar insights into system performance and user experience.

The study provides several actionable insights for policymakers and bike-sharing system operators. First, it identifies key issues related to QoS and QoE, highlighting areas where improvements can directly enhance service reliability and user experience. Second, it underscores the importance of conducting periodic, comprehensive reviews of QoS and QoE metrics. Such reviews help detect changes in operational performance and shifts in user expectations over time, enabling cities and operators to respond proactively. Third, these reviews can capture longitudinal trends, revealing fluctuations in demand across different seasons, times of day or in response to new policies. Based on data-driven insights, this allows decision-makers to adjust resource allocation, bike redistribution strategies and station infrastructure. Incorporating regular assessments of QoS and QoE into policymaking can ultimately help sustain bike-sharing systems, ensuring they remain responsive to user needs while improving overall efficiency and service quality.

One limitation of this study is the reliance on a single data source for user experience (Google Maps reviews), which may introduce bias since only certain users leave reviews, potentially underrepresenting the broader user base. Future research could incorporate multiple sources of user feedback, such as social media platforms and direct input from customer service records. Expanding data collection in this way would provide a more comprehensive view of user experiences and improve the accuracy of the models. Another limitation is that this study focuses on bike-sharing systems with fixed station locations. Given the increasing prevalence of free-floating bike-sharing systems, future research should consider utilising other data sources, such as land use data and transaction records that track the origin and destination of bike rentals, to better assess QoS.

Finally, this research method can be compared with another study [27] that also employed the concepts of QoS and QoE to evaluate public bike-sharing systems. Although the two studies differ in terms of the amount of data collected, the duration of data collection periods, and the scale of the case cities and programs (New York Citibike and New Taipei YouBike), both effectively demonstrate the relationship between QoS and QoE. Moreover, both studies highlight the potential of this approach for broader application across other systems, underscoring its value as a method for further in-depth research.

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鍾智林，樂宸豪，陶治中

以服務品質與體驗品質評估公共自行車系統：新北 YouBike 實證案例

摘要

顧客服務與騎乘體驗對於推動公共運輸系統的成功至關重要。本研究係利用公共自行車系統的營運資料，蒐集每 5 分鐘一筆的自行車與停車柱可用數量資料，涵蓋 1379 個租借站，共計 55 天，以構建服務品質（QoS）模型。本研究首先訂定績效指標，再以時空視覺化圖形協助營運管理，然後採用自然語言處理與深度學習演算法，進行自行車使用者在 Google Maps 的評論分析，以構建體驗品質（QoE）模型。QoE 模型資料共有 4256 筆文字評論與 4164 張圖片評論，本研究將其分類為意圖情緒、文本內容與圖片內容，並提出分類模型以進行細緻的意見分析。實證案例係選擇新北市 YouBike 系統，結果發現自行車短缺是最主要的癥結，特別是在小型租借站。QoS 模型指出自行車的短缺與 QoE 模型的使用者負面評論確實具有相關性，此凸顯出客觀營運資料與主觀騎乘者意見之間的關聯。此一 QoS-QoE 綜合模型將可提供公共自行車營運業者及都市交通主管機關一個評估公共自行車服務品質與騎乘體驗的參考工具。

關鍵詞

公共自行車系統；服務品質；體驗品質；情感分析；深度學習；自行車共享