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Listen to E-scooter riders: Mining rider satisfaction factors from app store reviews

Javad J.C. Aman [a,*], Janille Smith-Colin [a], Wenwen Zhang [b]

[a] Department of Civil and Environmental Engineering, Southern Methodist University, Dallas, TX 75275, United States
[b] Edward J. Bloustein School of Planning and Public Policy, Rutgers, the State University of New Jersey, New Brunswick, NJ 08901, United States

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ABSTRACT

In this study, app store reviews from two major micromobility companies are investigated using machine learning techniques to identify the factors that influence rider satisfaction. The Latent Dirichlet Allocation model is applied to over 12,000 rider-generated reviews to identify twelve topics discussed within the reviews. These topics cover areas such as pricing, safety, customer service, map, refund, payment, app interface, and ease of use, to name a few. Using logistic regression, the most significant factors influencing rider satisfaction were identified. Moreover, name-centered gender prediction analysis is employed to identify rider gender and then discover differences in review content and factors of satisfaction across gender. Results suggest rider satisfaction levels tend to vary across topics and gender. Women were more satisfied with the services and exhibited more positive sentiment than men. Yet, scooter is still a male dominated mode of transportation. Findings contribute to the existing literature by demonstrating the use of app store reviews in a transportation mobility study. The development of a method to assess factors contributing to rider satisfaction offers the ability to evaluate e-scooter rider needs and barriers. An apparent policy opportunity to increase scooter ridership includes an emphasis on contributing factors such as ease of use, safety (speed and riding lane), as well as app issues that showed significant influence on user satisfaction. It is recommended that a policy approach focused on improving rider satisfaction and delivering service improvements incorporate opinion mining as a methodology.

1. Introduction

Developments in battery technologies and supporting equipment have enabled a variety of shared and electronic micromobility services to flourish and expand (Shaheen and Cohen, 2019). The surge in public desire to use scooters as a mobility tool has surprised both the public and private sectors (Populus, 2018). In response, some private bike-share companies have even switched their fleets from bikes to scooters (Nacto, 2019). Within this environment, cities all around the U.S. are experiencing explosive and unprecedented growth in shared dockless scooters. While local governments seek to establish appropriate safety guidance, define pertinent regulations (McKenzie, 2019), and assess the impacts of the sharing economy, relatively little has been done to understand this novel transportation system from a user or rider point of view. Given that recently launched e-scooter sharing programs have generated 35.5 million trips in the U.S. in one year (Nacto, 2019) and are identified as first-mile/last-mile solutions for daily trips (Arendsen, 2019), it

* Corresponding author.
E-mail addresses: jjomehpour@smu.edu (J.J.C. Aman), jsmithcolin@mail.smu.edu (J. Smith-Colin), wenwen.zhang@ejb.rutgers.edu (W. Zhang).

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is critical that mobility companies, transportation planners, and decision-makers gain more insight into the factors that inspire or influence e-scooter user satisfaction and experience.

Costumer behavior studies characterize user satisfaction as “a customer’s subjective evaluation of a service or product provided based on expectations and actual performance” (Guo, Yue et al., 2017). Organizations often use this subjective evaluation as a “baseline standard of performance” (Cengiz, 2010). The core step in analyzing user satisfaction is to accurately ascertain the effective attributes corresponding to customer demands and expectations (Li et al., 2013). Traditionally surveys have been employed to understand and evaluate user expectations, experiences, and satisfaction (RSG, 2008). However, surveys are often not easy to perform and require a considerable amount of time and cost for large-scale deployment (Das et al., 2019). Furthermore, initial survey design usually relies on researcher knowledge or personal concerns about the subject, which often does not result in consistent or comprehensive measurement factors (Guo, Yue et al., 2017). Fortunately, advancements in user-generated reviews made available through the internet can help to eliminate common survey barriers (Li et al., 2013). More specifically, to the best of our knowledge, this study is among the first that has analyzed app store reviews in a transportation research context to understand e-scooter rider satisfaction.

This study conducts a first of its kind empirical analysis using text mining of big data to examine rider satisfaction with scooter use and factors impacting overall satisfaction. App store reviews from two major micromobility companies, including Lime and Bird, are investigated using state of the art machine learning techniques, to identify the factors that influence rider satisfaction. This study particularly aims to:

- extract general topics discussed within the reviews,
- identify how different topics coexist in app reviews,
- examine how sentiments vary across topics, and gender, and
- investigate how topics are associated with rider satisfaction across gender.

The research methodology consists of four primary steps. We first used Term Frequency - Inverse Document Frequency (tf-idf) and the Latent Dirichlet Allocation (LDA) model, a widely used topic modeling technique, to discover the hidden topical patterns in e-scooter app store reviews. We then examined sentiments across topics by applying polarity analysis to labeled reviews under each extracted topic. Third, we developed topic-coexistence networks to identify how different review topics coexist. We also adopted a novel approach, i.e., name-centered gender prediction, to ascertain user gender for a subsample of app reviews, and to determine whether review topics and sentiments vary across gender. Finally, we developed logistic regression models to investigate the key factors contributing to rider satisfaction across gender.

Research findings contribute to the existing literature in several ways. Very limited research, to date, has investigated the opinions, characteristics, and experiences of e-scooter users. Factors that influence rider satisfaction are still misunderstood as there has been limited use of traditional techniques (e.g., surveys) to examine e-scooter rider satisfaction or sentiment. Moreover, very few studies have investigated the impact of gender as an attribute relevant to riding experience and satisfaction. Assessing factors that contribute to user or rider satisfaction, therefore, offers the ability to evaluate current and future barriers to e-scooter access, rider needs, and willingness to ride. These results ultimately provide companies, planners, and policymakers the information needed to implement a consistent, effective, and integrated strategy for improving the e-scooter experience.

The rest of this article is organized as follows: related and previous work are presented next in the literature review; analysis methods are then discussed. Then we present the empirical results and discuss their implications. In the final section, we conclude by setting out the limitations of this study and future topics for research.

2. Literature review

2.1. Scooters and micromobility

While recent studies show that even congestion management strategies such as managed lanes are not able to reduce greenhouse gases (Sharifi et al., 2021), micromobility services seem a proper alternative for urban trips. Micromobility solutions consist of light-weight vehicles that are able to operate at speeds not more than 30 mph and include bicycles, scooters, skateboards, segways and hover-boards, and can be human-powered or electric (Abduljabbar et al., 2021). Most micromobility vehicles operational in the U.S. are owned and operated by private companies though they can be owned by individuals. Micromobility is now broadly utilized as an active mode of transportation for trips shorter than three miles, which represent 50–60% of the passenger distance travelled in China, the EU and the US (Abduljabbar et al., 2021). Dockless scooters provide short-term, flexible, sustainable and on-demand rentals without specified parking stations within a specified geofence (Moran et al., 2020). Shared scooters are generally offered in two types, (1) standing electric scooters that are typically designed with handlebars, wheels, brakes, lock, deck and powered by an electric engine, and (2) moped scooters that are seated and generally powered by electric or gas. We focus in this study on standing scooters. Various studies across the world have addressed and analyzed scooter features, characteristics and challenges e.g., USA (Almannaa et al., 2020; Jiao and Bai, 2020; McKenzie, 2019; Younes et al., 2020); France (Christoforou et al., 2021); Austria (Moran et al., 2020); Taiwan (Eccarius and Lu, 2020); New Zealand (Fitt and Curl, 2020); and Australia (Haworth et al., 2021), to name a few.

While scooter companies have launched a battle for space within urban transportation corridors, scooters are yet to receive sufficient attention. Though scooter studies have been on the increase, much remains to be learned about scooter interactions with pedestrians and bikes, or the increasing complexity of the transportation system (Gössling, 2020; Younes et al., 2020). Research to date has investigated topics such as e-scooter safety (Allem and Majmundar, 2019; Bai and Jiao, 2020; Dormanesh et al., 2020; Mayhew and

Bergin, 2019; Nellamattathil and Amber, 2020; Shah et al., 2021; Yang et al., 2020; Yang et al., 2020), micromobility systems (design, regulations, and policies) (Anderson-Hall et al., 2019; Gössling, 2020; Shaheen and Cohen, 2019; Tuncer and Brown, 2020), parking (Brown et al., 2020; Fang, 2019), temporal and spatial distributions (Chen et al., 2018; Espinoza et al., 2019; McKenzie, 2019; Younes et al., 2020; Zhu et al., 2020), business models (Degele et al., 2018), and social, cultural issues and riding behavior (Fitt and Curl, 2020; Kopplin et al., 2021; Nikiforiadis et al., 2021; Zhang et al., 2021).

Abduljabbar et al. (2021) have provided a systematic literature review on the association of micromobility and sustainable cities. In the safety area, Allem and Majmundar (2019) and a follow-up investigation by Dormanesh et al. (2020) assessed the extent to which micromobility companies highlighted safety issues on social media. Both studies concluded that companies rarely promote safety features on their accounts, though there might be potential benefits for public safety. In an attempt to understand the social outcomes of the scooter boom across cities, Bai and Jiao (2020), using crowdsourcing, analyzed parking violation reports in Austin, TX, and offered a shared responsibility framework as a notable feature in shared mobility systems. Gössling (2020) investigated media items concerning struggles across cities resulting from the advancement of shared scooters and inferred that issues that could be addressed by developing regulations included safety, speed, and space. Despite constant concerns expressed in the media about poorly parked vehicles, Fang (2019) and Brown et al. (2020), by observing parking behavior in cities across the United States, reported that the majority of the micromobility vehicles were, in fact, properly parked and "minimally disruptive." Ma et al. (2021) examined multiple local guidelines provided for shared scooters and highlighted the importance of actionable directions using more quantitative data. A few studies have also investigated the difference between micromobility modes. For instance, Younes et al. (2020) compared the temporal determinants of dockless scooters and docked shared bikes. Shah et al (2021) analyzed motor vehicle-involved scooter and bikes crashes and reported both crash types share many common aspects. Younes et al. (2020) compared the temporal determinants of dockless scooters and docked shared bikes. McKenzie (2019) also highlighted significant differences between shared bike and scooter trips. For example, scooters, unlike bikes, are rarely used for commuting to and from work. Zhang et al. (2021) modeled route choice behavior and reported that bike-friendly roads are a preferred infrastructure for scooter riders. Fitt and Curl (2020), one of the very few studies that considered the social impacts of scooter emergence, developed a survey to explore issues and concerns associated with the introduction of scooters in New Zealand. Kopplin et al. (2021) also conducted a survey and highlighted the differences between attitudes of owners and non-owner riders toward using scooter as an alternative mode of transportation and reported that people mostly consider scooters as a fun object. Nikiforiadis et al (2021) also surveyed scooter users and non-users and stated men are more eager to be engaged with scooters.

The performance of micromobility services can be characterized by user satisfaction in terms of availability, ease of use, safety, and security to name a few (Sohrabi et al., 2020). Whereas a growing body of literature has examined factors affecting bike rider or transit user satisfaction (Eboli and Mazzulla, 2007;Guo, Yanyong et al., 2017;Han et al., 2017;Manzi and Saibene, 2018), very few studies have attempted to investigate rider behavior and expectations, and no study has yet investigated factors impacting scooter rider satisfaction. A positive association has been reported between user satisfaction and loyalty to the services (Söderlund, 1998). Moreover, it is observed that highly satisfied users are more prone to recommend the services to other individuals, on the other hand dissatisfied users usually spread their negative experience to more people (Tatikonda, 2013). Therefore, overlooking the factors that influence rider satisfaction may lead to negative *word of mouth* around micromobility services and consequently loss of riders.

2.2. Text mining in transportation studies

Moreover, there are relatively few studies that have focused on text mining as a tool to investigate rider satisfaction. Text mining techniques provide consistent, time-efficient, and cost-effective approaches to acquire opinions and feedback from individuals. Opinion mining through text analysis has thus far evolved as an alternative to traditional survey methodologies (Guo, Yue et al., 2017). For example, social media mining as a more reliable source compared to conventional surveys, as survey participants have been found to impose self-censorship during attitudinal questions (Das et al., 2015). Therefore, by ignoring text mining as a tool a free, less biased and informative data will be neglected, and potential service improvements hints remain unknown.

Opinion mining studies were historically undertaken through the exploration of short-length textual content on social media such as Facebook, YouTube, Instagram, Flicker, and app stores (Genc-Nayebi and Abran, 2017). Beginning in the mid-2000s, following the introduction of the first smartphone application distribution platform (Apple App Store) (Genc-Nayebi and Abran, 2017), app review mining emerged as a source for data collection and analysis. Empirical studies have shown that app store reviews provide considerable information, including user demands and experience, service requests, and failure reports. It would, therefore, not be an exaggeration to consider feedback available through app store reviews the "voice of users" (Guzman and Maalej, 2014). App store reviews can therefore be characterized as user demands and expectations, stated and organized in a way that highlights user opinions. Thus, offering insights into user opinions regarding services they are utilizing or interacting with. Moreover, reviews underline user priorities in performance in addition to current satisfaction levels (Guo, Yue et al., 2017; Katz, 2011).

In general, little work has been done in the mining of app store reviews (Fu et al., 2013). App store review mining studies are mostly undertaken for app development purposes (e.g., bug removal and feature requirements), or to inform business decision making (e.g., user willingness to pay for specific paid apps or services). Although the textual content available on app stores, like other social media platforms, provides public beliefs, sentiments, and needs about services and products, few studies have used this data source to understand user needs and experience. A review of the literature reveals that text mining is frequently utilized as a tool to investigate transportation issues. Text mining techniques have been used in various areas of transportation studies. For instance, Yang et al. (2020) investigated 167 news reports related to scooter crashes and highlighted the distinctive characteristics of these crashes (Yang et al., 2020). Das et al. (2019) analyzed YouTube comments related to autonomous vehicle reviews in order to understand public opinion about autonomous vehicles and identify polarities based on content and automation classes. Das et al. (2015) also examined the popularity of shared bikes in Washington, D.C., by performing sentiment analysis of user comments on Twitter. Social media mining is also used as a tool to complement travel diary surveys (Maghrebi et al., 2015). Finally, a case study in Korea reported that utilizing text mining approaches to understand factors influencing bike sharing service quality contributes to improvement in public service (Kim and Hong, 2020). Though advances have been made in the use of text mining in the transportation literature very few studies can be found that focuse on app store reviews as a source for textual data.

3. Methodology

To identify the factors of satisfaction, first, topic modeling was implemented to extract hidden topics discussed within the reviews. In the next step, logistic regression was used to determine the dominant factors that influence satisfaction. Additionally, name-centered gender prediction enabled us to shed light on the differences between male and female riders' sentiment and factors of satisfaction.

3.1. Data extraction

The textual data utilized in this study is associated with two of the major private micromobility companies in the U.S. (Lime and Bird) and extracted from reviews on the Google Play Store and Apple App Store. Each review consisted of the title, text or review content, rating, date, username, and app version. For this study, 12,026 unique comments, from May 2019 to January 2020, without any duplicate data were analyzed. 130 comments were by the same username, however, they were included in the study as they might have beene from the same user writing reviews for different apps (Lime and Bird).

3.2. Gender prediction

One of the goals of this study is to investigate how satisfaction levels expressed in the reviews vary across gender. However, user's gender was not specified within the extracted dataset. Therefore, in order to predict gender, we implemented name-centered classification methods. Name-centered methods classify usernames to predict gender. In this method, names are matched with historical databases, as these databases provide the likelihood of whether names belong to men or women. Per the methodology, the gender with the higher likelihood match was assigned to the comment being examined (Blevins and Mullen, 2015; Wais, 2016). As not all names are included in the databases, this method was only able to predict 37% percent of the dataset. As not all names were included in the databases consulted, this method is only able to predict a portion of the dataset (almost one-third in this study). In this study, the "gender" open-source R package, which utilizes the United States social security and Census databases, was used to predict gender (Mullen, 2018). Gender prediction is challenging as users often select pseudonyms (e.g., FakeGenie1 and Freeotz) and sometimes have names that are not reflected in the databases.

3.3. Topic modeling

One of the main objectives of this study is to uncover the common topics within the reviews. Topics are the service-related factors frequently discussed or mentioned within user reviews (e.g., pricing, safety, or parking). Topics are also assumed to inform how services are rated or the level of satisfaction/dissatisfaction expressed by users. In topic modeling, Brett (2012) describes topics as "recurrent patterns of co-occurring words." Topic modeling is an unsupervised machine learning approach that scans sets of documents, discovers, and clusters hidden related groups of words. In situations where pre-categorized and labeled documents are not available or expensive to achieve, unsupervised learning approaches are used to classify datasets. The following sections elaborate on the steps we used to extract latent topics in app reviews.

3.3.1. Preprocessing

Preprocessing transforms the original raw texts into a "data-mining-ready" dataset (Srividhya and Anitha, 2010). Preprocessing starts with tokenization, which divides the content of the text into a list of single characters called tokens (Silva and Ribeiro, 2003). Next, all uppercase tokens are converted into lowercase. Then, non-informative terms such as stop words (e.g., "the", "to" or "me"), and common words (e.g., "scooter" or "ride") in addition to numbers and punctuations are removed. To correct typos, words with minor errors are replaced with the correct ones using the "hunspell" R-package (Ooms, 2017). Alterations are suggested by looking up a similar token in the dictionary. Furthermore, inflected words are transformed into their roots (lemmatization). The modified words would have an equal part of speech label, the same semantic meaning, but a different syntax (Guzman and Maalej, 2014). Finally, parts of speech tags (POS) are assigned to each token. POS tagging assists in the topic modeling step, where only adjectives and nouns are used to identify and extract features. Albeit different studies have used different POS tags for this matter. For instance, Benamara et al. (2007) suggested using adverbs and adjectives in semantic analysis, and Lucini et al. (2020) used only nouns for topic modeling (Benamara et al., 2007; Lucini et al., 2020). An example of preprocessing results is shown below:

Before preprocessing: "Brake was in poor condition. So expensive. BTW, why the app continues to attempt to grab my GPS location?"

After preprocessing: "brake be poor condition expensive why app continue attempt grab gps location"

3.3.2. Feature extraction

In this paper, term frequency-inverse document frequency (tf-idf) was used to identify and extract features. Features (keywords) are a collection of important words in a text that are able to provide a significant depiction of the content (Gupta and Lehal, 2009). tf-idf is a statistical technique that not only considers the frequency of the term use, but the importance of terms within the text. In other words, this technique helps to identify important words that often do not appear frequently within the text (Ghag and Shah, 2014).

3.3.3. Latent Dirichlet allocation

Latent Dirichlet Allocation (LDA) is a popular generative probabilistic approach, which is frequently utilized for fitting topic models (Jelodar et al., 2019). LDA relies on two basic principles: first, each document is a collection of topics that are sampled for that document; second, each topic is a collection of words (Formula (1)). Krestel et al. (2009) describe the modeling process of LDA as:

$$P(w_i|d) = \sum_{j=1}^{K} P(w_i|k_i = j)P(k_i = j|d), \tag{1}$$

where

$P(w_i|d)$:Probability of the ith word considering a given document.
$P(w_i|k_i = j)$: Probability of the w_i in topic k.
$P(k_i = j|d)$: Probability of choosing a word from topic k in the document.

The objective is to discover a collection of topics in each document (i.e.,$P(k|d)$),as each individual topic is defined by words based on another probability distribution (i.e.,$P(w|d)$).LDA discovers $P(w|d)$ and $P(k|d)$ by utilizing Dirichlet priors for the required distributions, in addition to the pre-selected number of topics (K) (Krestel et al., 2009). After fitting topic models, researchers generally interpret the top-twenty most related words per topic and assign a “descriptive label” to each topic for presentation purposes. Debortoli et al. (2016) warn researchers that following topic modeling they are likely to face low-quality topics which are “mixed” (i.e., contain subsets of words belonging to more than one topic), “identical” (i.e., semantically the same words in two topics) or “nonessential” (e.g., irrelevant topics). It is recommended that low-quality topics are split, merged, or excluded.

3.4. Polarity analysis

Dictionary-based polarity classification was conducted to interpret user sentiment (i.e., positive, neutral, or negative) toward identified factors of satisfaction. Polarity classification categorizes opinions based on the feelings conveyed within the text and can be performed on reviews of different levels, such as a word, a sentence, or a document (Jha et al., 2018). Dictionary-based classification is one of the most popular sentiment analysis approaches. This method relies on predefined labeled lists of words (lexicons) that specify the associated sentiment level/value of the words (Debortoli et al., 2016; Park and Kim, 2016). Polarity analysis is performed by the “sentimentr” R package (Rinker, 2019). Methods presented by Rinker (2019) are adopted here for polarity value calculation.

3.5. Logistic regression analysis

The unsupervised character of topic models provides no “ground truth” to test the outputs (Debortoli et al., 2016). However, previous studies (Debortoli et al., 2016; Lucini et al., 2020; Zhang et al., 2016) have proposed regression analysis to quantify the impact of the extracted topics (independent variables) on user satisfaction (dependent variable). As discussed previously, app stores enable users to rate their overall satisfaction level based on a five-star Likert scale. The star rating uses an ordinal scale, where one and two stars represent high and relative dissatisfaction, three implies a neutral stance, and four and five indicates a relative and high degree of satisfaction. Consequently, in this section, one star is considered overall dissatisfaction, two, three, and four-star reviews are discarded, and five-star reviews are deemed overall satisfaction. Two (and four) star reviews are dismissed, due to the mixed feelings often expressed within a review; in many instances both a degree of satisfaction (dissatisfaction) could be found in their content. Therefore, considering the binary nature of the dependent variable (satisfaction or dissatisfaction), Logistic Regression was identified as a reasonable approach for modeling. In the regression process, independent variables are represented by the weights of satisfaction factors identified using LDA, and the dependent variable is whether the user was satisfied (1) or not (0).

4. Results

In this study, statistical and machine learning techniques were utilized to investigate topic trends and explore the patterns within the reviews. In the sections that follow, detailed results regarding descriptive analysis, polarity classification, topic modeling, and topic validation are presented.

4.1. Gender prediction and descriptive analysis

As usernames do not necessarily contain actual names, name-centered analysis was applied and a resulting 37 percent of usernames predicted. The result shows that, from the predictable observations, 71 percent of users were men (i.e., 3197 reviews), and 29 percent women (i.e., 1256 reviews), with an average accuracy of the gender prediction score of 0.96. There were significantly more male reviewers than female reviewers, consistent with the existing literature that micromobility is not gender-neutral (Gauquelin, 2020), with substantially more male early adopters (Krizek and McGuckin, 2019). The percentage of app ratings generated by female and male users, as shown in Fig. 1-a, suggests that most users submitted ratings of the lowest (1) star or highest (5) stars. A J-shaped distribution in a five-star online rating is not an uncommon phenomenon (Debortoli et al., 2016). Pearson's chi-square test revealed a significant association between gender and rating ($\chi^2(4) = 22.713, pvalue < 0.001$). Women were more likely to submit higher ratings than men. The average rating of men was 3.7 (Std Dev: 1.72), and women 4.01 (Std Dev: 1.62). Fig. 1-b shows the word-count distribution by review (i.e., the total number of words in a review). What stands out is that lower-rated (1 and 2 star) reviews are noticeably longer (higher word-count), and potentially more informative than the higher rated reviews (4 and 5 stars). On the other hand, highly satisfied riders (5 stars ratings) used considerably fewer words to describe their experience.

4.2. Topic modeling

Topics ranging from 1 through 30 were investigated to determine the optimal number of topics. Given the results of prior research and researcher knowledge, 10–15 topics was selected as a reasonable number of optimal topics. Each set of topics was qualitatively assessed for cohesiveness and consistency. The final analysis resulted in 12 topics, shown in Table 1. As the process of topic modeling is an unsupervised learning approach, human involvement is required to label the topics (Bastani et al., 2019). Each topic needs a label to illustrate the content of the topic clearly. Labels were tagged, one by one, by a first researcher, then a second, and third researcher verified results (Guo, Yue et al., 2017). Each topic consisted of a set of closely related words. The labeling process was performed using the set of 20 words with the highest probability in each topic. For instance, the Customer Service topic is generally about contacting customer service, as both "customer" and "service" appear as words on the list. Moreover, other words such as "phone", "report", "help" and "reply" are also semantically linked to the act of contacting customer service. Similarly, the frequent appearance of terms such as "price", "expensive", "cheap", and "cent" in a particular topic suggests that this topic is related to Pricing or the monetary value of the service.

4.3. Topics distribution and coexistence

In addition to considering topics as a mixture of words, LDA is also able to estimate each review as a mixture of topics. For each review, we have estimated review and topic probabilities (also called "gamma"), which is the expected fraction of terms or words within a review that are generated from different topics (Silge and Robinson, 2017). Table 1 shows a sample review and its corresponding gamma value for each topic. For example, in the first row of Table 1, a gamma equal to 0.29 denotes that 29 percent of the words in that review are generated from the Refund topic. Gamma equal to 0.125 is specified as the threshold for assigning reviews to the topics. In other words, reviews with gamma lower than 0.125 were removed from further analysis. As a result, a review can be assigned to more than one topic, which is resealable, as users frequently discuss more than one topic in a single review. This threshold was first manually checked by authors to examine if there is a semantic connection between reviews and the label of topics.

Next, using co-occurrence analysis, a sensitivity analysis was performed to understand how different values of gamma assign reviews to different topics. Gammas lower than 0.125 provided inaccurate assignment, and higher thresholds resulted in an excessively strict designation (i.e., coexistence networks for gammas equal to 0.10 and 0.15 are provided in Appendix A). Fig. 2 indicates the coexistence network of topics considering gamma equal to 0.125 for men, women, and total reviews. Thicker edges describe a higher probability of coexistence of the topics in one review. As expected, Payment, Refund and Customer service; Safety (speed and riding

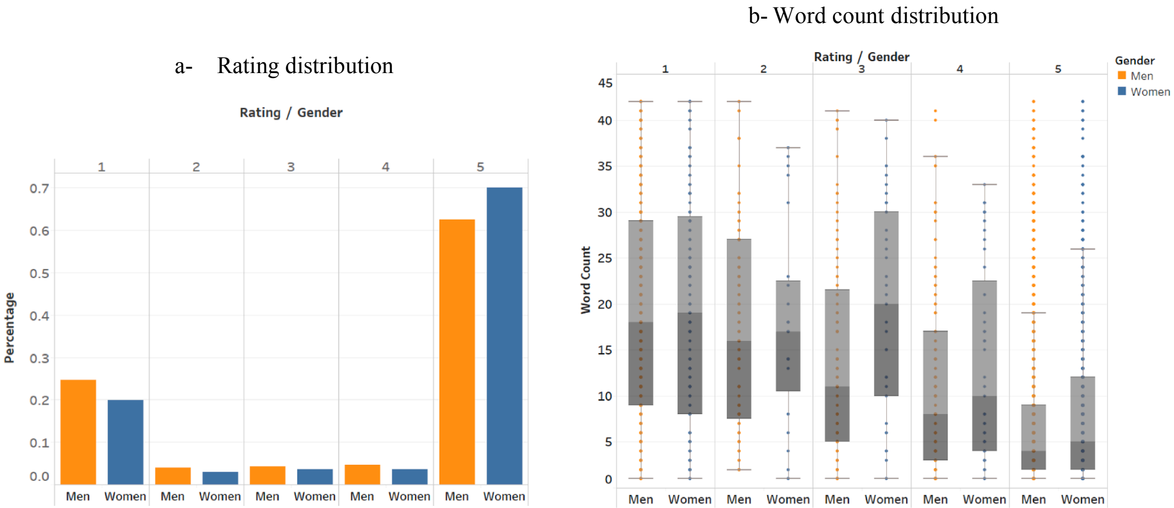

Fig. 1. Word count distribution and app rating among men and women.

Table 1
Topics description.

Topic		Description	Frequent Relevant Words	Example	Gamma
1	Refund	Customers usually ask for a refund of purchased credit, when charges are incorrect, or when service is unsatisfactory or unfulfilled.	Money, account, refund, support, call, multiple, contact, terrible, month, unable, response.	… I tried to get a refund of the unused money they were holding in my account goes by increments of 5 I think but after contacting customer service more than once I was still unsuccessful …	0.292
2	End of trip/ lock	To end the trip, and not to be charged anymore, scooters should be locked. Reviews were often concerned with finding the proper spot, broken devices, and unfamiliarity with the process.	Park, lock, bad, zone, slow, free, wait, spot, push.	…we cruised by finding a parking spot was irritating because the gps wouldn't calibrate to precise spot.	0.206
3	Ease of use	Users usually shared their positive renting and riding experience in their review.	Easy, fast, pretty, system, access, destination, super, smooth, friendly.	easy to set up easier to ride quite fast as well will definitely get some friends to ride.	0.248
4	Unlock/start	To start the trip, users usually first need to scan the barcode and unlock the scooter. Companies usually charge riders even for unlocking the scooter.	Start, unlock, friend, brake, move, die, low, rate, foot, horrible, wrong, expect.	first time using the app the scooter didn't work [..] Tried to start it I immediately cancelled the ride at least [other company] has a much better app you can report broken ones and they [..] wave fees when you cancel within a few seconds of unlocking.	0.206
5	App issues	User complaints described functional errors, feature requests, and app crashes.	Email, sign (in/out), load, login, crash, screen, button, mode.	the app keeps getting stuck on the launch screen I was able to sign in the very first time I installed it but all subsequent times it was stuck on the splash [..] tried reinstalling it but same issue	0.353
6	Payment	Under this topic users usually expressed challenges regarding payments with credit/ debit cards, their account balance, or ask for alternative payment methods, such as PayPal or their preferred credit card.	Pay, card, credit, option, add, payment, worth, balance, update, amount, auto, feature, bank.	please add options to pay with debit card maestro; ban contact PayPal; I do not have a credit card.	0.360
7	Pricing	Customers described their preferences and opinions about pricing and often compare different alternatives.	Time duration (hour, minute, or second), price, expensive, cheap, change, check, cent, top, ridiculous.	i was having so much fun riding these but they raised the prices its 31 cents a minute now unless they change it back to 15 cents, I won't be using these anymore.	0.264
8	Safety (Speed, riding lane)	This topic includes safety concerns related to speeding, riding condition, and riding lanes.	Drive, quick, safe, street, transportation, road, mph (mile per hour), light, sidewalk, fall, license.	scooter slows down to a walking pace in random places it considers pedestrian zones even though they are not busy; why is it illegal to ride on the sidewalk? this seriously endangering riders who are trying to keep up with traffic in the bike lane or on the street or while crossing the street as was the case for me.	0.378
9	Map/Juicer	Map/juicer is a mixed topic related to the app maps used for finding available scooters and juicers. Juicers are contract employees who pick up scooters and charge them at their homes, earning money for each charge. Juicers use a real-time map that identifies ready to charge scooters.	Company, day, map, fix, location, pick, night, drop, close, bring, juicer, respond, reserve.	pp has a frustrating zoom feature if you zoom out too far city view certain pick up and certain drop off locations disappear; you have to tediously zoom in on really confined areas of the map to find chargeable scooters and areas to drop them off …	0.438
10	Battery	Comments discuss battery charge level, which is represented by a bar graph on scooter screens (highly influences ride trip duration).	Battery, charge, delete, error, bar, message, finally, over.	… the battery percentage would be easier than battery points the overall mileage will change based on acceleration and braking so does the battery points but battery percentage will help us to know whether to pick or not [..] [moreover] being able to interchange the battery with our own is always a boon.	0.248
11	Safety (Technical issues)	This topic includes technical issues that contain subtopics such as complaints about scooter parts (tires, brakes, etc.) as well as reports of damages and accidents.	Break, car, hit, tire, dangerous, damage, brake	These things are dangerous; traffic passes you within inches of handlebars; wheels are so small and non-air filled yet have no flex; steering is scary loose; never again do not ride f***ing dangerous	0.27
12	Costumer service	Users often describe their experience with contacting the company via customer service.	Service, customer, phone, week, happen, business, report, hold, receive, product, help, reply.	…worst costumer service [..] was assured I would be receiving a call back regarding a lost item …	0.25

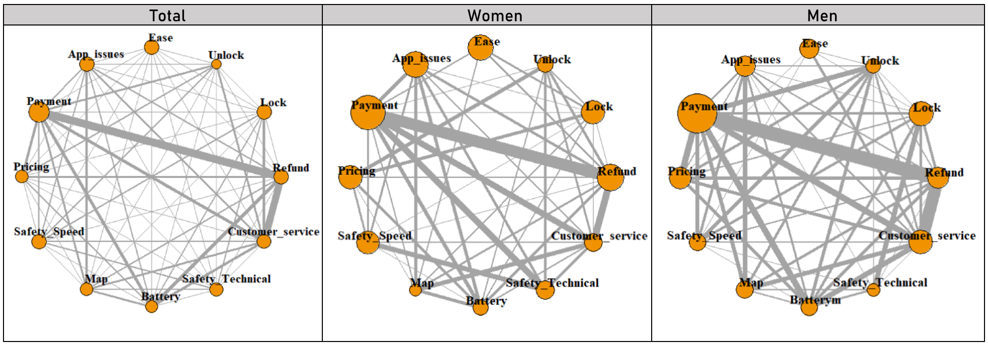

Fig. 2. Topic coexistence network.

lane) and Safety (technical issues); Unlock and Payment; Pricing and Payment; Customer service and Lock or Unlock; and App issues and Map often coexisted in the same reviews. There is a higher coexistence of Payment and App issues topics in women's reviews. Ease of use has the lowest coexistence among all topics in men and women.

Fig. 3 illustrates the percentage of reviews in the dataset related to each topic, and it also presents the distribution of topics across gender. As can be seen, Payment is the most discussed topic within the reviews for both men and women; more than 14 percent of the total reviews addressed the Payment process. The least discussed topic was Map/Juicer for women, and Safety (Technical issues) for men. Although there is no significant difference between male and female users in the distribution of topics, men appear to have greater interest in discussing topics related to Payment and Customer service, and women seem more interested in topics such as Ease of use and Safety. However, there is no evidence to suggest a significant association between gender and topic distribution.

4.4. Polarity analysis

Fig. 4 shows the distribution of reviews based on polarity values for each topic. As can be seen, topics usually contain positive sentiments. However, topics, such as Ease of use, App issues, Safety (speed and riding lane), and Safety (technical issues) are comparatively more positive than others, demonstrated by the height of the bar in each section of the graph. Additionally, women's reviews regarding Map/Juicer and End of trip/ Lock are relatively more negative than men. As previous studies have reported that women leave more positive comments on online platforms than men (Pettit, 2013), our findings corroborate earlier studies by showing that female riders generally exhibit more positive sentiments than male riders.

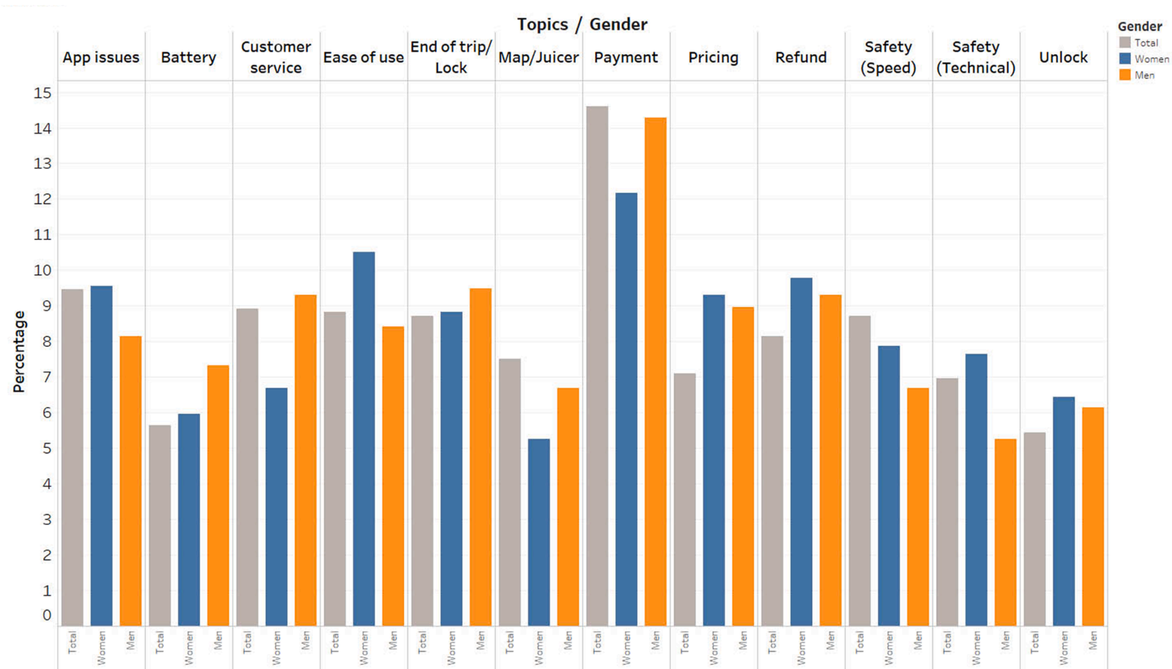

Fig. 3. Distribution of topics in reviews.

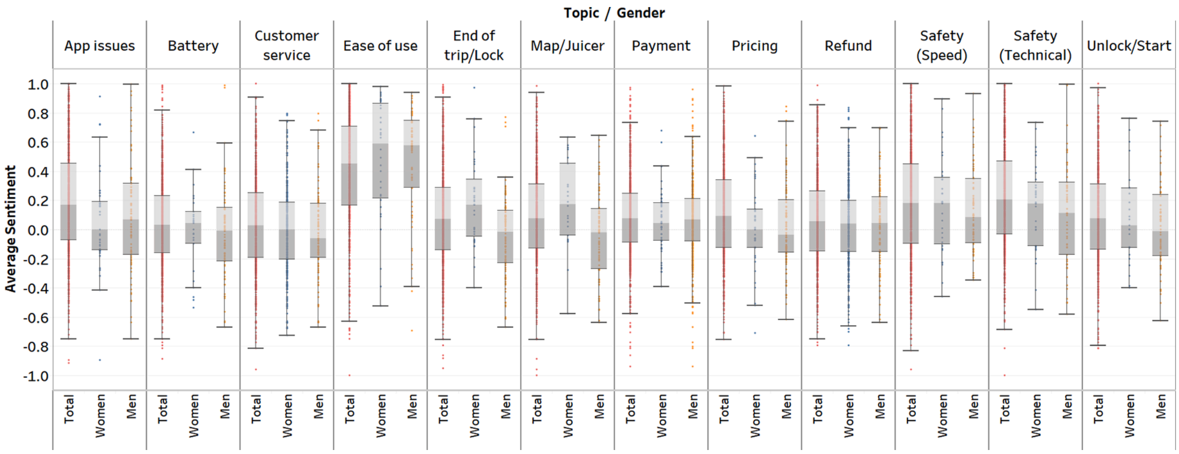

Fig. 4. Distribution of reviews polarity value in each topic across gender.

4.5. Logistic regression

In this section, the influence of identified topics on user satisfaction is examined by applying a logistic regression model. Logistic regression analysis was conducted to examine potentially significant predictors of rider satisfaction. Table 2 summarizes the estimated coefficient of factors in the logistic regression models for total reviews, men, and women reviews. Across all total reviews, Refund, Payment, Battery, and Customer service have the highest coefficient factors, indicating that these factors significantly influence overall rider satisfaction. For men, the most important factors were Refund, Ease of Use, Payment, and Pricing. For women, the highest coefficients were for Refund, Payment, and Pricing. Moreover, there was also a significant difference between men and women in the Refund topic. Safety (technical issues) was not significant in any of the three models. Safety (speed and riding lane) was not significant for men and women models. Map and Unlock were not significant in the women model.

Odds ratios in Table 3 for each variable indicates that how the odds change with a one percent increase in a topic weight while holding other variables constant. In total reviews, Refund odds ratio for being satisfied decreased by 0.866 (97.5% CI = 0.84 to 0.88) for each step increase of variables weight. For men, Refund and Payment have significantly larger odds ratio for dissatisfaction than other factors, and for women, Payment and Pricing play the same role.

5. Policy implications

Rider satisfaction studies help to communicate user satisfaction with a transportation service or technology. These studies help city officials and transportation companies understand perceptions of service quality and help to identify factors important for overall rider satisfaction. Previous studies have highlighted the importance of user-generated content, such as social media posts via Instagram, Facebook or Twitter in understanding public opinions towards micromobility services and related policy actions (Aman and Smith-Colin, 2021). This study demonstrates the value of app review comments for clarifying public perceptions, including individual

Table 2
Coefficient of factors in the logistic regression model.

Topics	Total			Men			Women		
	Coeff.	Std.	Signif.	Coeff.	Std.	Signif.	Coeff.	Std.	Signif.
(Intercept)	1.14	0.07	***	0.51	0.14	***	1.08	0.19	***
Refund	−14.35	1.13	***	−16.22	2.86	***	−12.21	2.90	***
Payment	−14.05	0.98	***	−10.98	1.71	***	−16.84	3.38	**
Ease of use	10.04	1.40	***	11.49	1.40	***	8.51	3.56	*
Pricing	−10.62	0.99	***	−10.37	2.06	***	−15.10	3.33	***
Battery	−13.37	1.17	***	−8.94	2.26	***	−10.50	3.56	**
Customer Service	−10.39	0.97	***	−10.26	1.98	***	−9.95	3.52	**
Lock	−7.55	0.86	***	−6.24	1.60	***	−6.95	2.36	**
Map	−8.23	0.93	***	−7.24	1.95	***	–	–	–
Unlock	−7.67	1.08	***	−7.65	1.60	***	–	–	–
App issues	−4.37	0.80	***	−4.33	1.61	**	–	–	–
Safety (Speed and riding lane)	−1.55	0.79	*	–	–	–	–	–	–
Safety (Technical issues)	–	–	–	–	–	–	–	–	–
Log Likelihood	−1755.5			−426.6			−165.9		
Sample Number	3335			834			330		

Significance codes: 0 '***', 0.001 '**', 0.01 '*'.

Table 3
Odds Ratios (OR) with 97.5% confidence interval.

Topics	Total		Men		Women	
	OR	97.5% CI	OR	97.5% CI	OR.	97.5% CI
Refund	0.866	)0.84, 0.88(	0.850	(0.79, 0.89)	0.885	(0.83, 0.93)
Payment	0.869	)0.85, 0.88(	0.896	(0.86, 0.92)	0.845	(0.78, 0.89)
Ease of use	1.106	)1.07, 1.13(	1.122	(1.07, 1.18)	1.089	(1.02, 1.17)
Pricing	0.899	(0.88, 0.91)	0.901	(0.86, 0.93)	0.860	(0.80, 0.91)
Battery	0.875	(0.85, 0.89)	0.914	(0.87, 0.95)	0.900	(0.83, 0.96)
Customer Service	0.901	(0.88, 0.91)	0.903	(0.86, 0.93)	0.905	(0.84, 0.96)
Lock	0.927	(0.91, 0.94)	0.940	(0.90, 0.96)	0.933	(0.88, 0.97)
Map	0.921	(0.90, 0.93)	0.930	(0.89, 0.96)		
Unlock	0.926	(0.90, 0.94)	0.926	(0.88, 0.96)		
App issues	0.957	(0.94, 0.97)	0.958	(0.92, 0.98)		
Safety (Speed and riding lane)	0.985	(0.97, 1.00)				

feelings towards services and factors influencing opinions. This process of examining public opinions and perceptions towards services may thus prove useful for shaping policy actions that respond directly to the needs of the public and improve user satisfaction. This study identified 12 topics of public concern expressed via app store reviews: Payment, App issues, Customer services, Ease of use, End of trip/Lock, Safety (Speed and riding lane), Refund, Map/Juicer, Pricing, Safety (Technical issues), Battery, and Unlock. Each of these topics represents an opportunity to improve rider satisfaction and experience through policy interventions. These policy actions may be implemented as rules or requirements, put in place for e-scooter vendors defining actions that "must" or "shall" be taken, actions that "may be taken" and actions that "shall not be taken."

Unexplained charges and automatic payments from, for example, parking in restricted zones likely led to customer complaints about Refund and Payment within the reviews. Moreover, scooter companies require debit/credit cards for payment or collateral while scooters are in use, making payment systems an integral part of the e-scooter rider experience. The prerequisite of a debit/credit card for scooter operation has also created a serious barrier for users, especially unbanked and underbanked households, raising serious equity concerns (Shaheen and Cohen, 2019), as equity is mainly concerned with the fair distribution of opportunities based on the demands and characteristics of the recipients (Aman and Smith-Colin, 2020); for instance, it is reported that 57% of the low-income persons of color do not have a credit card (McNeil et al., 2018). Discontentment with existing payment systems has prompted users to ask for alternative sources of payment. These requests have implications for the policy approach to e-scooter use as payment systems are often found to be a source of inequity in the management of new mobility technologies. Public policy actions and regulations can be used to facilitate public–private partnerships that enable more payment options, such as transit smart cards or passes, that leverage the need for and use of multimodal travel options. The results in general demonstrate an urgent need to integrate e-scooter or micromobility services into current land use and transportation planning systems.

The topic modeling results suggest that "expensive," "minute," and "price" were the most common words used in the Pricing topic. Scooter riding prices need to be low enough to satisfy riders, yet high enough for private companies to maintain a sustainable business model (Espinoza et al., 2019) as such companies offer various pricing models. Renting an available electric scooter often costs $1 to start/unlock and then $0.15 per each minute of riding. Espinoza et al. (2019) found that shared scooter pricing was relatively high when compared to transit pricing, and although typically available around transit stations, scooters are often still not used as a last-mile trip mode. Further demonstrating the impact of pricing, Fitt and Curl (2020) asked riders why they started using scooters, and only 7% of the respondents reported that "it was cheaper than the alternative." Shaheen and Cohen (2019) have proposed discounted or subsidized plans for underprivileged individuals to overcome cost-efficiency challenges. Public-private partnerships can also be used to negotiate equitable (pricing) structures including mileage based, frequency-based, as well as need-based options. Discount programs and passes similar to those instituted for traditional transit modes may also be an option.

The quality of the user interface, and technical shortcomings form a considerable share of user reviews focused on App issues and Customer service. Having to download the app from app stores, the registration process, finding the location of available scooters from the map (Map), scanning the code, unlocking the scooter (Unlock/Start), and locking the scooter afterward (End of trip/lock), all require a certain degree of knowledge and technological skill on the part of riders, as well a straightforward and user-friendly app interface. Several studies have reported that not being able to use the online interface of shared mobility technologies creates a considerable barrier to their use (Dowling and Kent, 2015; McNeil et al., 2018). For instance, according to Fitt and Curl (2020), 13% of their study sample believed that using a scooter app could be challenging at first; other studies have reported that individuals have refrained from using shared mobility services due to a lack of digital knowledge and perceptions that micromobilty apps are cumbersome and difficult to use. In our study, app related reviews also exhibit user difficulties. It should further be noted that these reviews do not capture the concerns of those that in general have difficulty using micromobility. Concerns about theapp have public policy implications when one considers requirements under the Americans with Disabilities Act (ADA) to ensure access to for persons of all abilities. As state and local governments pursue micromobility as an option to expand transportation alternatives, concerns about physical and cognitive barriers to access may require policy intervention. How can scooter vendors improve app functionality to reduce barriers? How can policies incentivize this behavior or disincentivize existing app limitations?

Related to app issues is customer service. More than nine percent of the reviews contained issues related to Customer service. In this study, topic coexistence analysis indicated that reviews under the topic of Customer Service mostly co-occurred with reviews related to

Refund, Payment, and Map/Juicer. Customer service describes the assistance or advice received by riders from the e-scooter company about the product or services being used. There have been numerous studies that investigate the relationship between customer service and user satisfaction. Higher quality customer service has been found to lead to higher user satisfaction (Steven et al., 2012). Here again full integration of e-scooter or micromobility services into current land use and transportation planning systems and/or policies that require specialized training for customer service operators may prove useful. Additionally, understanding perceptions of app-related functions and creating policies that expect improvements to app-related technology might help to increase the ridership of micromobility services.

Reviews from the Safety comments show that the lack of clear safety regulations regarding e-scooter use has been confusing for riders. Reviews, specifically, demonstrate confusion in choosing the proper path for riding scooters, as some reviews mention the risk of riding on streets near motor-vehicles, while other reviews expressed frustration about riding on sidewalks with pedestrians as well as incidents of aggression initiated by pedestrians. Our understanding of e-scooter rider expectations regarding infrastructure remains mixed. Unlike bike riders, scooter riders usually prefer to ride on the sidewalk as opposed to the street (Sikka et al., 2019). In contrast, the latest e-scooter routing study suggests that e-scooter users tend to favor bicycle-friendly infrastructure over pedestrian-oriented infrastructure (Zhang et al., 2021). As different roadways are characterized by different safety features (Khodadadi et al., 2021; Das et al., 2021), it is important to understand riders route choice behavior. Although some cities have forbidden riding on sidewalks, riders frequently ride and park scooters on sidewalks, often in direct conflict with pedestrians. Additionally, regulations and policies about proper speeds, minimum age to ride (driver license), riding under the influence (RUI), and helmet requirements vary from state to state and local jurisdiction to local jurisdiction and therefore generate numerous complaints and questions on the app stores. Transportation departments within cites and other location jurisdictions may need to partner with e-scooter companies to offer clear guidance on riding rules and regulations including wrong-way riding, right-of-way, speeding, and enforcement. Steps should also be taken to plan for revisions to existing bicycle and pedestrian infrastructure such that appropriate micromobility infrastructure can be incorporated in the transportation network – be it micromobility lanes, dedicated e-scooter space on the sidewalk or shared use paths.

In this study, coexistence analysis indicates that App related concerns tend to be discussed together with Map/Juicer and Safety (Speed) for men, and Map/Juicer, Payment, and Battery for women. Very few researchers have addressed the difference between the male and female e-scooter riding experience. Although our analysis showed that women exhibited more positive sentiments and are slightly more satisfied than men, it is widely recognized that micromobility is not a gender-neutral mode of transportation (Gauquelin, 2020); men are viewed as the dominant user group (Krizek and McGuckin, 2019). Gauquelin (2020) considers cultural factors as a reason behind lower usage of scooters by women and invites shared mobility stakeholders to become more aware of this gender gap. Another interesting finding of this paper is that women's satisfaction (unlike men) is not associated with technical features of the apps or vehicles including Lock, Map/Juicer, App issues, or Safety related factors. These findings present unique marketing and policy opportunities for cities and local jurisdictions. Recent work suggests the need for a more nuanced approach to encouraging active travel such as trips made by micromobility thus advocating for a more gendered approach to travel and transportation (Gauvin Laetitia et al., 2020;Haynes et al., 2019). A gendered approach to travel-related policy should be explored as an approach to improving rider satisfaction and experience.

Overall, the lack of a policy focus on scooter rider satisfaction may lead to the loss of users. A positive association has been reported between user satisfaction and loyalty to services (Söderlund, 1998). Highly satisfied users are more prone to recommend the service to other individuals; on the other hand, dissatisfied users usually share their negative experiences with other people including potential riders (Tatikonda, 2013). Additionally, the use of text mining as a tool increases chances of gaining a broad set of opinion results, thus increasing the potential effectiveness of service improvements. Overlooking factors that influence rider satisfaction can perpetuate negative perceptions about micromobility services and consequently lead to a loss of riders. By not using text mining as a tool for understanding user satisfaction transportation agencies are neglecting a lesser cost, potentially less biased and informative approach to data analysis. It is recommended that a policy approach focused on improving rider satisfaction and experience and delivering service improvements incorporate opinion mining as a methodology.

6. Conclusion

Traditionally, studies have implemented qualitative or quantitative surveys to understand rider satisfaction, which are typically expensive to perform, and lack consistent measurement factors. This research uses a text mining methodology to explore, identify, and validate hidden factors of scooter rider satisfaction utilizing app store reviews. The major barrier in analyzing online textual data is their substantial noise. Therefore, advanced text mining and machine learning approaches are employed in this study to clearly understand attributes that influence rider satisfaction. In this study, we also used a name-centered gender prediction algorithm to enable gender-based analysis.

This study identifies twelve topics in app reviews using the Latent Dirichlet Allocation topic model. Identified topics covered different attributes of scooter riding, including Payment, App issues, Customer services, and Safety, to name a few. The most discussed topic is the lack of options for payment or payment method, which tends to coexist with app issues, customer services, and refunds, as well as unexpected costs incurred through parking in restricted zones. There are also concerns regarding the safety and right of way among users. Some of the user concerns can be addressed directly by e-scooter companies, e.g., enhancing app design, diversifying payment options, enhancing the map/juicers design, as well as, improving the technical aspects of e-scooters. However, the results also suggest that some issues can only be mitigated through public private partnership, e.g., extending payment options to include transit passes, clear guidance regarding parking zones and the use of e-scooters in the public right of way, more public investments in bicycle-friendly infrastructure, and/or policy intervention and incentives. The gender-based analysis shows that e-scooters remain a male dominated travel mode, which is consistent with the existing literature. Female riders were found to have slightly more positive reviews than male riders.

Logistic regression results suggest user satisfaction levels also tend to vary across topics and gender groups. Ease of use, Safety (speed and riding lane), as well as App issues appeared to have a major influence on user satisfaction, based on the odds-ratios calculated using the logistic regression results. There was no significant difference in the odds ratio of different topics in women and men logistic model results. However, several topics, such as Map, Unlock, and App issues were found to be significant in the model for men, while insignificant in the model for women. This may be due to the fact that the female model has a more limited sample when compared to the numbers of reviews generating the male model. Overall, this study offers a helpful resource that officials and decision-makers who are dealing with the increasing phenomenon of shared e-scooters can use to examine rider satisfaction across their cities. Additionally, this study offers an approach for comparing and contrasting user needs, expectations, and satisfaction across cities and gender.

Results of this study raise several issues regarding public policy interventions for shared electric scooters, particularly given that polices about e-scooters still remain unclear and continue to evolve in many cities. Each of the topics uncovered in this analysis represents an opportunity to improve rider satisfaction and experience through policy interventions. These policy actions may be implemented as rules or requirements, put in place for e-scooter vendors defining actions that “must” or “shall” be taken, actions that “may be taken” and actions that “shall not be taken.” Discontentment with existing payment systems has prompted users to ask for alternative sources of payment. Public policy actions and regulations can be used to facilitate public–private partnerships that enable more payment options, such as transit smart cards or passes. Discounted or subsidized plans for underprivileged individuals to overcome cost-efficiency challenges and public–private partnerships can be used to negotiate equitable pricing structures for e-scooters. As state and local governments pursue micromobility as an option to expand transportation alternatives, concerns about physical and cognitive barriers to access may require policy interventions. Additionally, understanding perceptions of app-related functions and creating policies that expect improvements to app-related technology might help to increase ridership of micro-mobility services. As it relates to micromobility infrastructure, policy-oriented steps should also be taken to plan for revisions to existing bicycle and pedestrian infrastructures such that appropriate micromobility infrastructure can be incorporated in the transportation network – be it micromobility lanes, dedicated e-scooter space on the sidewalk or shared use paths. In general, the results demonstrate an urgent need to integrate e-scooter or micromobility services into current land use and transportation planning systems. Finally, recent work suggests the need for a more nuanced approach to encouraging active travel, such as trips made by micromobility. A gendered approach to travel-related policy should be explored. Overall, the lack of a policy focus on scooter rider satisfaction may lead to the loss of users, as a positive association has been reported between user satisfaction and loyalty to services. A policy approach focused on improving rider satisfaction and experience and delivering service improvements that incorporates text mining and other opinion mining methodologies is recommended.

The main limitation of this study is that app store reviews were used as the only source of data. Although app store reviews often discuss the scooter rider experience and provide valuable information, the content of reviews were in general related to user experience with the app as opposed to the riding experience. In other words, it is possible that topic modeling algorithms made a biased allocation overemphasizing scooter topics related to app performance and app user experience while overlooking rider experience. Additionally, service delivery topics were often not discussed in the context of the app store reviews. For instance, equity or inequities in micromobility facilities is a topic of great significance that was not mentioned directly within the app store reviews. Moreover, using app store reviews (or other forms of social media information) as a research tool may cause selection bias since the sample is drawn from individuals -typically younger, affluent, or more engaged with technology. Reviews are also typically written by those who have at least tried to rent a scooter by downloading the app. Therefore, reviews are the voice of a fraction of riders and hardly the voice of those who have not or cannot ride scooters (e.g., individuals who do not own smartphones, those who live where scooters are unavailable, or those with physical or cognitive disabilities that limit scooter use). Therefore, caution should be made in generalizing the results. However, it should be restated that app store data also reduces bias that present themselves in traditional methods. Furthermore, dissatisfied users are more eager to write longer, therefore more informative, reviews, in this case functions and features that delight users might be overlooked. In future research, studies may use other sources of data (such as tweets and surveys) to more accurately capture user satisfaction factors thus potentially integrating these and other topics relevant to the scooter rider experience, expectations, and satisfaction. Finally, methods used for name-centered gender prediction present a source of uncertainty. Given that app store users often use pseudo names, or that riders may be using someone else’s phone to book a ride or write a review, there exits the potential for incorrectly predicting the gender of users. The area of gendered travel analysis in shared micromobilty, therefore, presents opportunities for further study and improved methodologies. For instance, using other attributes such as profile picture, or the text itself can probably strengthen gender prediction accuracy.

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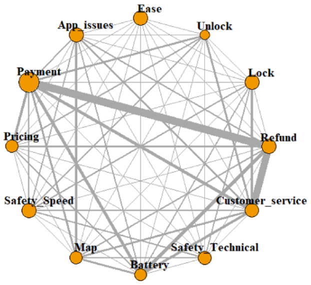
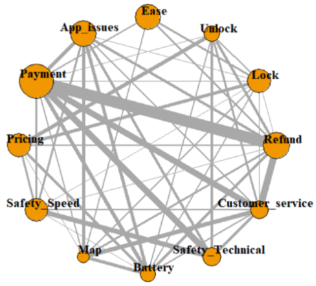
Author contributions

The authors confirm contribution to the paper as follows: study conception and design: Aman, Smith-Colin, and Zhang. Analysis and interpretation: Aman, Smith-Colin, and Zhang. Writing: Aman, Smith-Colin, and Zhang. All authors reviewed the results and approved the final version of the manuscript.

Appendix A

Gamma = 0.10	Gamma = 0.15
	

References

Abduljabbar, R., Liyanage, S., Hussein, D., 2021. The role of micro-mobility in shaping sustainable cities: A systematic literature review. Transportation Research Part D: Transport and Environment. https://doi.org/10.1016/j.trd.2021.102734.

Allem, J., Majmundar, A., 2019. Are electric scooters promoted on social media with safety in mind? A case study on Bird's Instagram. Prevent. Med. Rep. 13, 62–63.

Aman, J.J.C., Smith-Colin, J., 2021. Leveraging Social Media to Understand Public Perceptions of Micromobility Policies: The Dallas Scooter Ban Case. Transport Find.

Almannaa, M., Ashqar, H., Elhenawy, M., Rakotonirainy, A., Rakha, H., 2020. A comparative analysis of e-scooter and e-bike usage patterns: Findings from the City of Austin, TX. International Journal of Sustainable Transportation 1–9.

Aman, J.J.C., Smith-Colin, J., 2020. Transit Deserts: Equity analysis of public transit accessibility. J. Transport Geogr. 89, 102869.

Anderson-Hall, K., Bordenkircher, B., O'Neil, R., Scott, S.C., 2019. Governing micro-mobility: a nationwide assessment of electric scooter regulations.

Arendsen, K., 2019. Shared mobility for the first and last mile: exploring the willingness to share.

Bai, S., Jiao, J., 2020. From shared micro-mobility to shared responsibility: Using crowdsourcing to understand dockless vehicle violations in Austin, Texas. J. Urban Affairs 1–13.

Bastani, K., Namavari, H., Shaffer, J., 2019. Latent Dirichlet allocation (LDA) for topic modeling of the CFPB consumer complaints. Expert Syst. Appl. 127, 256–271.

Benamara, F., Cesarano, C., Picariello, A., Recupero, D.R., Subrahmanian, V.S., 2007. Sentiment analysis: Adjectives and adverbs are better than adjectives alone. ICWSM 7, 203–206.

Blevins, B., Mullen, L., 2015. Jane, John... Leslie? A Historical Method for Algorithmic Gender Prediction. Digital Humanities Quarterly 9.

Brown, A., Klein, N.J., Thigpen, C., Williams, N., 2020. Impeding access: The frequency and characteristics of improper scooter, bike, and car parking, *Transportation Research Interdisciplinary*. Perspectives 100099.

Cengiz, E., 2010. Measuring customer satisfaction: must or not. J. Naval Sci. Eng. 6 (2), 76–88.

Chen, Y., Cheng, C., Li, S., Yu, C., 2018. Location optimization for multiple types of charging stations for electric scooters. Appl. Soft Comput. 67, 519–528.

Christoforou, Z., Gioldasis, C., Bortoli, A., Seidowsky, R, 2021. Who is using e-scooters and how? Evidence from Paris. Transportation Research Part D: Transport and Environment 92. https://doi.org/10.1016/j.trd.2021.102708.

Das, S., Dutta, A., Medina, G., Minjares-Kyle, L., Elgart, Z., 2019. Extracting patterns from Twitter to promote biking. IATSS Res. 43 (1), 51–59.

Das, S., Sun, X., Dutta, A., 2015. Investigating user ridership sentiments for bike sharing programs. J. Transport. Technol. 5 (02), 69.

Das, S., Tsapakis, I., Khodadadi, A., 2021. Safety performance functions for low-volume rural minor collector two-lane roadways. IATSS Research. https://doi.org/10.1016/j.iatssr.2021.02.004.

Debortoli, S., Müller, O., Junglas, I., vom Brocke, J., 2016. Text mining for information systems researchers: An annotated topic modeling tutorial. Commun. Assoc. Inform. Syst. 39 (1), 7.

Degele, J., Gorr, A., Haas, K., Kormann, D., Krauss, S., Lipinski, P., Tenbih, M., Koppenhoefer, C., Fauser, J., Hertweck, D., 2018. Identifying E-Scooter Sharing Customer Segments Using Clustering. In: 2018 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC), pp. 1–8.

Dormanesh, A., Majmundar, A., Allem, J., 2020. Follow-Up Investigation on the Promotional Practices of Electric Scooter Companies: Content Analysis of Posts on Instagram and Twitter. JMIR Publ. Health Surveillance 6 (1), e16833.

Dowling, R., Kent, J., 2015. Practice and public–private partnerships in sustainable transport governance: The case of car sharing in Sydney, Australia. Transport Policy 40, 58–64.

E. Guzman, W. Maalej, 2014. How Do Users Like This Feature? A Fine Grained Sentiment Analysis of App Reviews. In: 2014 IEEE 22nd International Requirements Engineering Conference (RE), pp. 153–162.

Eboli, L., Mazzulla, G., 2007. Service quality attributes affecting customer satisfaction for bus transit. J. Publ. Transport. 10 (3), 2.

Espinoza, W., Howard, M., Lane, J., Van Hentenryck, P., 2019. Shared E-scooters: Business, Pleasure, or Transit? arXiv preprint arXiv:1910.05807.

Eccarius, T., Lu, C., 2020. Adoption intentions for micro-mobility–Insights from electric scooter sharing in Taiwan. Transportation research part D: transport and environment 84.

Fang, K., 2019. Do They Block the Way in San Jose? Where Do Riders Park Dockless, Shared Electric Scooters and Their Implications for Sidewalk Users. J. Transport Health 14, 100787.

Fitt, H., Curl, A., 2020. The early days of shared micromobility: A social practices approach. J. Transp. Geogr. 86, 102779.

Fu, B., Lin, J., Li, L., Faloutsos, C., Hong, J., Sadeh, N., 2013. Why people hate your app: Making sense of user feedback in a mobile app store, pp. 1276–1284.

Gauquelin, A., 2020. The Gender Gap in Shared Micromobility, 2020 (June 15).

Laetitia, Gauvin, Michele, Tizzoni, Simone, Piaggesi, Andrew, Young, Natalia, Adler, Stefaan, Verhulst, Leo, Ferres, Ciro, Cattuto, 2020. Gender gaps in urban mobility. Hum. Soc. Sci. Commun. 7 (1), 1–13.

Genc-Nayebi, N., Abran, A., 2017. A systematic literature review: Opinion mining studies from mobile app store user reviews. J. Syst. Softw. 125, 207–219.

Ghag, K., Shah, K., 2014. SentiTFIDF-Sentiment classification using relative term frequency inverse document frequency. Int. J. Adv. Comput. Sci. Appl. 5 (2).

Gössling, S., 2020. Integrating e-scooters in urban transportation: Problems, policies, and the prospect of system change. Transport. Res. Part D: Transp. Environ. 79, 102230.

Guo, Y., Zhou, J., Wu, Y., Li, Z., 2017a. Identifying the factors affecting bike-sharing usage and degree of satisfaction in Ningbo, China. PloS One 12 (9), e0185100.

Guo, Y., Barnes, S.J., Jia, Q., 2017b. Mining meaning from online ratings and reviews: Tourist satisfaction analysis using latent dirichlet allocation. Tourism Manage. 59, 467–483.

Gupta, V., Lehal, G.S., 2009. A survey of text mining techniques and applications. J. Emerg. Technol. Web Intell. 1 (1), 60–76.

Han, H., Meng, B., Kim, W., 2017. Bike-traveling as a growing phenomenon: Role of attributes, value, satisfaction, desire, and gender in developing loyalty. Tourism Manage. 59, 91–103.
Haworth, N., Schramm, A., Twisk, D., 2021. Comparing the risky behaviours of shared and private e-scooter and bicycle riders in downtown Brisbane, Australia. Accident Analysis & Prevention 152.
Haynes, E., Green, J., Garside, R., Kelly, M.P., Guell, C., 2019. Gender and active travel: a qualitative data synthesis informed by machine learning. Int. J. Behav. Nutrit. Phys. Activity 16 (1), 1–135.
Jelodar, H., Wang, Y., Yuan, C., Feng, X., Jiang, X., Li, Y., Zhao, L., 2019. Latent Dirichlet allocation (LDA) and topic modeling: models, applications, a survey. Multimedia Tools Appl. 78 (11), 15169–15211.
Jha, V., Savitha, R., Shenoy, P.D., Venugopal, K.R., Sangaiah, A.K., 2018. A novel sentiment aware dictionary for multi-domain sentiment classification. Comput. Electr. Eng. 69, 585–597.
Katz, G., 2011. Nine myths about the voice of the customer, Visions (October) 2425.
Jiao, J., Bai, S., 2020. Understanding the Shared E-scooter Travels in Austin, TX. ISPRS international journal of geo-information. https://doi.org/10.3390/ijgi9020135.
Khodadadi, A., Tsapakis, I., Das, S., Lord, D., Li, Y., 2021. Application of different negative binomial parameterizations to develop safety performance functions for non-federal aid system roads. Accid. Anal. Prevent. 156.
Kim, N.R., Hong, S.G., 2020. Text mining for the evaluation of public services: the case of a public bike-sharing system. Serv. Bus. 14 (3), 315–331.
Kopplin, C.S., Brand, B.M., Reichenberger, Y., 2021. Consumer acceptance of shared e-scooters for urban and short-distance mobility. Transport. Res. Part D: Transp. Environ. 91, 102680.
Krestel, R., Fankhauser, P., Nejdl, W., 2009. Latent dirichlet allocation for tag recommendation, pp. 61–68.
Krizek, K.J., McGuckin, N., 2019. Shedding NHTS Light on the Use of'Little Vehicles' in Urban Areas. Transp. Find.
Li, H., Ye, Q., Law, R., 2013. Determinants of Customer Satisfaction in the Hotel Industry: An Application of Online Review Analysis. Asia Pacific J. Tourism Res. 18 (7), 784–802.
Lucini, F.R., Tonetto, L.M., Fogliatto, F.S., Anzanello, M.J., 2020. Text mining approach to explore dimensions of airline customer satisfaction using online customer reviews. J. Air Transp. Manage. 83, 101760.
Ma, Q., Yang, H., Ma, Y., Yang, D., Hu, X., Xie, K., 2021. Examining municipal guidelines for users of shared E-Scooters in the United States. Transportation Research Part D: Transport and Environment 92. https://doi.org/10.1016/j.trd.2021.102710.
Maghrebi, M., Abbasi, A., Rashidi, T., Waller, S., 2015. Complementing Travel Diary Surveys with Twitter Data: Application of Text Mining Techniques on Activity Location, Type and Time. IEEE 18th International Conference on Intelligent Transportation Systems 208–2013. https://doi.org/10.1109/ITSC.2015.43.
Manzi, G., Saibene, G., 2018. Are they telling the truth?Revealing hidden traits of satisfaction with a public bike-sharing service. Null 12 (4), 253–270.
Mayhew, L.J., Bergin, C., 2019. Impact of e-scooter injuries on Emergency Department imaging. J. Med. Imag. Radiat. Oncol. 63 (4), 461–466.
McKenzie, G., 2019. Spatiotemporal comparative analysis of scooter-share and bike-share usage patterns in Washington, D.C. J. Transp. Geogr. 78, 19–28.
McNeil, N., Broach, J., Dill, J., 2018. Breaking barriers to bike share: Lessons on bike share equity. Inst. Transport. Eng. ITE J. 88 (2), 31–35.
Nacto, 2019. Shared Micromobilityin the U.S.: 2018.
Mullen, L., 2018. Predict gender from names using historical data. Available at: https://cran.r-project.org/ (Accessed: May 15, 2020).
Moran, M., Laa, B., Emberger, G., 2020. Six scooter operators, six maps: Spatial coverage and regulation of micromobility in Vienna, Austria. Case Studies on Transport Policy. https://doi.org/10.1016/j.cstp.2020.03.001.
Nellamattathil, M., Amber, I., 2020. An evaluation of scooter injury and injury patterns following widespread adoption of E-scooters in a major metropolitan area. Clin. Imaging 60 (2), 200–203.
Nikiforiadis, A., Paschalidis, E., Stamatiadis, N., Raptopoulou, A., Kostareli, A., Basbas, S., 2021. Analysis of attitudes and engagement of shared e-scooter users. Transport. Res. Part D: Transp. Environ. 94, 102790.
Ooms, J., 2017. hunspell: High-Performance Stemmer, Tokenizer, and Spell Checker for R. R package version 2.6.
Park, S., Kim, Y., 2016. Building thesaurus lexicon using dictionary-based approach for sentiment classification, pp. 39–44.
Pettit, A., 2013. Identifying the Real Differences of Opinion in Social Media Sentiment. Int. J. Market Res. 55 (6), 757–767.
Populus, 2018. The micro-mobility revolution: The introduction and adoption of electric scooters in the United States.
Rinker, T.W., 2019. sentimentr: Calculate Text Polarity Sentiment, 2.7.1.
RSG, 2008. Regional transportation authority: 2016 customer satisfaction study, CTA Customer Satisfaction Survey.
Shah, N.R., Aryal, S., Wen, Y., Cherry, C.R., 2021. Comparison of motor vehicle-involved e-scooter and bicycle crashes using standardized crash typology. J. Saf. Res.
Shaheen, S., Cohen, A., 2019. Shared Micromoblity Policy Toolkit: Docked and Dockless Bike and Scooter Sharing, UC Berkeley Transportation Sustainability Research Center.
Sharifi, F., Meitiv, A., Shelton, J., Xu, X., Burris, M., Vallamsundar, S., Xu, Y, 2021. Regional traffic operation and vehicle emission impact assessment of lane management policies. Research in Transportation Economics. https://doi.org/10.1016/j.retrec.2021.101067.
Sikka, N., Vila, C., Stratton, M., Ghassemi, M., Pourmand, A., 2019. Sharing the sidewalk: A case of E-scooter related pedestrian injury. Am. J. Emerg. Med. 37 (9), 1807. e5-1807. e7.
Silge, J., Robinson, D., 2017. Text Mining with R. O'Reilly, Sebastopol.
Silva, C., Ribeiro, B., 2003. The importance of stop word removal on recall values in text categorization, vol. 3, pp. 1661–1666.
Söderlund, M., 1998. Customer satisfaction and its consequences on customer behaviour revisited. Int. J. Serv. Ind. Manage. 9 (2), 169–188.
Sohrabi, S., Paleti, R., Balan, L., Cetin, M., 2020. Real-time prediction of public bike sharing system demand using generalized extreme value count model. Transport. Res. Part A: Policy Practice 133, 325–336.
Srividhya, V., Anitha, R., 2010. Evaluating preprocessing techniques in text categorization. Int. J. Comput. Sci. Appl. 47 (11), 49–51.
Steven, A.B., Dong, Y., Dresner, M., 2012. Linkages between customer service, customer satisfaction and performance in the airline industry: Investigation of non-linearities and moderating effects. Transport. Res. Part E: Logist. Transport. Rev. 48 (4), 743–754.
Tatikonda, L.U., 2013. The hidden costs of customer dissatisfaction. Manage. Acc. Quart. 14 (3), 34.
Tuncer, S., Brown, B., 2020. E-scooters on the Ground: Lessons for Redesigning Urban Micro-Mobility, pp. 1–14.
Wais, Kamil, 2016. Gender Prediction Methods Based on First Names with genderizeR. R J 8 (1), 17.
Yang, H., Ma, Q., Wang, Z., Cai, Q., Xie, K., Yang, D., 2020. Safety of micro-mobility: Analysis of E-Scooter crashes by mining news reports,. Accid. Anal. Prev. 143, 105608.
Younes, H., Zou, Z., Wu, J., Baiocchi, G., 2020. Comparing the Temporal Determinants of Dockless Scooter-share and Station-based Bike-share in Washington, D.C. Transport. Res. Part A: Policy Practice 134, 308–320.
Zhang, W., Buehler, R., Broaddus, A., Sweeney, T., 2021. What type of infrastructures do e-scooter riders prefer?A route choice model. Transport. Res. Part D: Transp. Environ. 94, 102761.
Zhang, X., Jeske, D.R., Li, J., Wong, V., 2016. A sequential logistic regression classifier based on mixed effects with applications to longitudinal data. Comput. Stat. Data Anal. 94, 238–249.
Zhu, R., Zhang, X., Kondor, D., Santi, P., Ratti, C., 2020. Understanding spatio-temporal heterogeneity of bike-sharing and scooter-sharing mobility. Comput.Environ. Urban Syst. 81, 101483.