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Electric Scooty Purchasing Recommendations Using Customer Review

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Abstract

As environmental awareness and sustainable practices have grown, E-scooters, often known as electric scooters, have gained popularity as a replacement for traditional automobiles This research focuses on developing a recommendation framework for purchasing e-scooters, leveraging customer reviews as the primary data source. By analyzing reviews from diverse platforms, the framework aims to identify critical factors influencing customer satisfaction, including performance, battery life, design, comfort, and cost-efficiency. When we are considering things online, we frequently start by reading online reviews. When assessing a possible acquisition, we might have particular question in mind. We have to either search through many customer evaluations in an attempt to locate pertinent information, or we may use a Q&A system to ask the community directly for an answer. The rapid growth of electric bike market has led to overwhelming number of available options for consumers, making the process of customer feedback the most suitable process of selecting the bike and in enhancing product quality and promoting the adoption of sustainable transportation solutions.

Keywords: E-Bike, brand comparison, natural language processing (NLP), Eco-friendly vehicles, review based analysis

INTRODUCTION

The growing popularity of electric bikes (e-bikes) has significantly impacted transportation, providing an economically responsible alternative. As the market for e-bikes continues expand, consumers face a plethora of options, making it increasingly difficult to choose the best model for their specific needs. To aid in this decision-making process, customer review has become an essential source of information. These reviews provide real-world feedback on e-bike performance, quality, durability, and user satisfaction, allowing potential buyers reacquire insightful knowledge prior to buying. Around the globe, policymakers are working to improve urban living conditions and reduce negative environmental effects. Transportation is one of the areas of importance in this respect. In the EU, 23% of greenhouse gas emissions come from urban mobility. Planners are worried about traffic problems and their effects on the economy in addition to the environmental impact. In Europe, traffic jams cost about 1% of GDP annually. As a result, we urgently need sustainable alternatives. Analysis of sentiments examines how people feel about particular things. In terms of sentiment data, the internet is a resourceful place. Due to their ability to facilitate smooth mobility in constrained ancient streets that are impassable by automobile, they are particularly well-suited for dense urban settings, such as city centers. When it comes to journey time, freight electric scooters can compete

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with traditional motorized vehicles in a number of scenarios. Moreover, they do not produce any emissions locally.

As the market for e-bikes keeps expanding and evolve, leveraging customer reviews to make better recommendations is becoming increasingly critical. Why this research is particularly connected to current issues has been explained below:

Sustainability and Urban Mobility

The world is facing significant environment challenges, particularly in urban areas, where congestion, pollution, and traffic related emission are major contributors to climate changes.

Trust and Authenticity in Online Review

As online shopping has become the norm, the authenticity of product review has come into questions. Fake reviews, and review manipulation are significant issues for e-commerce platforms, as consumers are often unsure whether the reviews they read are genuine.

Technical Advancements and AI in Recommendation Systems

Artificial intelligence and machine learning have revolutionized the way e-commerce platforms provide recommendations to consumers. In researches that explore the electric bike purchasing recommendations using customer reviews, various methodologies are employed to extract valuable insights from user generated content, integrate them into recommendation systems, and evaluate the effectiveness of these systems. Below are some methodological approaches commonly used in this, along with key techniques such as sentiment analysis, machine learning, and NLP:

a. Data collection and Review Extraction.
b. Data Preprocessing and Review Cleaning.
c. Sentiment Analysis and Opinion mining.
d. Feature Extraction and Review mining.

An average of 60% of people can read 200 words per minute, according to Othman *et al.* [1]. According to a study by Mudambi and Schuff, the average word count of 1587 evaluations for five electronic devices was 186.63, with a standard deviation of 206.43 words [2]. A person would need about 800 min to read all of the evaluations for a cell phone, for instance, as there are an average of 860 reviews for five of the best-selling models. Until you have styled and formatted the text, keep your graphic files and text files apart. Avoid using hard tabs and only use hard returns only once at the end of a paragraph.

RELATED WORK

Finding out if a document (or a word inside a document) is relevant to a certain question is a crucial part of the aforementioned area of work. "Relevance" might refer to a variety of factors, such as the text's "quality" [3], lexical salience [4], or diversity in relation to previously chosen materials [5]. One requires a query-specific concept of relevance in query-focused situations, i.e., to Assess the relevance of a document in relation to a specific query. Okapi BM25, a cutting-edge TFIDF-based relevance ranking measure, is one of the straightforward (but efficient) word-level similarity measures created for this job [6, 7].

Word-level measures may not work because of the inherent constraint that enquiries and documents may be linguistically varied [8]. Grammar rules and phrase-level strategies (such ROUGE measures [9]) or probabilistic language models, which range from traditional approaches [8] to more contemporary ones based on deep networks [10], can help with this. The ranking measures are described in more depth in Figure 1.

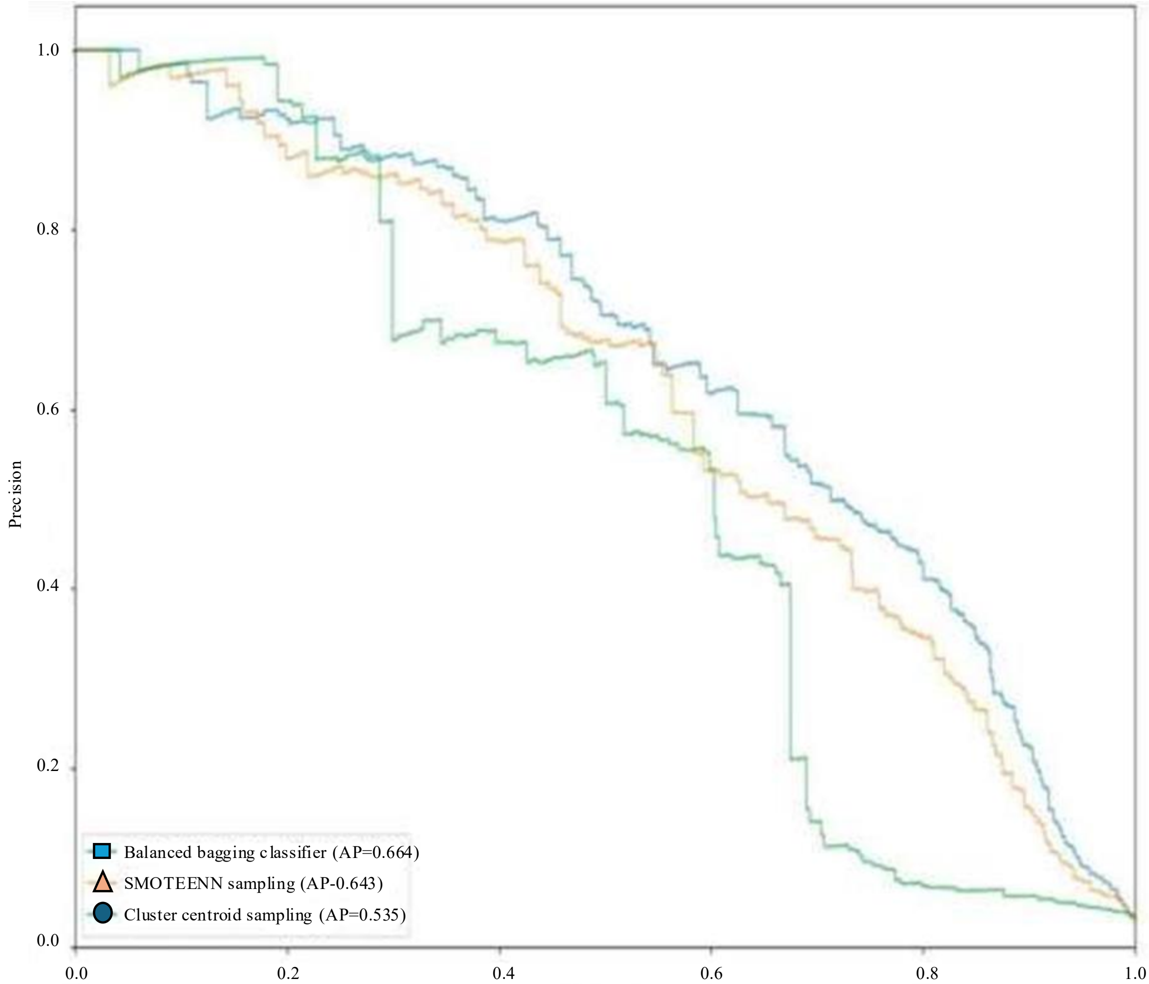

Figure 1. Each sampling technique's P-R curve.

MARKET GROWTH OF POWERED TWO-WHEELER

Globally, the market for powered two-wheels (PTWs) is expanding rapidly due to factors such growing urbanization, the demand for reasonably priced personal transportation, and a move towards sustainable mobility options. The market is projected to develop from its estimated value of about USD 100 billion in 2023 to Compound yearly growth rate (CAGR) of 4–6% to 2030. Due to their dependence on two-wheelers for everyday commuting, Asia Pacific developing economies, including those in China, India, and Indonesia, dominate the market. On the other hand, demand for luxury motorcycles and electric two-wheeler for leisure and enjoyment is rising in places like North America and Europe. Key growth drivers include rising traffic congestion in urban areas, the electrification of two wheeler, and advancements in battery technology, while challenges like safety concerns, emission regulations, and inadequate charging infrastructure persist. With increasing government incentives and a focus on sustainability, the PTW market is poised to expand further, particularly in the electric segment, offering innovative and ecofriendly mobility solutions worldwide. This study focusses on EMs. Unlike electric bicycles, or e-bikes, EMs are not pedal-powered. E-bikes and EMs are both subcategories within the methodology section, which serves as a broader category.

LITERATURE REVIEW

Often referred to as e-scooties or e-scooters, electric scooters have gained immense popularity as an economical, ecofriendly, and sustainable mode of transportation. While recent studies show that even managed lanes and other congestion management strategies cannot reduce greenhouse gas emissions, Bicycles, scooters, stake boards, Segways, hover boards, and other human-powered, lightweight vehicles with a top speed of 30 mph are examples of micromobility solutions, according to Soliman *et al.* [1], who claim that micromobility services appear to be a good substitute for urban transportation. Although the majority of electric mobility vehicles in the United States are privately owned and run.

In a predetermined offense, these electric scooters provide flexible, short-term, on-demand, and environmentally friendly rentals without assigned parking spaces, according to Mudambi and Schuff [2]. Electric scooters typically have handlebars, wheels, brakes, locks, and a deck in addition to sitting [11] moped scooters, which are typically powered by gas or electricity. We focus on electric scooters that are standing in this investigation. Scooters' features, traits, and issues have been the subject of numerous studies in the USA [12], New Zealand [13], and Hungary [14], to name a few.

Understanding the demographics of e-bike users helps plan this mode of transportation for a large user base. Numerous studies have found that e-bikes are beneficial for older people, but none of them have examined the comfort concerns that older adults may have with this mode. An e-bike, for instance, makes riding easier, but older people may find it difficult to control and steer the bike in certain circumstances. Several research have shown that gender disparities are significant [15]. However, it is still unknown how gender affects e-bike users' ages.

According to a study by A Quarter of Freight, which surveyed experts and examined pertinent literature, Electric shared scooter mobility systems may be used for city center transit [16, 17]. Additionally, they conclude that at least 30% of existing operators could simply add freight electric scooters to their fleet. Poullikkas estimates that electric scooters may be used for 66 to 83% of deliveries for direct courier travels [18].

The weight and volume of the cargo, the travel distances, and a comparison of bicycles and scooters with products from 2001 to 2014 form the basis of this conclusion that electric in Paris, electric scooter freight amounted to approximately 1,107 km/day in 2014, compared to 103 km/day in 2001. Of the 1,107 km/day, 63% were covered by e-cargo cycles. Based on a 2 km linear distance, Baptista *et al.*, found that 10% of conventional vans in Porto, Portugal, might be replaced with electric ones, i.e., scooter mobility systems without sacrificing the network's overall effectiveness [19]. Electric scooters are becoming more and more popular around the world. Such a review of the literature will be helpful to the reader because it should include a wide variety of works and make inferences supported by the references provided [19].

Therefore, the primary goal of this research is to perform an extensive analysis of the literature regarding e-bikes in the environmental context for a variety of elements of their applications, including typology, penetration, impacts, and required laws. However, historical observations are not always correct. Taiwan, for example; in terms of GDP per capita, for instance, it now ranks similarly to Germany in terms of purchasing power adjusted economic ranking. Taiwan still holds the record for the highest number of registered PTWs per capita worldwide, despite a significant drop.

Technical and use variables are used by several two-wheeled vehicle classification systems to eliminate uncertainty. Each country has its own legal peculiarities. Separated two-wheelers into three groups for a study of the Chinese market: bicycles, electric and motorbikes. In Europe, Bozzi and Aguilera categorize electric two-wheeler in terms of speed and power, in accordance with the regulations governing e-motorcycles/e-scooters, e-bikes, and e-mopeds [20]. Pike Research studied laws in many nations and made a distinction between e-bikes, e-scooters, and e-motorcycles [21]. Also, they discussed all the quantitative and qualitative analyses which explained the various technologies and models.

Micromobility services appear to be a suitable substitute for in-city travel, even if recent research indicates that even congestion control measures like controlled lanes cannot lower greenhouse gas emissions [12]. Micromobility solutions are lightweight vehicles, such as bicycles, scooters, skateboards, segways, and hoverboards, that can be driven by electricity or human power and travel at a maximum speed of 30 mph [12]. Although individuals may own micromobility cars, private companies own and operate the majority of them in the United States. Nowadays, micromobility is widely used as an active form of transportation for trips under three miles, which account for 50–60% of passenger distances in China, the EU, and the US [12]. Dockless scooters offer on-demand, flexible, sustainable, and temporary rental without designated parking spaces inside a designated geofence [13]. Two varieties of shared scooters are frequently available: (1) standing electric scooters, which are usually equipped with handlebars, wheels, brakes, a lock, and a deck, and are propelled by an electric engine; and (2) sitting moped scooters, which are normally propelled by gas or electricity. This study focuses on standing scooters.

A comprehensive overview of the literature on the relationship between micromobility and sustainable cities has been given by Zakaria *et al.* [12]. Karahan *et al.* [13] and a follow-up study by Larminie and Lowry [14] evaluated the degree to which micromobility businesses brought attention to safety concerns on social media. Both research found that although there may be potential advantages for public safety, businesses hardly ever advertise safety features on their accounts. A shared responsibility framework was presented as a noteworthy element in shared mobility systems in an effort to comprehend the social effects of the scooter boom across cities. This was accomplished by employing crowdsourcing to evaluate parking infraction complaints in Austin and Texas [15]. News stories on conflicts in several towns brought on by the development of shared scooters and concluded that safety, speed, and space were potential areas for regulation development [16.

SUPPORTED METHODS

There are significantly more NHR cyclists in the sample than HR riders, which may lead to overfitting problems. As a result, the training data-set should be balanced through the use of sampling techniques. An ensemble approach, which stands for balanced bagging classifier (BBC), an under-sampling technique, which stands for cluster center-fold method (CC), and an oversampling methodology, which stands for synthetic minority oversampling technique (SMOTE), were compared in this work. Performance metrics were measured using average precision values (Aps).

Decision Support System

DCS is a machine learning technique used to disambiguate product reviews according to their shape, function, and behavior. This study used the machine learning technology to detect the reviews and used the algorithm data acquisition and preprocessing to take the decision from reviews.

Investigation of Lithium Battery Charging Monitoring for Electric Bikes Using CNN and BILSTM Model

For data processing in this study, we use a technique that blends BILSTM networks with traditional neural networks (CNN). A variety of traditional and bidirectional recurrent neural networks are used to efficiently extract intricate patterns and characteristics from the data. CNNs are particularly good at handling issues pertaining to text point of view question answering, picture processing and sentimental analysis in natural language processing. CNNs stand out due to their unique architecture which makes it easier to use their primary learning algorithm sampling methods as shown in Figure 1.

Sentimental Analysis Using Product Review Data by Using Negation Phrases Identification

This review separates or divides the reviews into positive, negative and neural reviews. This review used the negation identification of an algorithm to predict that the review is positive or neural for the further processing of data.

The self-centered (CC) method, which uses a k-means algorithm to decrease the number of samples in a majority class, is the under-sampling technique used in this investigation. The SMOTE strategy, which synthesizes data based on the K nearest neighbor was considered a straightforward and practical oversampling method used in the initial samples in the minority class.

The balanced bagging method, an ensemble approach that integrates sampling and classification approaches, is employed in this work. The imbalanced dataset is initially split up into multiple subsets using this procedure. Finally, by combining the outcomes of each subset, the training set was balanced using the three sample procedures previously stated and a few specific formulas; a random forest (RF) classifier was made accessible for the model training process. Precision-recall and accuracy curves, together with the AP values.

It is evident that the balanced bagging strategy works well. It was determined to use it as the usual sampling strategy in order to further train and compare four different tree-structured algorithms for machine learning (RF, Adaboost, XGboost, and GBDT).

Training of Modelling

The RF method, the AdaBoost algorithm with a decision tree, the XGBoost approach, and the gradient boosting decision tree (GBDT) were the four tree structured tree machine learning strategies used in this work to train the model. As decision tree-based ensemble machine learning algorithms, they are all easier to understand than other machine learning models.

Forest at Random

The decision-based approach is optimized by the random forest model. The approach becomes immune to noise and challenging to overfit due to the random forest's introduction of two types of randomness: randomly chosen feature variables and randomly chosen samples. In order for this process to function, n subgroups of the dataset are chosen at random, and m attributes are extracted for every subset. Then, using the randomly chosen samples and features, an incomplete decision tree can be created. Finally, each decision tree's output result can be combined, and voting is used to determine each sample's final categorization outcome.

AdaBoost

Schapire and Freund first presented the AdaBoost classification method in 1995. AdaBoost's primary concept is to create a powerful classifier by combining weak classifiers with appropriate weights [22, 23]. Several iterations can be used to calculate the weighted value. For instance, the sample's weights will be raised if it is placed in the incorrect class, and vice versa.

XGBoost

XGBoost is the final algorithm used in this investigation. This algorithm's basic concept is quite similar to GBDT's. By iterating the prior classifier, they are both attempting to create a powerful classifier. The following two factors show how XGBoost and GBDT differ from one another. First off, according to GBDT, there is more to XGBoost's objective function than just a loss function. The decision tree will add a new term $\Omega(h(x; s))$ after the loss function to make it simpler. Second, only the first order gradient of the loss function is fitted by the tree in GBDT. But by using both the first and second order gradients in place of the first order gradient, XGBoost will produce a new option.

Models of Multi-Output Regression

The following time series linear regression model is taken into consideration in the analysis at the national level:

$$Y=W\cdot X+b$$

Where,

Y stands for multi-output goal variables (such as performance rating, battery life, speed, or price range).

X= Input features extracted from customer reviews (e.g., sentiment, specific keywords, ratings, etc.).

W= Weight matrix mapping inputs to outputs. b= Bias vector for each output.

K-Means Clustering Model

Creating a model of the MoE kind that can answer binary (yes/no) queries is rather easy. A binary prediction about whether the question is justified by the review's content must be provided by each of the "experts", or reviews. Additionally, to do this, we employ a bilinear scoring system:

ψ(q)=(q, r) ψ(r) equals vΘ0 The formula for ϑ 0+ψ(q)XY T ψ(r) T

Even though their topologies are similar, this is not the same as the function of significance. To vote on a binary outcome, determines the weight or relevance of this vote. These summaries support a positive or negative answer viewpoint which is indicated by the positive/negative v(q, r).

Inputs (XXX)

Customer reviews are analyzed using Natural Language Processing (NLP) to extract features like:

- *Sentiment analysis:* A score reflecting positive or negative sentiment about the scooty.
- *Mention frequencies:* How often the review mentions battery life, speed, or performance.
- *Keywords:* Words associated with specific features (e.g., "long-lasting battery").

Outputs (YYY)

Predicted recommendations based on reviews:

- *Price range:* Affordable, mid-range, or premium.
- *Battery life:* Predicted duration in hours.
- *Performance rating:* Speed and overall use.

Weights (WWW)

Defines how much each input feature contributes to predicting each output. This model can be trained using data from customer reviews and corresponding real-world data (e.g., actual prices, performance metrics) using techniques like linear regression, neural networks, or ensemble methods.

Latent Dirichlet Allocation

Often used for topic model fitting, Latent Dirichlet Allocation (LDA) is a well-liked generative probabilistic technique [18]. Each document is a collection of topics that have been sampled for that document, and each topic is a collection of words. These are the two fundamental foundations upon which LDA is based. Baptista *et al*. define LDA's modeling procedure as [19]:

∑K j=1=P(wi|d) The formula P(wi|ki=j)P(ki=j|d)

Where,

The probability of the ith word in a given document is expressed as P(wi|d).
The wi's probability in subject k is P(wi|ki=j).
The probability that a word from subject k in the document will be selected is P(ki=j|d).

Since each subtopic is defined by words based on another probability distribution that means to (P(w|d)), the goal is to find a group of subjects in each document that mean P(w|d) and P(k|d) are found using LDA by estimating the probabilities of words and topics given a document, respectively.

In addition to the pre-selected number of topics (K), Dirichlet priors are used for the necessary distributions [19]. Some researchers typically interpret the top 20 most related words for each topic after fitting topic models and then give each topic a "descriptive label" for presenting purposes. Xing *et al*. caution researchers that after topic modelling, they will probably encounter low-quality topics that are "mixed" (i.e., contain subsets of words from more than one topic), "identical" (i.e., have the same terms semantically in two topics), or "nonessential" (i.e., irrelevant subjects) [24]. It is advised that inferior themes be divided, combined, or left out.

Analysis of Polarity

User attitude (i.e., positive, neutral, or negative) toward the identified factors of satisfaction was interpreted using dictionary-based polarity classification. Classifying thoughts according to the emotions expressed in the text is known as polarity classification, and it may be applied to reviews of various levels, including words, sentences, and documents [24]. Classification based on dictionaries is one of the most often used sentiment analysis techniques. Using predetermined labeled lists of words (lexicons) that describe the words' associated sentiment degree or value is the foundation of this approach [20]. The R package "sentiment" is used to perform polarity analysis [25]. In this case, the polarity value is calculated using the methods introduced by Rinker [21].

Showing the reviews according to polarity values for each issue is the primary goal. It is evident that subjects typically feature good thoughts. However, as seen by the height of the bar in each area of the graph, some themes are somewhat more positive than others, including ease of use, app issues, safety (speed and riding lane), and safety (technical issues). Furthermore, as the aforementioned analysis demonstrates, women are primarily looking for positive or negative feedback on online purchasing platforms [22, 23, 26–29]. The results support previous research by demonstrating that female riders tend to express more favorable feelings than male riders.

RESULT ANALYSIS

In this study, the model was trained using 75% of the data, with the remaining 25% being used for testing. The precision-recall (P-R) and receiver operating characteristic (ROC) curves for the models: The true positive and false positive rates are displayed on a ROC curve [30–33]. The number of NHRs that were misidentified was divided by calculating the false positive rate as HR by the total number of valid NHR analyses. The true positive rate is the proportion of HR that is correctly identified by the model. The performance of the model on unbalanced datasets is commonly evaluated using a P-R curve, which offers precision and recall information. Accuracy is the proportion of HR projections that were generated correctly or with high precision.

The substantial area-under-curve (AUC) of all four models suggests that they can generally detect the HR and NHR. The P-R curves showed that the four machine learning models (RF, XGBoost, AdaBoost, and GBDT, respectively) had average precisions of 0.683, 0.686, 0.705, and 0.719 on the testing dataset. According to the results, GBDT appears to be the most successful model since it can more precisely estimate e-bike riders' heart rates.

Additionally, the criteria can be further adjusted to reduce the recall and provide even greater precision for e-bike users' heart rates. Samples make up the testing collection; 1,651 of them are HR riders, while 17,958 are NHR riders. In Table 1, the outcomes of the improved GBDT model forecast are displayed.

The research approach is divided into four main steps. The Latent Dirichlet Allocation (LDA) model, a popular topic modeling technique, and Term Frequency-Inverse Document Frequency (TF-IDF) were initially utilized to uncover the underlying thematic patterns in e-scooter app store reviews. After that, we used polarity analysis to categorize reviews under each extracted topic in order to investigate attitudes across topics.

Table 1. Table of confusions for HR-high risk and NHR-non-high risk in the modified gradient boost decision tree (GBDT) model.

NHR rider	HR rider	Threshold	Evaluation index
17,829	129	0.959	Recall =0.569
263	388	0.959	Precision =0.750
17,682	276	0.909	Recall =0.700
196	455	0.909	Precision =0.622

Third, we created topic coexistence networks to determine the ways in which various review themes coexist. For a subsample of app reviews, we also used a unique method called centered gender prediction to identify the gender of the user and ascertain whether review themes and attitudes differ by gender. In order to look at the main elements influencing rider satisfaction for both genders, we lastly created logistic regression models to look into the thoughts and experiences of e-scooter riders and assess their attitude or level of pleasure [34–39].

Furthermore, the influence of gender as an attribute pertinent to riding pleasure and happiness has been the subject of relatively few studies. Therefore, evaluating the elements that affect user or rider happiness allows one to assess rider demands, willingness to ride, and present and future obstacles to e-scooter availability. In the end, these findings give businesses, planners, and legislators the knowledge they need to put into practice a unified, consistent, and successful plan for enhancing the e-scooter experience. Due to the limited application of conventional methods (such as surveys), factors influencing rider satisfaction are still poorly understood.

In this comprehensive analysis of various studies, previous studies on e-scooter adoption have concentrated on users' perceptions related to anticipated use. For this reason, researchers investigating e-scooters have mainly utilized survey-based methodologies and used descriptive statistics, regression analysis, and structural equation modelling. Nevertheless, understanding shared e-scooter experience is still challenging since researchers have no common language.

These result analyses provide the value to our continued support and collaboration in the journey to create efficient, sustainable, and user-friendly e-bikes.

CONCLUSION

This research work focused on developing a customer-centric approach to electric scooter purchasing by utilizing customer recommendation and feedback. The main objective was to close the gap between product offerings and consumer preferences in order to increase customer loyalty and happiness.

Our findings highlight the critical role of integrating customer reviews and recommendations into the decision-making process. By incorporating real time feedback, the proposed app fosters transparency, builds trust, and aligns product offering with customer desires.

The system not only processes but also strengthens the relationship between the brand and its customers, ultimately driving sustainable growth in the electric scooter market and enhancing customer loyalty. The study scores the importance of leveraging technology to create meaningful customer interactions, paving the way for a more personalized and efficient purchasing experience.

This piece demonstrates how technology can improve the consumer journey in a revolutionary way. Businesses can develop individualized experiences that connect with their audience by giving priority to user preferences and recommendations. Moreover, the proposed app contributes to a sustainable future by promoting electric mobility solutions tailored to the evolving needs of modern consumers.

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