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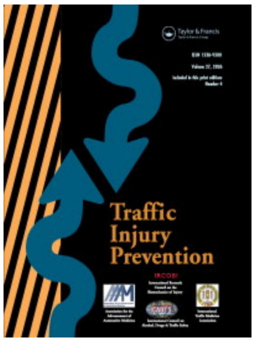

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LSTM-based classification of e-scooter trajectory features for single vs tandem riding detection

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ABSTRACT

Objectives: Dockless electric scooters (e-scooters) have emerged as a popular mode of short-distance transportation in urban environments, offering convenience and flexibility in rental and usage. However, users often engage in unsafe behaviors while riding, posing risks to themselves and others. In this study, we aim to identify unsafe riding behaviors through analysis of riding trajectories, to reduce safety incidents and promote safer e-scooter usage.

Methods: This study explores the classification of single and tandem e-scooter riding behaviors using a data-driven approach. Leveraging trajectory data from Gothenburg, Sweden, collected over 11 days in November 2023; we utilize Long Short-Term Memory (LSTM) neural networks to analyze dynamic temporal features.

Results: The LSTM model demonstrated significant performance advantages over both RNN and Random Forest models, achieving an accuracy of 92.65%, precision of 91.69%, recall of 93.85%, F1 score of 95.56%, and an AUC of 0.9169.

Conclusions: Additionally, optimizing the input sequence length to 240 s of continuous trajectory features balanced computational efficiency with prediction accuracy and stability. Dynamic trajectory features such as acceleration, turning angle, speed, and start SOC play pivotal roles in differentiating riding patterns. The proposed method can assist city authorities and e-scooter operators in real-time risk detection, operational monitoring, and targeted safety interventions, contributing to safer shared micromobility systems.

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KEYWORDS
E-scooter; data-driven method; LSTM; tandem riding

Introduction

Dockless electric scooters (e-scooters) have gained popularity as a convenient and efficient mode of short-distance transportation in urban areas. With the flexibility to be rented, picked up, and returned at various locations throughout the city, e-scooters have effectively bridged significant demand-supply gaps in public transportation markets.

Previous studies have extensively compared e-scooters and bicycles in terms of their role in last-mile transportation. These studies have analyzed various aspects such as user preferences (Nikiforiadis et al. 2021), travel characteristics (Yang et al. 2021), and their competitive and complementary roles in the market (Almannaa et al. 2021). With the rapid expansion of e-scooters, there has been increasing attention paid to the impact of regulatory policies governing their deployment and usage. Governments are implementing measures to regulate the number and spatial distribution of e-scooters in urban areas (Riggs et al. 2021). Operators have focused on optimizing efficiency through improvements in battery performance (Kim et al. 2024) and reducing operational costs (Button et al. 2020; Dias et al. 2021; Latinopoulos et al. 2021).

Despite their popularity, the safety concerns surrounding e-scooters have garnered increasing public attention. Alongside the surge in e-scooter usage, there has been a notable increase in injuries and fatalities involving these vehicles (Karpinski et al. 2023). Fitt and Curl (2019) conducted a survey of Lime e-scooter users in New Zealand cities, revealing that more than 90% of the 536 respondents had used e-scooters in daily life, and safety concerns ranked highest among reasons cited for not using e-scooters. Kazemzadeh (2025) conducted an online video-based experiment involving 920 e-scooter users in Sweden to evaluate their safety perceptions when interacting exclusively with cyclists. The findings reveal that women report feeling less safe in shared spaces compared to men, while young adults perceive meeting interactions as more unsafe than overtaking scenarios. Some researchers have conducted surveys or observational studies to explore the impacts of e-scooter riders conflicting with vehicles and other vulnerable road users (Sikka et al. 2019; Yang et al. 2020). Operators and governments have proposed various measures to enhance safety in response to these concerns. For instance, requiring riders to

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wear helmets (Siebert et al. 2021), prohibiting teenagers and children from riding e-scooters (Kjærup et al. 2021), and implementing bike lanes for e-scooters (Anke et al. 2023) are among the suggested measures.

Although significant efforts have been made by governments and operators, user misconduct continues to pose safety risks, such as riding under the influence of alcohol or drug (Mehdizadeh et al. 2023), using smartphones while riding (Gioldasis et al. 2021), and engaging in tandem riding on the same e-scooter. Current research heavily relies on survey data and questionnaires to analyze which user characteristics and trip patterns are more prone to engaging in these risky behaviors. However, there is a need to adopt data-driven approaches, such as real-time trajectory analysis, to detect abnormal driver behaviors. In addition, research on tandem riding remains under-explored. Tandem riding refers to two individuals sharing the same e-scooter. It differs from single riding by potentially increasing weight, affecting vehicle control, and promoting unsafe riding practices. It imposes significant safety risks, especially on narrow roads, slopes, or during abrupt maneuvers, potentially increasing collision and injury risks. Therefore, this paper proposes a data-driven model to identify anomalous trajectory patterns and unsafe tandem riding behaviors. The contribution of this work is as follows.

- This is the first study that classifies single and tandem e-scooter riding based on a data-driven method.
- This paper utilizes the Long Short Term Memory (LSTM) model to identify anomalous trajectory patterns based on temporal features.

The remaining paper consists of four sections. The second section discusses relevant existing work for e-scooters. The third section provides a detailed explanation of the data collection and preparation process. The fourth section presents an overview of the framework and methodology used in this study. In the fifth section, the results of the data analysis are exhibited. Lastly, the sixth section summarizes the conclusions drawn from this research.

Literature review

We first analyze e-scooter trip characteristics, then examine safety issues associated with e-scooters, and finally analyze their operations and related policies.

E-scooters are one of the latest additions to shared micromobility modes. Researchers have analyzed demand patterns for e-scooters and compared these patterns with those of other micro mobility services, such as bike-sharing (Liu et al. 2019; McKenzie 2019; Reck et al. 2021). Nawaro (2021) found that there was little difference between the speeds of e-scooters and bicycles and that the placement of bicycle docks influenced the number of e-scooter trips, indicating that they competed for the same market. E-scooter trip data also showed that they complemented rapid public transport and might help address the last-mile problem (Kobayashi et al. 2019). Kazemzadeh and Sprei (2024) examined the effect of shared e-scooter programs on modal shift in Sweden and found that e-scooter users achieved a 46% modal shift for short trips, indicating a substantial replacement of other transport modes. Laa and Leth (2020) differentiated between two basic groups of e-scooter users: renters and owners. While e-scooter trips in both groups primarily replaced walking and public transport, e-scooter owners also exhibited a significant shift from private car trips. Abouelela et al. (2023) found that trip characteristics such as speed, duration, and distance were remarkably consistent across the five North American cities studied. Hosseinzadeh et al. (2021) employed a spatial analysis approach, Geographical Weighted Regression (GWR), to examine how factors such as demographics, density, diversity, design, urbanism scores, distance to transit, and other transportation-related variables influenced e-scooter trips in Louisville, KY.

The rapid growth of e-scooter services also causes significant operational challenges. E-scooters inevitably require overnight charging and spatial repositioning (or rebalancing) to better meet demand the following day. Osorio et al. (2021) developed a systematic optimization approach to address the joint decision-making process for charging and rebalancing operations in e-scooter systems, incorporating a hybrid method of discrete inventory routing and continuous approximation to handle large-scale problems effectively. Masoud et al. (2019) developed a mixed integer linear programming (MILP) model and adapted the college admission algorithm (ACA) to solve the E-Scooter-Chargers Allocation problem, minimizing chargers' travel distance. Deveci et al. (2023) developed a hybrid fuzzy multi-criteria decision-making model combining the Logarithmic Methodology of Additive Weights (LMAW) and the Ranking of Alternatives through Functional mapping of criterion sub-intervals into a Single Interval (RAFSI) method to determine optimal e-scooter parking locations. The hybrid operation with geo-fencing hubs in primary catchment areas of public transportation was the most practical and environmentally friendly solution for sustainable e-scooter parking operations.

E-scooters are a highly debated mode of urban transportation, often deemed unsafe due to poor visibility and the absence of dedicated lanes (Benhamed et al. 2022; Della Mura et al. 2022; Gehrke et al. 2022). Busby et al. (2020) analyzed the perceived risks associated with e-scooter use. They found that using e-scooters on pavements was thought to endanger pedestrians, while riders were considered vulnerable on roads due to limited visibility of cars and lorries and concerns about vehicle stability. Benhamed et al. (2022) conducted a cross-sectional analysis of e-scooter and bicycle riders injured in traffic collisions using data from the Rhône Road collision registry. The study found that most e-scooter and bicycle road collisions resulted from falls or loss of vehicle control.

Another significant concern is that many countries do not require a driving license for their use or rental. Additionally, helmet use is not consistently mandated, and even when it is, compliance is often low (Currans et al. 2022). Riders may also exhibit risky behaviors, such as driving under the influence of alcohol or drugs or double-riding on a single vehicle. Andersson and Djärv (2023) included all patients involved in electric scooter accidents that required visits to emergency departments across Stockholm, Sweden. Among them, 102 individuals (28%) had a documented history of alcohol consumption prior to the incident. Kültür et al. (2023) aimed to describe the demographic characteristics and fracture patterns of patients admitted to the emergency department following an e-scooter accident. The study also identified that alcohol use and recreational scooter use rates were statistically higher in patients who required surgery compared to those treated conservatively.

Despite extensive research on e-scooter trip characteristics, operational challenges, and safety issues, notable gaps remain. Specifically, there is limited focus on the safety risks of tandem riding and a reliance on self-reported survey data, which can be biased. Additionally, while operational optimization has been explored, technological interventions for safety enhancements are underrepresented. This paper addresses these gaps by developing a data driven model to classify single and tandem e-scooter riding and identify anomalous trajectory patterns, offering new insights into improving e-scooter safety.

Data description

Riding data is collected from five testers in Gothenburg, Sweden. The data were gathered over 11 days in November 2023; all during the daytime with good visibility and clear weather conditions. Records included trajectory ID, timestamp, latitude, longitude, altitude, vehicle type, start SOC (State of Charge), end SOC, rider ID, riding type, and rider weight. Sample data from the riding dataset is presented in Table 1.

The study area is shown in Figure 1. Due to the undulating terrain of Gothenburg, the energy consumption of vehicle trips varies not only with distance but also due to uphill and downhill gradients. As shown in Figure 1, the yellow color indicates higher altitudes, while the blue color represents lower altitudes.

The dataset includes three vehicle types: Ninebot, Bolt, and Niu. According to the vehicle design specifications, when the battery is fully charged and operating at a speed of 20 km/h, Ninebot can travel up to 65 km, while Bolt can cover 50 km. Initially, Niu had a range of 45 km when fully charged. However, after two years of use, its practical range has been reduced to approximately 30 km. This diversity is consistent with real-world deployment practices, where operators often maintain mixed fleets composed of multiple vehicle generations to accommodate operational and logistical needs. Even within a single vehicle model, performance can vary due to aging components or battery degradation. Including multiple scooter types in our dataset allows the model to capture this realistic variation, improving its robustness and applicability. To account for such variability, vehicle type was encoded as a categorical input in the classification model and considered in the exploratory analysis phase.

The dataset contains 226 trips in total, with 5 trips involving tandem riding. The travel distance is calculated by Haversine 3D formula, which calculates the 3-Dimensional distance between two points on Earth given their latitude, longitude, and altitude (Mahmoud & Akkari 2016). We first calculate the 2-Dimensional distance between two points on Earth's surface using the Haversine formula. The 3-dimensional travel distance is then calculated by incorporating the altitude difference. Supplementary Appendix Table A1 presents the statistical analysis of the trips.

To ensure full compliance with the General Data Protection Regulation (GDPR), several safeguards were implemented during data collection and processing. All participating testers provided informed consent prior to data acquisition. Each rider was assigned a pseudonymous identifier, and no personally identifiable information (PII), such as names, contact details, or device IDs, was collected or stored. The dataset was used exclusively for academic research purposes.

Methodology

The framework of the riding type identification is shown in Figure 2. We use the total trip data to perform regression on the partial trip energy consumption and then proceed to classify the riding type based on the extracted features such as estimated energy consumption, speed, acceleration, slope angle, and turning angle.

Regression model

In this study, we introduce a Lasso Regression model to predict partial trajectory trip energy consumption during specified periods. The need arises from the substantial storage space and computational resources required to process complete trajectory data for identifying abnormal trajectories. To improve data processing efficiency and computational speed, we propose using partial trajectory data to determine riding types (e.g., single rider vs. tandem rider). Key features extracted from partial data segments, such as speed, acceleration, and elevation change, are incomplete without a critical index on partial trajectory energy consumption over a given period. Thus, we aim to develop a regression model to

Table 1. Sample data from riding data.

Timestamp	Altitude	Vehicle Type	Rider	Riding Type	Weight
2023/11/22 08:09:22	10.6	Bolt	Rider1	Single	80
2023/11/22 08:09:23	10.7	Bolt	Rider1	Single	80
2023/11/22 08:09:24	10.9	Bolt	Rider1	Single	80
2023/11/22 08:09:25	11.1	Bolt	Rider1	Single	80
2023/11/22 08:09:26	11.1	Bolt	Rider1	Single	80
2023/11/22 08:09:27	11.2	Bolt	Rider1	Single	80
2023/11/22 08:09:28	11.2	Bolt	Rider1	Single	80

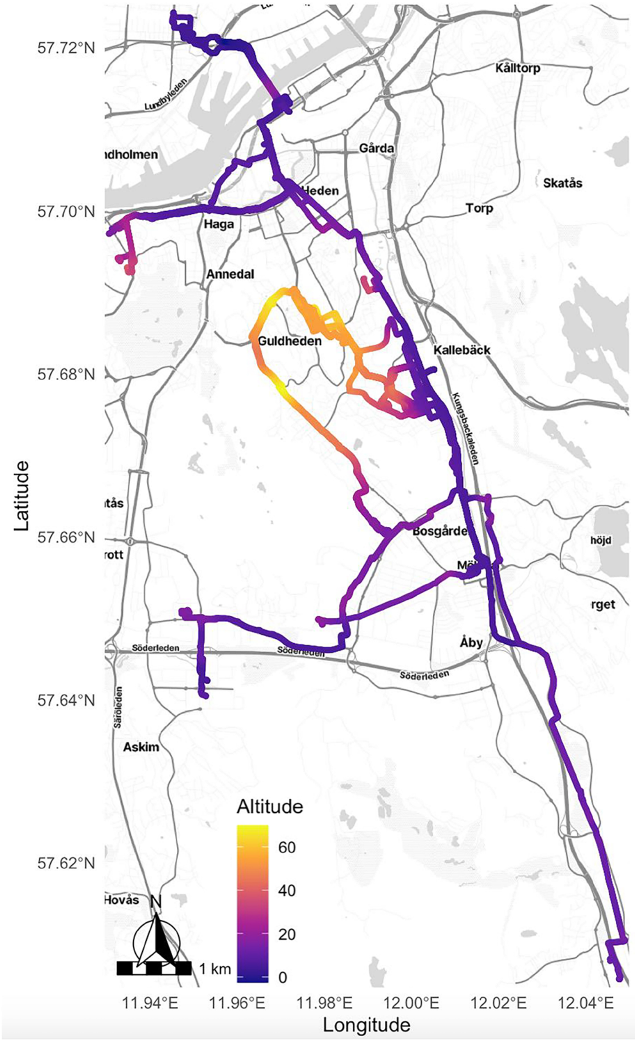

Figure 1. The study area of the city of Gothenburg.

estimate energy consumption based on partial trajectory data features, laying the foundation for subsequent abnormal trajectory identification.

Lasso Regression offers several notable advantages in regression analysis. Firstly, it facilitates effective feature selection by shrinking the coefficients of less important or irrelevant features to zero, thereby promoting model simplicity and reducing the risk of overfitting. Secondly, it addresses the issue of multicollinearity by preferentially selecting one feature from highly correlated ones and nullifying the coefficients of the others. This characteristic enhances model interpretability by focusing on the most influential predictors. Additionally, Lasso Regression promotes model generalizability, ensuring robust performance on unseen data. Its propensity for producing sparse models, where only a subset of predictors are active, further enhances computational efficiency and reduces storage requirements, making it particularly suitable for large-scale and high-dimensional datasets.

The Lasso Regression model can be formulated as follows:

$$\hat{\beta}^{lasso} = \arg\min_{\beta}\left\{\frac{1}{2n}\sum_{i=1}^{n}\left(y_i - x_i^{T}\beta\right)^2 + \lambda\sum_{j=1}^{p}\left|\beta_j\right|\right\} \quad (1)$$

where:

x_i: the predictor vector for the i-th observation;

y_i: the observed response for the i-th observation;

β: the coefficient vector to be estimated;

λ: the regularization parameter controlling the penalty on β.

Here, $\breve{\beta}^{lasso}$ represents the estimated coefficient vector in the Lasso Regression. The objective function combines a least squares loss term with an ℓ_1-norm penalty term on the coefficients, where λ controls the tradeoff between model simplicity (fewer non-zero coefficients) and goodness of fit to the data.

Classification model

We employ a Long Short-Term Memory (LSTM) neural network to classify riding types based on extracted features from e-scooter data. The LSTM model is well-suited for riding-type classification tasks due to its ability to leverage the characteristics of time-series data, learning and extracting temporal patterns automatically. For instance, variations in speed and acceleration patterns may differ between single and tandem riding, and the LSTM can capture and distinguish these patterns. Additionally, changes in turning angles

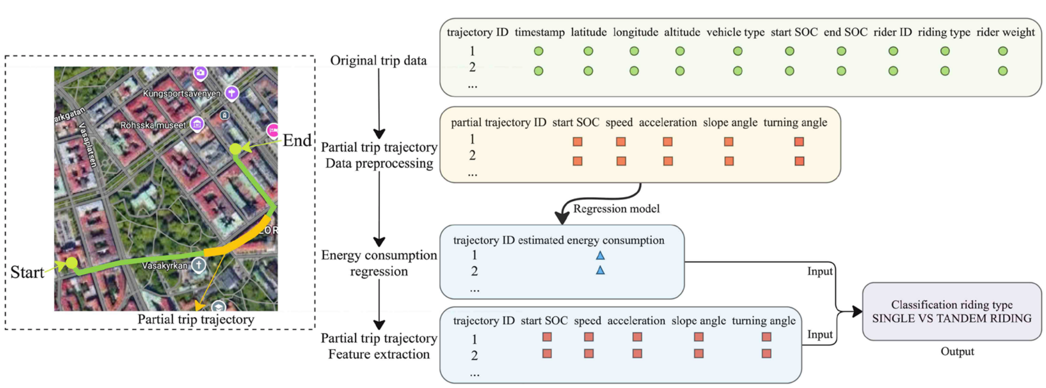

Figure 2. The framework of the riding type classification.

might indicate different riding styles, which the LSTM can learn and utilize. By modeling time-series data, the LSTM effectively classifies and differentiates between single and tandem riding, thereby achieving accurate classification results.

The LSTM model architecture follows a sequence of input data through an LSTM layer that processes and remembers information over time, followed by an output layer that produces the final predictions or classifications. The LSTM cell is shown in Supplementary Appendix Figure A1.

The LSTM layer is the core of the model where the LSTM units process sequential data. Each LSTM unit maintains a cell state that can store information over long sequences, allowing the model to learn long-term dependencies. The LSTM layers can be stacked to create deeper networks for more complex tasks. The forward pass through each LSTM cell at timestep t can be represented as:

$$i_t = \sigma\left(W_{xi}x_t + W_{hi}h_{t-1} + b_i\right) \tag{2a}$$

$$f_t = \sigma\left(W_{xf}x_t + W_{hf}h_{t-1} + b_f\right) \tag{2b}$$

$$g_t = \tanh\left(W_{xg}x_t + W_{hg}h_{t-1} + b_g\right) \tag{2c}$$

$$o_t = \sigma\left(W_{xo}x_t + W_{ho}h_{t-1} + b_o\right) \tag{2d}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot g_t \tag{2e}$$

$$h_t = o_t \odot \tanh\left(c_t\right) \tag{2f}$$

where:

x_t: the input at timestep t;

h_t: the hidden state at timestep t;

i_t: the input, forget, cell, and output gates respectively;

σ: the sigmoid activation function;

$\odot$: element-wise multiplication;

W and b: the weights and biases of the LSTM cells.

Numerical experiments

Energy consumption estimation

The independent variables used in the energy consumption estimation model were selected based on prior studies on e-scooter and micromobility energy modeling. Gioldasis et al. (2024) demonstrated that travel distance, velocity, and acceleration patterns are key predictors of energy consumption, with additional influence from battery aging. Prati et al. (2021) further highlighted that uphill travel and steep road gradients significantly increase energy usage. Hieu and Lim (2023) provided simulation-based evidence that rider weight, vehicle mass, wind resistance, and slope grade substantially affect energy dynamics. Building upon these findings, we selected the following variables: (1) Rider weight, to reflect load-related energy demand; (2) Total uphill and downhill distances, to capture elevation-related resistance; (3) Travel distance and time, which jointly serve as proxies for velocity and trip intensity; (4) Start SOC, to account for battery condition at departure; and (5) Vehicle type, to control for inter-model differences in motor efficiency and degradation. This variable set allows the model to incorporate both physical resistance factors and scooter-specific operational heterogeneity. We compare the performance of Linear Regression, Ridge Regression, and Lasso Regression using Mean Squared Error (MSE) and the coefficient of determination (R^2) as evaluation metrics. Table 2 shows the regression results for the models.

- Linear Regression: A basic regression model that attempts to establish a linear relationship between the independent variables and the dependent variable (Montgomery et al. 2021).
- Ridge Regression: A linear regression model that includes a regularization term (L2 penalty) to prevent overfitting by shrinking the coefficients of less important features (McDonald 2009).
- Lasso Regression: Similar to Ridge Regression, but uses an L1 penalty, which can lead to sparse models by setting some coefficients to zero, effectively performing feature selection (Ranstam and Cook 2018).

Lasso regression obtains the best results with an MSE of 17.9425 and R^2 of 0.8036. The regression equation is as follows:

$$\begin{aligned}\mathrm{Energy\_consumption} &= 11.0885 + \left(1.4843 \times \mathrm{rider\_weight}\right)\\ &+ \left(2.1415 \times \mathrm{total\_uphill}\right) + \left(-1.1917 \times \mathrm{total\_downhill}\right)\\ &+ \left(4.6139 \times \mathrm{travel\_distance}\right) + \left(-0.0000 \times \mathrm{travel\_time}\right)\\ &+ \left(-0.6686 \times \mathrm{start\_SOC}\right) + \left(-0.0000 \times \mathrm{vehicleType\_Bolt}\right)\\ &+ \left(-1.4654 \times \mathrm{vehicleType\_Ninebot}\right) + \left(2.7600 \times \mathrm{vehicleType\_Niu}\right)\end{aligned} \tag{3}$$

From the regression equation, we can conclude that as the rider's weight and travel distance increase, the energy consumption also increases. Additionally, energy consumption rises when riding uphill and decreases when riding downhill. The higher the start SOC, the more energy is available, which is a characteristic of the battery itself. Furthermore, under the same conditions, the vehicle type Niu consumes the most energy, while Ninebot consumes the least. This variation in energy consumption corresponds to the design parameters of the vehicles.

Hyperparameter settings

The trajectory data comprises six features recorded each second: start SOC, speed, acceleration, slope angle, turning

Table 2. Regression results for linear regression, ridge regression, and lasso regression.

Model	MSE	R^2
Linear Regression	19.3292	0.7884
Ridge Regression	18.982	0.7922
Lasso Regression	**17.9425**	**0.8036**

angle, and estimated energy consumption. To address the class imbalance between single and tandem riding, we employed a random temporal sampling strategy. For each single-riding trip, five non-overlapping 240-second sequences were randomly extracted, resulting in over 1,100 samples. For tandem riding, 100 segments were extracted per trip from the five available trips, yielding 500 tandem samples. This procedure reduced the original imbalance (1:44) to approximately 1:2.2 and allowed the model to better learn tandem patterns despite limited trip diversity.

The LSTM model consists of an input layer that accepts sequences of 240 timesteps with 6 features each, followed by two LSTM layers with 30 units each. To mitigate overfitting risks due to the small number of unique tandem trips, we applied dropout regularization (rate = 0.2) after each LSTM layer. Additionally, we adopted early stopping with a patience of three epochs based on validation loss, restoring the best-performing weights. These measures jointly improved the model's generalization capability. The final output layer is a dense layer with a sigmoid activation function, yielding binary classification results. The model is trained with the Adam optimizer and optimized using binary cross-entropy loss.

Classification results

This paper evaluates the LSTM classification results using the metrics: Accuracy, Precision, Recall, F1 Score, and AUC (Area Under the ROC Curve).

- Accuracy: The ratio of correctly predicted instances to the total instances.

$$Accurancy = \frac{True\,Positives + True\,Negatives}{Total\,Instances} \tag{4}$$

- Precision: The ratio of correctly predicted positive instances to the total predicted positives.

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \tag{5}$$

- Recall: The ratio of correctly predicted positive instances to all instances that should have been predicted positive.

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \tag{6}$$

- F1 Score: The harmonic means of Precision and Recall.

$$F1\,Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{7}$$

- AUC: Measures the ability of the model to distinguish between classes.

$$AUC = \int_0^1 TPR\left(x\right) \mathrm{d}x \tag{8}$$

We comprehensively analyze the LSTM model's performance across various hyperparameters to assess its efficacy in our study. Table 3 presents a summary of outcomes from experiments that varied epochs, batch size, and learning rate. The results reveal discernible trends in model performance. Increasing the number of epochs consistently enhances key metrics including accuracy, precision, recall, F1 score, and AUC. Specifically, when configured with 40 epochs, a batch size of 32, and a learning rate of 0.001, the LSTM model achieved its peak performance metrics: an accuracy of 92.65%, precision of 91.69%, recall of 93.85%, F1 score of 95.56%, and AUC of 0.9169. This configuration demonstrates robust performance across all evaluated metrics, highlighting the model's capability to accurately classify data.

Table 4 presents the performance metrics of different classification models evaluated in our study. The results demonstrate the LSTM model's superior effectiveness in accurately classifying data compared to other models. Specifically, LSTM outperforms RNN with increases of approximately 1.78% in Accuracy, 1.71% in Precision, 1.81% in Recall, 4.84% in F1 Score, and 1.74% in AUC. Compared to Random Forest, LSTM showed improvements of about 0.69% in Accuracy, 0.50% in Precision, 0.30% in Recall, 2.87% in F1 Score, and 1.48% in AUC. These outstanding results highlight the LSTM model's ability to analyze and classify temporal sequence data effectively, leveraging its capability to recognize and utilize temporal dependencies to enhance classification accuracy and stability.

Time series length

When evaluating the impact of varying time series lengths on classification accuracy, consideration must be given to the richness of data and the variability of features over different time spans. Longer time series can encompass a greater diversity of trip characteristics, notably including changes in slopes, turning angles, and

Table 3. LSTM model performance with different hyperparameters.

Epochs	Batch Size	Learning Rate	Accuracy	Precision	Recall	F1 Score	AUC
30	16	0.0005	0.9123	0.9012	0.9234	0.9076	0.9012
30	16	0.001	0.9087	0.8976	0.9201	0.9045	0.8976
40	16	0.001	0.9178	0.9067	0.929	0.9134	0.9067
40	32	0.0005	0.9215	0.9103	0.9321	0.9179	0.9103
40	**32**	**0.001**	**0.9265**	**0.9169**	**0.9385**	**0.9556**	**0.9169**
50	16	0.0005	0.9201	0.909	0.9312	0.9165	0.909
50	32	0.001	0.9256	0.9142	0.9378	0.9221	0.9142

Table 4. Different classification model results.

Model	Accuracy	Precision	Recall	F1 Score	AUC
LSTM	**0.9265**	**0.9169**	**0.9385**	**0.9556**	**0.9169**
RNN	0.9102	0.9015	0.9218	0.9115	0.9012
AdaBoost	0.8923	0.8856	0.9001	0.8928	0.8805
Random Forest	0.9201	0.9123	0.9357	0.9289	0.9034
SVM	0.9056	0.8978	0.9123	0.9049	0.8987

Table 5. Different input length for classification accuracy.

Time Series Length	Mean	Standard Deviation
90	0.8645	0.0331
120	0.8914	0.0309
150	0.9014	0.0284
200	0.9146	0.0135
240	**0.9265**	**0.0087**

accelerations, which are crucial for discerning ride types. Conversely, shorter time series may not adequately capture significant variations in trip features. Despite this, operational constraints often necessitate effective identification with limited data samples. Therefore, we compare different time series lengths to analyze the stability of results, aiming to identify the most suitable approach for practical applications.

Table 5 summarizes the classification accuracy metrics for various time series lengths. To ensure rigorous evaluation, we conduct 20 training runs to derive average values and compute standard deviations. As the length of the time series increases from 90 to 240, there is a discernible trend toward higher mean accuracy. Additionally, longer time series show reduced standard deviation, indicating greater consistency in classification results. Remarkably, at time series lengths of 150, 200, and 240, their prediction accuracies are comparable, with the 240- time series demonstrating the lowest standard deviation, highlighting its stability.

Feature analysis

In the test set, we randomly select the prediction results of 5 single rides and 5 tandem rides and compare four feature plots: slope angle, turning angle, speed, and acceleration in Figure 3. Due to the slope angle being significantly influenced by the trip route, there is little difference between single and tandem rides, indicating that both types of rides experience similar slope variations. However, the turning angle feature plot clearly shows significant differences between single and tandem rides, with tandem rides exhibiting more frequent or sharper turns, likely due to changes in vehicle handling with two riders. The speed feature plot reveals clear distinctions as well, with single rides displaying more stable speeds while tandem rides show greater variability, possibly because the increased load during tandem riding causes more speed fluctuations. The acceleration feature plot also demonstrates significant differences, where single rides have more consistent acceleration, whereas tandem rides show more variability, consistent with the speed trends. Given our 1-s time interval, the similarity in speed and acceleration further reflects the differing riding states. In summary, while the slope angle shows minimal differences between single and tandem rides, the turning angle, speed, and acceleration features can significantly distinguish between these two riding modes.

Figure 4 illustrates the relative importance of various features in the LSTM model used to distinguish between single and tandem riding modes. The bar chart presents the importance scores of each feature along the x-axis. Among the features, the acceleration feature is identified as the most critical, demonstrating the highest importance score and indicating its substantial influence on the classification task. The start SOC feature also exhibits significant importance, suggesting that users may choose vehicles with higher initial charges for tandem riding, while this factor is relatively less critical for single riding. turning angle and speed features follow in importance, highlighting that trajectory features are crucial for distinguishing between riding patterns. Conversely, slope angle and estimated total SOC show relatively lower importance scores, indicating that these features are more related to the trip itself rather than the riding type, making them less critical for classification. This analysis underscores that dynamic features such as acceleration, turning angle, and speed, along with the start SOC, play pivotal roles in differentiating riding patterns, whereas static or less variable features like slope angle and estimated total SOC are less impactful.

Policy, planning, and safety recommendations

In addition to the model findings, this study holds implications for both policy and safety concerning e-scooter operations. The distinction between single and tandem riding is essential not only for energy efficiency but also for safety considerations. Tandem riding tends to involve higher weight loads, which can affect vehicle stability, braking distance, and maneuverability, potentially leading to increased accident risk. While our model excels in distinguishing between these two riding types, its application can be expanded to inform safety guidelines.

For instance, policy recommendations could involve restricting tandem riding in certain high-risk areas, such as sharp turns or steep slopes, where our analysis identified greater variability in features like acceleration and turning angles. By understanding these dynamics, municipalities can implement real-time safety measures, such as adjusting speed limits or issuing alerts to riders based on the detected riding type. Furthermore, these insights can support the development of safety regulations, particularly regarding vehicle design specifications and rider capacity limits.

However, future work should explore more directly how riding maneuvers differ in terms of safety outcomes, incorporating incident data to refine the model's predictions on

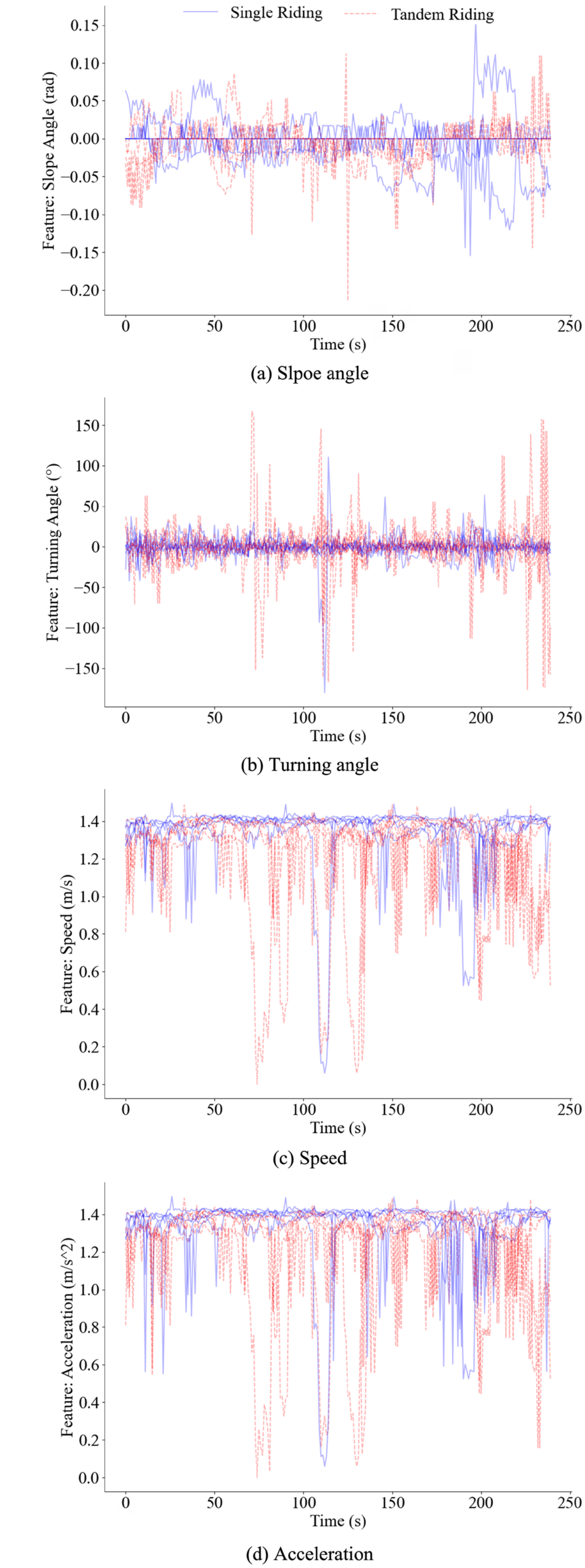

Figure 3. Comparison of dynamic features between single and tandem riding.

riskier behaviors. By doing so, the model could better guide policymakers toward improving both safety and operational efficiency in e-scooter services.

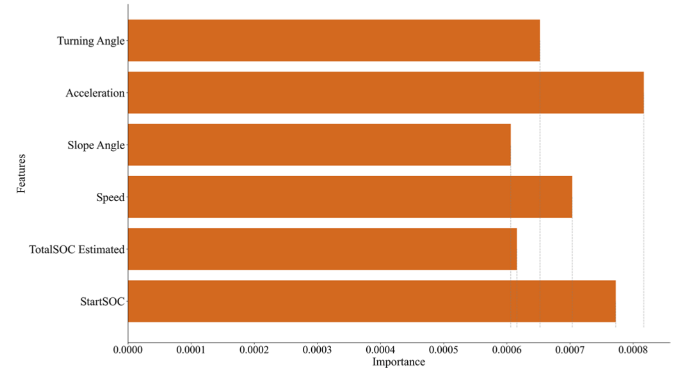

Figure 4. Feature importance analysis from the LSTM model.

Beyond safety enforcement, our findings offer broader implications for urban planners and policymakers tasked with regulating micromobility. First, the classification framework enables cities to identify spatial and temporal patterns of risky riding behavior, which can support data-informed zoning policies (e.g., high-risk zones where stricter riding rules or infrastructure changes are warranted). Second, the model's ability to capture behavioral differences based on slope, rider weight, and vehicle type suggests its utility in guiding infrastructure investment, such as prioritizing smoother pavements, wider lanes, or protective barriers in high-risk corridors. Furthermore, policymakers can incorporate such predictive analytics into adaptive governance models. For example, real-time behavior detection can be used to trigger insurance adjustments, enforce vehicle suspension rules, or update operator scorecards for license renewals. This paves the way for a performance-based regulatory environment that not only improves rider safety but also holds operators accountable for systemic risk. In this sense, our work contributes to the development of more responsive and evidence-driven micromobility governance frameworks.

Discussion

This study advances the existing body of micromobility safety research by addressing the specific yet underexplored behavioral risk of tandem riding on e-scooters. While prior investigations have primarily relied on user surveys, observational studies, or post-collision injury reports to assess riding behavior, these approaches are inherently constrained by subjective bias, limited temporal resolution, and their retrospective nature. In contrast, the present work adopts a data-driven framework utilizing high-resolution trajectory information to enable the real-time classification of riding behavior, thereby offering a proactive approach to risk identification.

The proposed LSTM model exhibits clear advantages over traditional classifiers in distinguishing between single and tandem riding. Its ability to capture long-term temporal dependencies makes it well-suited for analyzing dynamic mobility patterns. The incorporation of sequential features such as acceleration, turning angle, and speed, shown to systematically differ between riding modes, reinforces the model's behavioral sensitivity and practical applicability.

In relation to existing literature, this study makes several notable contributions. First, it represents the first attempt to classify tandem riding behavior using a deep learning approach grounded in temporal trajectory features, thereby expanding the methodological repertoire for behavior detection in shared micromobility systems. Second, the integration of an energy consumption estimation model provides an enriched feature set that enhances both model interpretability and classification robustness. Third, the identification of a moderate input sequence length also demonstrates a viable compromise between computational cost and predictive performance, supporting real-time deployment.

The methodological and practical implications of this research are considerable. From a methodological perspective, the integration of sequential deep learning techniques with physically meaningful trajectory features offers a scalable and transferable framework for the detection of other anomalous riding behaviors, such as erratic braking or riding under influence. From an operational standpoint, the proposed framework provides a foundation for the development of real-time monitoring systems capable of informing policy enforcement and operator-level interventions. These may include automated warnings, dynamic insurance adjustments, or geofencing strategies in high-risk zones.

Conclusion

In conclusion, this study introduces a data-driven approach using LSTM neural networks to classify e-scooter riding types, leveraging partial real-time trajectory data. To enhance efficiency, we selectively utilize real-time trajectory data rather than all trip records. Initially, we employ Lasso regression to predict the energy consumption of partial trajectories over specified periods. Subsequently, utilizing LSTM with dynamic trajectory features, start SOC, speed, acceleration, slope angle, turning angle, and estimated energy consumption, we predict single and tandem riding scenarios. The LSTM model outperforms RNN, Random Forest, AdaBoost, and SVM models with an accuracy of 92.65%, precision of 91.69%, recall of 93.85%, F1 score of 95.56%, and AUC of 0.9169. When assessing the impact of varying time series lengths on classification accuracy, considerations are made for data richness and feature variability across different periods. We compare time series lengths from 90 s to 240 s, finding that a sequence length of 240 s achieves a balance between prediction accuracy and stability. Dynamic trajectory features, including acceleration, turning angle, and speed, as well as the start SOC, are crucial in distinguishing riding patterns. Practically, the proposed classification framework holds potential for integration into operational systems used by e-scooter operators and city authorities. By enabling real-time identification of unsafe riding behaviors, such as tandem use, the model can support targeted safety warnings, insurance assessments, and dynamic regulation enforcement, contributing to improved user safety and micromobility governance.

However, our work has limitations. Primarily, in predicting energy consumption, we train the model solely on single-riding data due to significant differences in energy consumption between single and tandem riding. Consequently, using the regression equation derived from single-riding data to predict energy consumption for tandem riding trajectories leads to notable errors. Additionally, in practical applications, trajectories of single riders carrying heavy loads exhibit similarities to tandem riding, posing challenges in accurately distinguishing between these scenarios. These challenges present opportunities for future research to refine models and methods, thereby advancing the accuracy and practicality of e-scooter anomaly trajectory feature classification.

Authors contributions

The authors confirm their contribution to the paper as follows: study conception and design: JiamingWu, Jiahui Zhao, Sida Jiang; data collection: Jiahui Zhao; analysis and interpretation of results: Jiahui Zhao, Jiaming Wu, Pan Liu; draft manuscript preparation: Jiahui Zhao, JiamingWu, Zhibin Li, Pan Liu, Sida Jiang. All authors reviewed the results and approved the final version of the manuscript.

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