Machine Learning in Micromobility: A Systematic Review of Datasets, Techniques, and Applications

Sen Yan, *Graduate Student Member, IEEE*, Chinmaya Kaundanya,
Noel E. O'Connor, *Senior Member, IEEE*, Suzanne Little, and Mingming Liu, *Senior Member, IEEE*

***Abstract*—Micromobility systems, which include lightweight and low-speed vehicles such as bicycles, e-bikes, and e-scooters, have become an important part of urban transportation, with the potential to address traffic congestion, air pollution, and high transportation costs. Successful utilisation of micromobility requires optimisation of complex systems for operational efficiency, environmental impact mitigation, and user safety. Machine Learning (ML) methods are increasingly used to support prediction and decision-making in these systems. Existing reviews differ in their coverage of micromobility datasets, ML methods, and application settings. This review synthesises 95 studies from January 2019 to July 2024, providing a structured review of datasets, ML techniques, and their applications in micromobility. Specifically, we collect and analyse micromobility-related datasets in terms of their spatial, temporal, and feature-based characteristics. We also review ML models applied in micromobility, discussing their principles, strengths, limitations, and application settings. Furthermore, we examine applications including demand prediction, energy management, and safety, focusing on their evaluation conditions and practical implications. Finally, we identify research challenges and directions related to generalisation, fairness and equity, privacy, public transport integration, model deployment, and operational evaluation.**

***Index Terms*—Micromobility, Dataset, Machine Learning, Intelligent Transportation, Computer Vision**

List of Abbreviations & Acronyms

ARIMA	Auto-Regressive Integrated Moving Average
CNN	Convolutional Neural Networks
DT	Decision Tree
GCN	Graph Convolutional Network
GNN	Graph Neural Network
GRU	Gated Recurrent Unit
KNN	K-Nearest Neighbours
LGBM	Light Gradient-Boosting Machine
LR	Linear Regression
LSTM	Long Short-Term Memory
ML	Machine Learning
MLP	Multi-Layer Perceptron
MLR	Multiple Linear Regression
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RF	Random Forest
RNN	Recurrent Neural Networks
STGCN	Spatio-Temporal Graph Convolutional Network
SVM	Support Vector Machines
XGB	Extreme Gradient Boosting

This publication has emanated from research conducted with financial support from Taighde Éireann — Research Ireland under Grant Nos. *21/FFP-P/10266* and *SFI/12/RC/2289_P2*, and from Dublin City University through the ECIU Seed Programme 2025 under the E-SAMoD project.(*Corresponding author: Suzanne Little.)*

S. Yan was with the School of Electronic Engineering and Insight Research Ireland Centre for Data Analytics, and is now with the School of Chemical Sciences, Dublin City University, Dublin 9, Ireland (e-mail: sen.yan@dcu.ie).

N. O'Connor, and M. Liu are with the School of Electronic Engineering and Rinn Artificial Intelligence at Dublin City University, Dublin 9, Ireland. (e-mail: noel.oconnor@dcu.ie; mingming.liu@dcu.ie).

C. Kaundanya was with the School of Computing and Insight Research Ireland Centre for Data Analytics at Dublin City University, Dublin 9, Ireland. (e-mail: chinmaya.kaundanya3@mail.dcu.ie)

S. Little is with the School of Computing and and Rinn Artificial Intelligence at Dublin City University, Dublin 9, Ireland. (e-mail: suzanne.little@dcu.ie).

I. Introduction

A. Micromobility in Urban Transportation

As cities become more densely populated, demand for efficient and environmentally friendly transport continues to grow. The term "micromobility" has been defined in various ways. In this study, we adopt a working definition consistent with recent conceptualisations [1]–[3], characterising micromobility as lightweight (<350 kg), low-speed (<45 km/h) vehicles designed for short-distance urban travel, including bicycles, e-bikes, and e-scooters. Its growth has been driven by efforts to address traffic congestion, air pollution, and transportation costs [4]–[6]. By providing last-mile connectivity, reducing dependence on private cars, and improving access to conventional public transport, micromobility has become an important component of urban mobility [7]–[9]. Governments and policymakers are therefore increasingly incorporating micromobility into sustainable transport strategies[1][2][3].

B. Conventional Approaches for Micromobility

Conventionally, transport-related problems have been addressed using established statistical, rule-based, optimisation, and engineering-driven approaches, e.g., GIS-based spatial analyses for demand characterisation [10], gravity and network-based formulations for spatial interaction analysis [11], [12], and shortest-path or optimisation algorithms for route planning [13], [14]. However, the suitability of these methods depends on their assumptions and the available observations, including traffic, weather, and vehicle availability. With the increase in high-resolution spatiotemporal data and improved computing and toolchains, Machine Learning (ML)

[1]https://www.gov.ie/en/publication/e62e0-electric-vehicle-policy-pathway
[2]https://highways.dot.gov/public-roads/spring-2021/02
[3]https://www.intertraffic.com/news/urban-mobility/china-mobility-revolution

has increasingly been applied to modelling nonlinear micromobility dynamics and enabling real-time decision support.

C. Machine Learning Methods for Micromobility

ML methods are increasingly used in micromobility to identify patterns from large-scale data and support prediction and adaptive decision-making. They can learn complex relationships from data and update predictions as new information becomes available, supporting responsive analysis of changing micromobility conditions. Applications include demand prediction [15]–[17] and energy management [18]–[20], with potential benefits for vehicle distribution and energy use. Overall, ML can support more efficient, safe, and responsive micromobility systems.

D. Contributions & Paper Structure

While some surveys have discussed ML in broader mobility contexts [21]–[23], existing reviews differ in their coverage of micromobility-specific datasets, modelling assumptions, evaluation protocols, and application settings. This motivates our review of existing datasets, ML techniques, and their applications, as summarised in Fig. 1. The main contributions are:

- A wide range of datasets relevant to micromobility are documented and analysed, providing insights into their spatial, temporal, and feature-based characteristics.
- Various ML models applied in micromobility are introduced, categorised by their principles, advantages, and challenges, and discussed in their specific applications.
- Different applications of ML methods are discussed in key areas of micromobility, such as demand prediction, route planning, and rider safety, together with their evaluation conditions and practical implications.
- Critical challenges in the current application of ML to micromobility are identified, including issues related to fairness and equity, privacy, public transport integration, model deployment, and operational evaluation, along with future research directions to address these issues.

This paper is structured as follows: Section II compares existing micromobility survey papers, followed by the review methodology in Section III. Section IV, Section V, and Section VI review datasets, ML techniques, and applications, respectively. Section VII discusses research directions and challenges, and Section VIII concludes the paper and outlines its limitations.

II. Related Survey Papers

This section positions this review relative to existing survey papers by comparing their scope and coverage, as summarised in Table I. Existing surveys span broader urban mobility systems [3], [24]–[26], mode-specific topics such as bike sharing and e-scooters [27], [28], and specific technical objectives such as e-mobility energy management [29]. However, micromobility is often treated as one component of broader transportation systems or examined through individual modes or applications. Dataset-related issues receive limited attention [25],

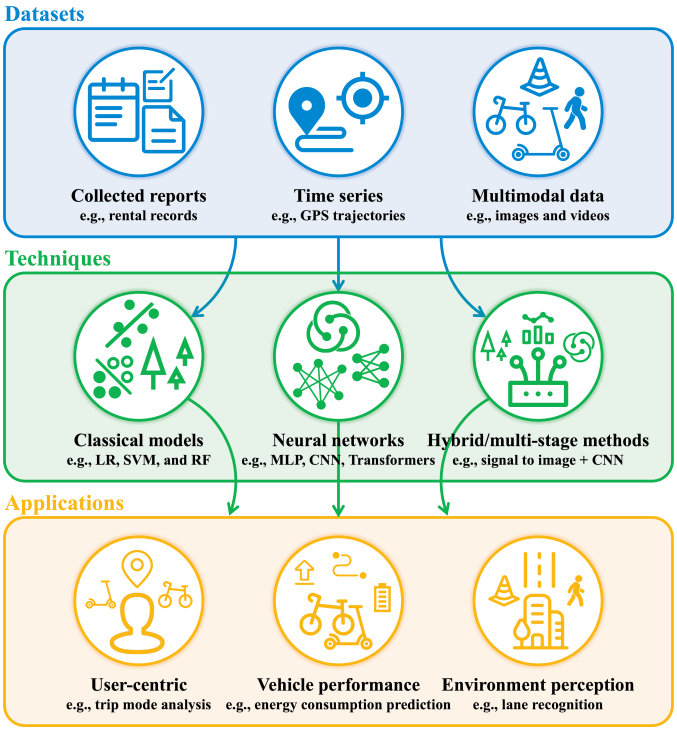


Fig. 1. Research scope in this review paper.

[26], while cross-mode comparison and micromobility-specific demand analysis also remain limited [3], [27], [28]. Recent methodological surveys have also reviewed graph-based and spatiotemporal learning for transportation forecasting [30], but their focus is primarily on graph-learning methodologies rather than the relationships among micromobility datasets, modelling assumptions, evaluation protocols, and application settings.

Cross-comparison of the surveys in Table I reveals three recurring gaps in the existing literature: (1) broader reviews often examine micromobility within general mobility systems and emphasise accessibility, sustainability, or safety rather than micromobility-specific modelling issues [3], [24]–[26]; (2) technically focused surveys tend to concentrate on individual modes or tasks, such as bike-sharing demand prediction [27], e-scooter systems [28], or e-mobility energy management [29], limiting cross-mode and cross-task comparison; and (3) dataset treatment remains uneven, with limited systematic comparison of data modalities, feature structures, and their suitability for different ML tasks.

This review addresses these gaps by placing micromobility at the centre of analysis and synthesising datasets, ML techniques, and application domains within a common framework. It also complements graph-learning surveys by focusing on how micromobility-specific data characteristics, modelling assumptions, validation practices, and application objectives are connected.

III. Review Methodology

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework was used to organise and report the literature identification and screening process

TABLE I
SUMMARY OF RECENT RELATED SURVEY PAPERS.

Ref.	Brief Descriptions	Modalities			Topics				
		bicycle	e-bike	e-scooter	datasets	ML methods	energy analysis	demand analysis	safety
[24]	The impact of micromobility on accessibility, air pollution, safety, physical activity, and subjective well-being.	×	×	×			×		×
[27]	ML techniques in bike-sharing systems, with a focus on usage pattern detection and demand prediction.	×				×		×	
[25]	ML methods in shared transportation systems, with a focus on user analysis, demand analysis, dispatching, and infrastructure planning.	×	×	×	×	×	×		
[26]	ML methods applied to urban transportation, focused on public datasets, passenger localisation, transportation mode detection and pattern recognition, and generative mobility models.	×	×		×	×			
[3]	Journal articles in the Scopus database from 2000 to 2020, focusing on benefits, technology, policy, and behavioural model choices, with a very brief technical discussion.	×	×	×		×		×	×
[28]	The properties of shared e-scooter systems and their impacts on the environment, user social, economic, safety, and transportation performance.			×			×		×
[29]	ML approaches for energy management of e-mobility services.		×	×		×	×		
[30]	Graph neural networks for traffic forecasting, including bike-sharing and e-scooters; graph construction, spatio-temporal models, and open datasets.	×		×	×	×		×	
[∗]	**ML methods applied in shared micromobility, focused on datasets, applications, and methodologies using multimodal data.**	×	×	×	×	×	×	×	×

The last item marked in **bold** represents our work conducted in this paper.

[31]. The review procedure followed the detailed search-reporting guidance in [32]. The methodology is described through the study objectives, eligibility criteria, and search strategy.

A. Study Objectives

The formulation of study objectives is guided by the purpose of the literature review. The review was guided by three research questions:

- What datasets related to micromobility have been published or used in existing research?
- Which ML technologies have been employed in micromobility-relevant research papers?
- Which research problems have these ML methods been applied to address?

These questions structure the review around micromobility datasets, ML techniques, and application domains. Unlike broader surveys in which micromobility is typically considered alongside other transport modes, this review places micromobility at the centre of analysis.

B. Eligibility Criteria

This review focuses on ML techniques applied to micromobility research rather than providing an exhaustive review of ML algorithms. The application scope follows the gaps identified in Section II: demand and destination prediction, travel behaviour, energy management, route and fleet planning, and rider safety. We included peer-reviewed studies applying ML or fitted statistical methods, together with relevant data-driven optimisation and network analyses within this scope, and excluded studies not written in English, focused solely on conventional transport modes, or lacking clear quantitative methods or results relevant to these applications. Datasets recorded in other languages were included when they were used in English-language publications. Eligibility was determined by the research task, fitted model, and evaluation rather than by a strict distinction between statistical and ML methods. Spatial statistical approaches, such as Gaussian processes, geographically weighted regression, and spatial autoregressive models, were not explicitly targeted by the original search terms. Their limited representation in the reviewed corpus therefore should not be interpreted as evidence that such methods are absent from micromobility research.

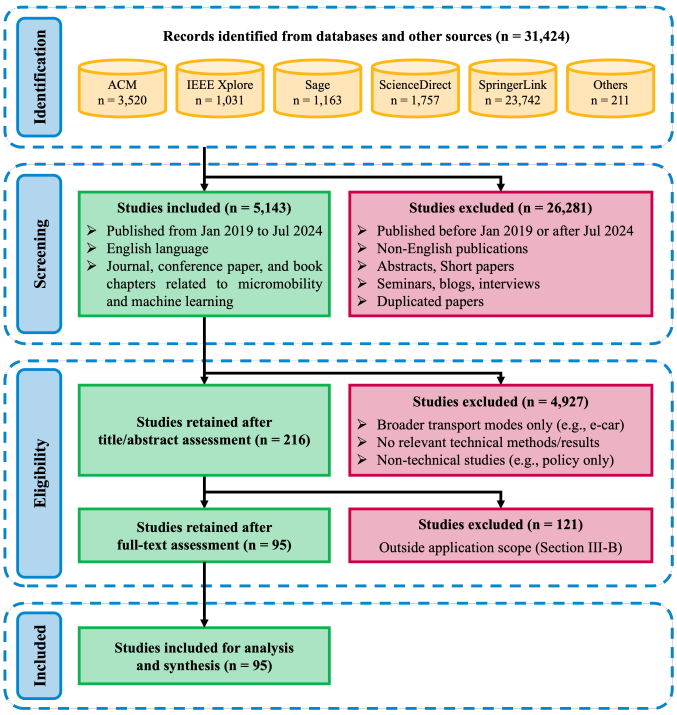


Fig. 2. PRISMA flow diagram for literature review in our study.

C. Search Strategy

We searched the following databases for literature related to computer science and data science: ACM Digital Library (Association for Computing Machinery), IEEE Xplore (Institute of Electrical and Electronics Engineers), MDPI (Multidisciplinary Digital Publishing Institute), SAGE Journals (SAGE Publishing), ScienceDirect (Elsevier), and SpringerLink (Springer Nature). Besides, we also used Google Scholar to capture relevant papers that may not be indexed in the databases above, and Kaggle was consulted for publicly available micromobility datasets.

To ensure comprehensive coverage, multiple synonymous terms and spelling variants were considered during the search process. The core Boolean search structure combined three groups of terms as follows:

> *("micromobility"* **OR** *"micro-mobility"* **OR** *"bike"* **OR** *"bicycle"* **OR** *"e-bike"* **OR** *"bike-sharing"* **OR** *"e-scooter"* **OR** *"e-mobility")*
> **AND**
> *("machine learning"* **OR** *"deep learning"* **OR** *"neural network"* **OR** *"computer vision")*
> **AND**
> *("dataset"* **OR** *"trip history"* **OR** *"demand" OR "resource-constrained"* **OR** *"energy consumption"* **OR** *"safety")*

The search was restricted by publication date only, from January 1, 2019, to July 31, 2024. No additional search-field restrictions were applied. The Boolean query was used across the selected databases, with minor syntax adaptations where required by the individual search interfaces. The retrieved records were subsequently screened through title and abstract assessment followed by full-text eligibility assessment.

Screening was conducted by two reviewers with responsibilities divided by topic. Image- and video-based studies and related computer vision applications were screened separately from the remaining studies. Records were not independently assessed by both reviewers, so no inter-reviewer agreement statistic or formal disagreement-resolution procedure was applied.

Fig. 2 summarises the review process. In total, 31,424 records were identified. After initial screening, 5,143 studies met the criteria for publication date, language, publication type, and general relevance to micromobility and ML. Title and abstract assessment reduced this set to 216 potentially relevant studies. Full-text assessment applied the application-focused scope in Section III, retaining 95 studies and excluding the remaining 121 from the focused synthesis. A study-level evidence table for the 95 included studies, with full bibliographic references indexed S01–S95, is provided in the *Supplementary Material*.

IV. Datasets

This section introduces the micromobility datasets identified in our review and summarises them in Table II, including 15 tabular, 6 image/video, and 1 multimodal dataset for different research tasks. An overview of these datasets is displayed in Fig. 3. Generally speaking, the tabular datasets [33]–[47] usually contain data from multiple sensors attached to micromobility or installed at parking spots, while the image datasets [48]–[54] include pictures or video frames from cameras attached to micromobility or other vehicles. They are sourced from various micromobility devices around the world.

To provide a structured understanding of these datasets, we analyse them from multiple complementary perspectives: **(1) Spatial & Temporal Analysis**, **(2) Vehicle Type Analysis**, **(3) Tabular Dataset Feature Analysis**, and **(4) Image-Based Dataset Analysis**. These perspectives are intended to highlight how different dataset properties support specific analytical objectives and machine learning applications in micromobility research.

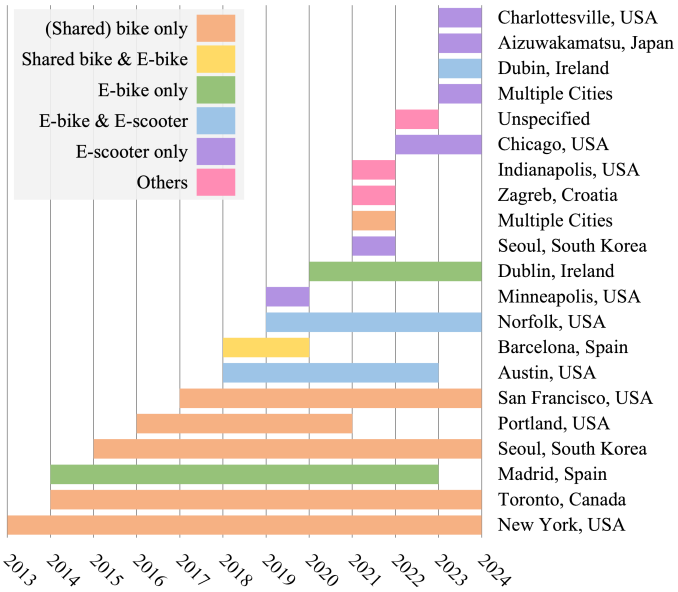


Fig. 3. An overview of the micromobility datasets reviewed.

A. Spatial & Temporal Analysis

Among the 21 datasets for which temporal coverage is shown in Fig. 3, four of the longest-running datasets are [33]–[35], [37], with several remaining ongoing. These datasets are mainly provided by micromobility operators through local open-data portals and provide valuable long-term records for analysing temporal trends and system changes. Twelve datasets span two years or less, with the duration of ongoing datasets calculated up to July 31, 2024. These shorter datasets are more commonly associated with specific research objectives or recent methodological studies, reflecting growing research interest in micromobility.

From a spatial perspective, the reviewed datasets cover North America, Europe, and Asia. The USA contributes datasets from several cities, including New York, San Francisco, Austin, and Chicago. Smaller cities are also represented [46], [51], [52], showing that micromobility data collection is not limited to major metropolitan areas.

Some datasets do not specify an exact collection location. The Pothole dataset [48], [49], for example, was compiled at Stellenbosch University, but its collection location was not reported and is therefore excluded from Fig. 3. Two datasets

are labelled "Multiple Cities". CYCLANDS [44] and the Micromobility Lane Recognition Dataset [53] cover multiple geographical areas, while PolyMMV [54] was constructed from publicly available videos with unspecified geographical coverage. However, geographic coverage across multiple locations does not itself indicate that a model has been trained and evaluated for cross-city or cross-operator generalisation.

B. Vehicle Type Analysis

From the perspective of vehicle type, 6 of the 21 datasets reviewed focus on bicycles or shared bikes, including long-running datasets from Toronto and Seoul. These datasets provide relatively long-term records of bicycle and shared-bike use. Similarly, e-scooter datasets are also well represented in the reviewed literature [39], [40], [45], [51], [52]. Several datasets cover multiple vehicle types [38], [40], [41], [47], [54], including combinations of bicycles, e-bikes, and e-scooters. These mixed-mode datasets enable comparisons across different micromobility vehicle types.

Three datasets are labelled "Others" in Fig. 3. The dataset in [46] was collected through a smartphone application and covers several travel modes, including walking, cycling, and driving. The dataset in [50] contains images of pedestrians and e-scooter riders captured from cars, while [54] integrates publicly available videos rather than using a dedicated vehicle-mounted collection platform.

C. Tabular Dataset Feature Analysis

Most tabular datasets consist of trip or usage records containing four main feature groups: user and vehicle information (e.g., user ID and vehicle type), spatial and temporal data (e.g., departure time and arrival position), trip attributes (e.g., distance and duration), and operational variables (e.g., battery state of charge).

The user and vehicle information recorded varies across data providers but can support analysis of usage patterns and user behaviour. Spatial and temporal features capture mobility dynamics such as peak usage periods, seasonal variation, and spatial demand patterns, while trip attributes describe journey characteristics and system use. Operational variables support fleet and energy management. Among the reviewed electric micromobility datasets, the Moby Bikes dataset [43] records battery state of charge before and after trips, while [47] provides real-time battery state-of-charge information.

D. Image-Based Dataset Analysis

Image-based micromobility datasets are mainly developed for safety-related perception tasks using cameras mounted on e-scooters, e-bikes, or other vehicles. Datasets such as [50], [54] support object detection of pedestrians, vehicles, traffic lights, signs, and other micromobility users. Other datasets include road and infrastructure features such as lanes, potholes, bumps, fences, walls, and traffic cones [48], [49], [51], [53]. The Micromobility Lane Recognition dataset [53], for example, is designed for multilabel classification of the riding environment to support real-time lane recognition.

Existing open-source autonomous-driving datasets [55]–[60] can provide relevant visual information but are not directly transferable to micromobility because of differences in sensing perspective, vehicle motion, and operating environment. E-scooters experience frequent vibration and operate under diverse lighting, weather, and road conditions, which can further affect perception performance.

Nevertheless, these datasets remain useful resources for safety-related research, although autonomous-driving datasets require micromobility-specific validation before direct application to micromobility scenarios.

V. Techniques

This section summarises the ML methods identified in the reviewed papers, as shown in Table III, ranging from single-model approaches (e.g., Linear Regression (LR) and Graph Convolutional Network (GCN)) to hybrid and multi-stage frameworks. The categorisation is literature-driven and reflects how these methods are used and reported in micromobility studies rather than a comprehensive taxonomy of ML.

A. ML Process in Micromobility

This subsection provides an overview of the typical ML workflow as observed in the reviewed micromobility literature. As shown in Fig. 4, the workflow is organised into four conceptual dimensions, i.e., problem, data, model, and knowledge, following prior studies [72], [73]. It covers problem formulation, data preparation, model development, evaluation, and deployment, while reflecting the practical requirements and data characteristics of micromobility systems.

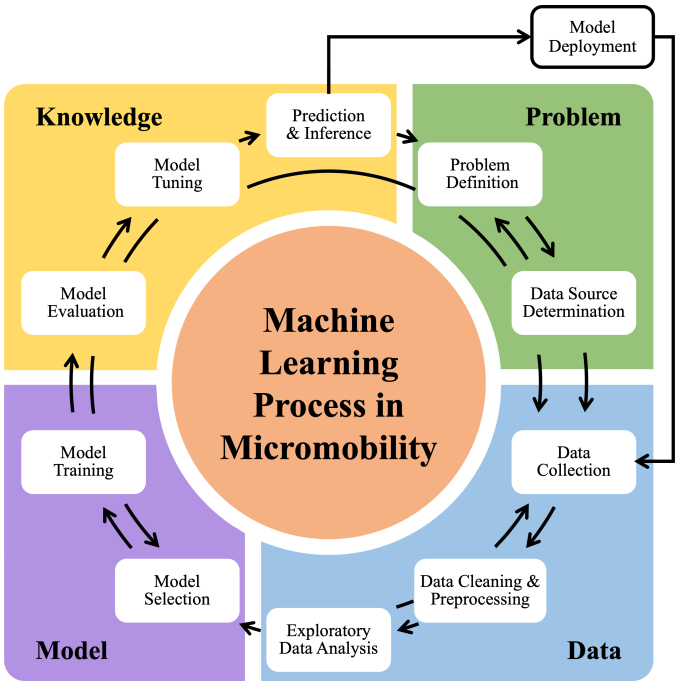


Fig. 4. A typical ML workflow as observed in micromobility studies.

The workflow begins with **Problem Definition**, where the target variable and objectives of the ML task are specified according to the micromobility application. This is followed

TABLE II
DATASETS.

Dataset Name	Year	Size	Vehicle Type	Purpose	Data Modalities	Labels or Annotations	Availability
Structured Tabular Datasets							
New York Lyft Citi Bike Trip Data [33]	2013	700 MB per month	shared bike	demand prediction	trip record	"*Start Station ID*", "*End Station ID*"	public
Madrid BiciMAD E-bike Daily Usage Record* [34]	2014	4.35 MB	e-bike	general	usage record	"*Total Uses*"	public
Bike Share Toronto Ridership Data [35]	2014	60 MB per month	shared bike	demand prediction	trip record	"*Trip Start Station ID*", "*Trip End Station ID*"	public
San Francisco Lyft Bay Wheels E-Bike Dataset [36]	2017	6 MB per month	shared bike	general	trip record	"*Start Station ID*", "*End Station ID*"	public
Seoul Bike Sharing Rental History* [37]	2017	600 MB per season	shared bike	demand prediction	rental record	"*Rental Station ID*", "*Return Station ID*"	public
Barcelona Bicing Shared Bike Usage Record [38]	2018	1.57 MB	shared bike e-bike	general	usage record	"*bikesInUsage*", "*electricalBikesInUsage*"	public
Motorized Foot Scooter Trips Dataset [39]	2019	15.5 MB per month	e-scooter	general	trip record	"*StartCenterlineID*", "*EndCenterlineID*"	public
Norfolk Lime Micromobility Dataset [40]	2019	300 MB	e-scooter, e-bike	general	trip record	"*Starting Tract*", "*Ending Tract*"	public
Austin Shared Mobility Vehicle Trips [41]	2019	3.7 GB	e-scooter, e-bike	demand management	trip record	"*Census Tract Start*", "*Census Tract End*"	public
Portland Biketown Trip Data [42]	2020	6 MB per month	shared bike	demand prediction	trip record	"*StartHub*", "*EndHub*"	public
Moby Bikes Bikeshare Data [43]	2020	10 MB per month	e-bike	general	GPS record	"*LastGPSTime*", "*Latitude*", "*Longitude*"	public
CYCLANDS: CYCling geo-Located AccideNts, their Details and Severities [44]	2021	18 kB to 29 MB	bicycle	rider safety	accident record	"*Location Details*", "*Personal Characteristics*", "*Vehicle Characteristics*"	public
Chicago E-scooter Trip Data [45]	2022	1.1 GB	e-scooter	general	trip record	"*Start Centroid Location*", "*End Centroid Location*"	public
Collecty Dataset [46]	2023	24.86 GB	multimodal transport	mobility analysis	activity details	mobility analysis	public
Dublin Electric Micromobility Dataset [47]	2024	7.2 MB	e-scooter e-bike	energy management	trip record	"*SoC*"	public
Image & Video Datasets							
Road Pothole Images for Pothole Detection [48], [49]	2015	9.5 GB	car	rider safety	image	potholes	public
IUPUI-CSRC E-Scooter Rider Detection Benchmark Dataset [50]	2021	536 MB	car	rider safety	image	e-scooter riders, pedestrians	public
Outdoor Hazard Detection Dataset [51]	2023	13.27 GB	e-scooter	rider safety	image	outdoor hazard	public
ScooterDet Dataset [52]	2024	1.1 GB	e-scooter	rider safety	image	road objects	public
Micromobility Lane Recognition Dataset [53]	2024	18.10 GB	e-scooter	micromobility safety	image	lanes	public
PolyMMV Dataset [54]	2024	298 MB	e-scooter, e-bike	rider safety	video	micromobility vehicles	public
Multimodal Datasets							
Real-time Vibration Sensor Dataset for E-scooter [61]	2021	NA	e-scooter	rider safety	multimodal	riding behaviour	private

[1] For image datasets, the "Label or Annotations" column shows the target object(s) in the image, while for tabular datasets, it shows the key column name(s).
[2] Datasets marked with * were recorded in other languages and used in English publications. For the convenience of readers, the column names are translated into English and presented in the corresponding "Label or Annotations" column.

by **Data Source Determination** and **Data Collection**, during which relevant sources, such as vehicle-to-everything communication systems, roadside sensors, and weather monitoring stations, are identified, assessed, extracted, and organised. During **Data Preprocessing & Cleaning**, missing values, outliers, duplicated records, GPS errors, and temporal or spatial inconsistencies are addressed, together with transformations and feature engineering where required. **Exploratory Data Analysis** then examines data distributions and relationships to identify spatial, temporal, and behavioural patterns and to inform subsequent model development.

Based on the prepared data, **Model Selection** considers the task, data availability, spatial and temporal resolution, and deployment requirements. During **Model Training**, model parameters are learned from the available training data, followed by **Model Evaluation** using unseen data and task-specific metrics. Classification tasks commonly use accuracy, precision, recall, and F1 score, while regression tasks report measures, e.g., mean absolute error, root mean square error, and R^2. For micromobility applications, evaluation should also consider

TABLE III
TECHNIQUES.

Technique Family	Representative Methods	Typical Modality	Primary Use Cases	Strengths & Limitations	References
Statistics-based	LR, MLR, ARIMA	structured features	demand prediction energy consumption prediction	Strong interpretability and simple baselines Sensitive to outliers; limited nonlinearity	[17], [20]
Distance-based	kNN, SVM, K-means	structured features	driving behaviour clustering dispatching clustering	Few distributional assumptions; kernels capture nonlinearity Sensitive to metric/kernel; costly at scale	[19], [62]
Tree-based	DT, RF, XGB, LGBM	structured features	demand prediction energy consumption prediction	Captures nonlinearity and feature interactions; partly interpretable Higher complexity and tuning cost	[18], [63]
MLP	MLP	structured features	destination prediction energy consumption prediction	Simple and effective for tabular data Weak inductive bias for complex data structures	[64], [65]
CNN-based	CNN, MobileNetV2	images, videos	lane recognition object detection	Strong local feature extraction; supports lightweight edge models Often label-hungry; compute-accuracy trade-off	[53], [61]
RNN-based	RNN, LSTM, GRU	time series	trajectory prediction demand prediction	Models temporal dynamics effectively Costly training and latency for long sequences	[64], [66]
GNN-based	GCN, STGCN	graphs, networks	demand prediction traffic flow prediction	Uses topology and neighbourhood dependencies Relies on graph structure; high deployment cost	[67], [68]
Transformers	Vision Transformer, Transformer encoders	images, time series	demand prediction lane detection	Self-attention captures long dependencies; flexible architectures High memory and compute cost on edge devices	[69], [70]
Hybrid & multi-stage frameworks	STFT + CNN, optical flow + detector, segmentation + detector	multimodal sensors (vibration+vision)	multimodal fusion multi-task safety pipelines flow + detection segmentation + tracking	Combines complementary signals for robust real-time decisions Pipeline complexity and error propagation risks	[51], [71]

human and operational factors, including asymmetric error costs, e.g., missed hazards versus false alarms, and whether outputs are sufficiently timely, stable, and interpretable to support decision-making. **Model Tuning** further refines hyperparameters, features, or model configurations, after which **Prediction & Inference** applies the resulting model to unseen data to support the original application objective.

Finally, **Model Deployment** introduces additional challenges because micromobility systems are affected by policy changes, infrastructure updates, weather and seasonality, fleet strategies, and shifting user demographics [74]. Deployed models may require ongoing monitoring and periodic updates, e.g., through retraining or rolling-window approaches [75]. For streaming settings, online or continual learning may also be considered together with time-aware evaluation to maintain valid performance assessment as operating conditions change.

B. Classical ML Models

In this study, we divided classical ML models included in this paper based on their core principles and primary objectives into statistics-based, distance-based, and tree-based models. Models in each category have their own characteristics and are used in different situations.

1) Statistics-Based Models: Statistical models, such as LR, Multiple Linear Regression (MLR), and Auto-Regressive Integrated Moving Average (ARIMA), are based on statistical theory and use probability models to describe and predict targets. Their assumptions concern the relation between predictors, targets, and errors, with parameter estimation or hypothesis testing depending on the task [76]–[78]. For example, LR was used as a baseline for battery range prediction [79], MLR for e-mobility energy consumption prediction [80], and ARIMA and seasonal ARIMA for destination and hourly demand prediction [17], [68]. While linear specifications restrict functional form, statistical models can also represent nonlinear or spatial structures.

Spatial statistical approaches, such as Gaussian processes, geographically weighted regression, and spatial autoregressive models, were not explicitly targeted by the original search terms and are therefore not comprehensively represented in the reviewed corpus.

2) Distance-Based Models: Distance-based models rely on proximity or similarity between data points for classification or clustering. Methods such as K-Nearest Neighbours (KNN) and K-Means operate using explicit distance metrics, such as Euclidean or Manhattan distance, while Support Vector Machines (SVM) can represent similarity through kernel functions in a transformed feature space. The choice of distance metric or kernel therefore affects neighbourhood structure, cluster assignments, or decision boundaries, particularly for nonlinear or high-dimensional data [81], [82]. In micromobility studies, KNN was used as a baseline for trip destination prediction [64], K-Means for e-scooter vehicle routing [62], and SVM for e-scooter battery range prediction [79]. However, these methods can be computationally intensive and sensitive to the selected distance metric or kernel, while noisy or poorly separated data may further reduce their performance.

3) Tree-Based Models: Decision Tree (DT) and tree-based ensemble methods, including Random Forest (RF), Extreme Gradient Boosting (XGB), and Light Gradient-Boosting Machine (LGBM), model nonlinear relationships and feature interactions through recursive partitioning of the feature space [83], [84]. In micromobility studies, DT and RF were used as baseline models for e-mobility energy consumption prediction [63], while XGB and LGBM were applied to e-bike energy needs estimation [18]. Tree-based ensemble models can require greater computational resources than simpler baseline models, particularly as the number and depth of trees increase.

C. Artificial Neural Networks

Based on their architectures and the types of data they process, we discuss Multi-Layer Perceptron (MLP), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Graph Neural Network (GNN), and Transformer models commonly used in micromobility research.

1) Multi-Layer Perceptron: MLP consists of multiple fully connected layers and is particularly suitable for structured or tabular data, but lacks specialised mechanisms for modelling spatial or temporal dependencies [85], [86]. In micromobility studies, MLP were used as a baseline for destination prediction [64] and for modelling e-mobility energy consumption [65].

2) Convolutional Neural Networks: They use convolutional operations to extract local spatial features, making it well suited to image and video data. In micromobility research, CNN models have been applied to safety-related tasks including real-time lane recognition [53], [87], rider attentiveness prediction [61], rider fall detection [88], object detection [48], [49], and object tracking and trajectory estimation [89]. Beyond native visual inputs, signals can also be transformed into 2D representations, such as spectrograms or time-frequency maps, before being analysed using CNN architectures [90]–[93]. This enables local temporal–frequency patterns to be captured using established image-based network designs.

3) Recurrent Neural Networks: RNN models, including Simple RNN, Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and their variants, are designed to model sequential and temporal dependencies [94], [95]. Simple RNN can struggle with long-term dependencies, while LSTM and GRU use gating mechanisms to improve information retention, with GRU providing a simpler architecture than LSTM. Convolutional LSTM further incorporates spatial processing, making it suitable for spatiotemporal data at the cost of additional computational complexity. In the reviewed literature, Simple RNN and LSTM were used in [64], while GRU and Convolutional LSTM were applied in [66] to predict trip destinations from spatiotemporal sequences.

4) Graph Neural Networks: GNN models, including GCN, Spatio-Temporal Graph Convolutional Network (STGCN), and other variants, are designed to process graph-structured data [96], [97]. GCN aggregates information from neighbouring nodes through graph convolution, allowing relationships between connected nodes to be modelled, although deeper architectures may suffer from over-smoothing as node representations become increasingly similar. STGCN extends this framework by incorporating temporal dependencies, making it particularly suitable for spatiotemporal tasks such as traffic flow and mobility demand prediction. An important distinction among graph-based models lies in how relationships between locations are represented. Earlier multi-graph approaches to bike-sharing demand prediction constructed multiple graphs to capture heterogeneous inter-station relationships [98], while adaptive graph methods such as Graph WaveNet learn latent dependencies directly from data rather than relying solely on a predefined graph structure [99]. Within the reviewed micromobility literature, GCN has been employed for trip destination prediction in [68], while STGCN was used to predict hourly shared-bike demand in [67]. These studies illustrate that graph construction itself is an important modelling choice, particularly when spatial proximity alone does not fully represent demand interactions.

5) Transformers: Transformer models use self-attention to capture long-range dependencies. Transformer-based sequence models have been explored for demand forecasting [69], [100], [101] and battery range estimation [79]. In [69], the Transformer-based model achieved the lowest mean absolute error for pickups and returns, but a graph recurrent baseline achieved lower root mean square error. Its reported superiority therefore depended on the evaluation metric. The multi-graph Transformer in [100] jointly represents heterogeneous spatial relationships for dockless scooter demand forecasting in the USA. However, the evaluations use within-city temporal splits, so results from the two cities do not demonstrate cross-city or cross-operator generalisation. Similarly, a temporal fusion Transformer is applied to bike-sharing activity prediction in [101], but its reported advantage over recurrent models remains specific to the selected aggregation interval, forecast horizon, dataset, and evaluation protocol. Vision Transformers extend the architecture to image analysis by representing images as sequences of patches [70]. Related studies have applied Transformer-based vision models to lane detection and road scene understanding [102]–[105], providing relevant methodological background for micromobility perception tasks. Computational and memory costs can constrain deployment on micromobility devices [106].

D. Hybrid & Multi-Stage ML Frameworks

Hybrid and multi-stage ML frameworks combine multiple modelling components in sequence or parallel, allowing the output of one stage to support subsequent tasks. In micromobility research, such frameworks are commonly used for multimodal data and multi-task applications, e.g., vibration analysis, motion estimation, segmentation, and object detection under real-time or resource-constrained conditions.

1) Data Transformations & Image Processing: Data transformations can convert non-image signals into representations suitable for image-based models. In [61], short-time Fourier and wavelet transforms were used to convert e-scooter vibration signals into images, which were then analysed using multimodal CNN models for rider-attentiveness monitoring. This study illustrates how complementary representations of vibration signals can be combined within a multimodal learning framework for rider-attentiveness monitoring.

2) Optical Flow & Object Detection: Optical flow is a technique used to describe the apparent position of objects of interest by tracking reference points across multiple frames over a certain period and calculating the displacement of corner points among these frames. Combined with object detection techniques, optical flow can approximate the speed of e-scooters and predict potential collision times with stationary objects. This idea has been employed to develop an accident prevention system in [54], [71] to provide real-time warnings to micromobility riders in situations of potential accidents.

3) Semantic Segmentation & Object Detection: Combining semantic segmentation with object detection provides a balanced approach that enhances both accuracy and efficiency, especially in resource-limited scenarios. In [51], these techniques were integrated using "cells of interest" to classify objects rather than traditional pixel-based methods. This approach reduces the computational load while maintaining high precision, making it suitable for micromobility applications, where accuracy and computational efficiency are both essential.

VI. Applications

ML methods have been applied to a range of prediction, optimisation, and safety-related tasks in micromobility systems. These applications are summarised in Table IV, with selected examples illustrated in Fig. 5. They are grouped into *Demand Prediction*, *Trip Destination Prediction*, *Energy Consumption Prediction*, *Route Planning with Constraints*, and *Safety*. Safety-related applications include *Lane Recognition*, *Object Detection*, *Object Tracking*, and *Trajectory Estimation*, which support collision-risk reduction, situational awareness, and real-time warning or intervention.



Fig. 5. A pictorial representation of selected ML applications in micromobility, such as safety and energy management, to improve efficiency, accuracy, and user experience.

A. Demand Prediction

Demand prediction is one of the most common ML applications in micromobility, involving the forecasting of trip demand, vehicle usage, or availability across spatial and temporal intervals. It typically combines temporal forecasting with spatial analysis, while urban dynamics and regional scalability remain important challenges [29], [107]. Existing studies have applied time-series models, neural networks, and graph-based methods [15]–[17], [67], [90], [108]–[118]. Their performance depends on data completeness, spatial and temporal resolution, contextual variables, and implementation conditions [25], [27], [107], [119].

Forecasting errors should be interpreted with the forecast horizon and spatial aggregation because these settings support different operational decisions. Observed trips also omit unmet demand when vehicles are unavailable, so evaluation should consider vehicle availability, unmet requests, rebalancing distance, and operating cost alongside prediction errors. Demand forecasting has been linked with rebalancing optimisation [111], providing decision-level evidence beyond forecast error, although not from a live operational trial.

B. Trip Destination Prediction

Trip destination prediction requires modelling temporal patterns, spatial relationships, and user-specific behaviours. Time-series, tree-based, and neural network methods have been applied to this task [120]–[127]. However, the reported performance depends on the prediction target, spatial representation, available user information, and evaluation protocol, so results across different destination-prediction settings are not directly comparable. Detailed trajectories and user-specific mobility histories also raise privacy concerns because they can reveal individual travel patterns [128], [129].

C. Energy Consumption Prediction

ML methods have been applied to energy consumption prediction in electric micromobility vehicles. This task is typically formulated as regression or time-series forecasting using driving conditions, weather, battery characteristics, and trip attributes. Linear models, ensemble methods, and neural networks have been investigated [18]–[20], with predictions supporting battery management and route planning [80], [130], [131]. However, differences in vehicle type, battery capacity, rider behaviour, route profile, weather, and target definition limit direct comparison across studies and mean that prediction accuracy alone does not demonstrate operational or energy-saving benefits [131], [132].

D. Route Planning with Constraints

Route planning has been investigated under constraints including travel time [133], air quality [5], and trip mode preferences [134]. Electric micromobility may additionally require consideration of battery state and remaining range. These problems typically combine prediction of quantities such as travel time or energy consumption with optimisation of competing objectives and constraints. Statistics-based, tree-based, and neural network models have been investigated as predictive components [62], [79], [135]. Route quality also depends on how dynamic constraints and competing objectives are represented [136], [137]. Lower prediction error therefore does not necessarily imply a better route without evaluation against the intended operational objectives.

E. Lane Recognition

Lane recognition identifies whether a micromobility rider is travelling in a designated lane or an unauthorised area. This is particularly relevant because e-scooter riders may use sidewalks due to traffic congestion, poor infrastructure, or simply for amusement, increasing collision risk with pedestrians.

Lightweight models such as MobileNetV2 have been investigated for lane recognition on resource-constrained devices [53], [138]. However, classification performance and model size alone do not establish deployability. Target-device latency, memory and energy requirements, and end-to-end warning performance also require evaluation.

F. Object Detection

Object detection supports hazard recognition by localising and classifying moving and stationary objects in images or videos. The purpose is to provide information about moving and stationary objects that can support hazard recognition and downstream safety-related decision-making. Moving targets include pedestrians, vehicles, and other micromobility users [50], [54], while stationary hazards include potholes, traffic signs, and cones [51]. Detection accuracy alone does not establish collision reduction because safety also depends on sensing latency, false alarms, missed hazards, warning logic, and rider response.

G. Object Tracking & Trajectory Estimation

Object tracking and trajectory estimation use current and past positions to anticipate future motion and potential collisions. In micromobility, these methods can also be applied to advanced collision prevention systems. For instance, [89] presents a bicycle-based system that predicts pedestrian trajectories to anticipate potential collisions. Unlike systems that rely only on current positions, this approach forecasts whether and when a pedestrian may cross the bicycle's path, allowing warnings to be generated earlier. Real-world safety benefits additionally depend on warning latency, false-alarm rates, rider response, and deployment conditions.

H. Other Applications

In addition to the applications mentioned, ML methods have also been employed in micromobility for other purposes.

a. *Battery Health Prediction:* Battery health prediction can support maintenance and charging decisions in electric micromobility by identifying degradation patterns and potential battery issues [139], but its practical value depends on whether improved predictions lead to measurable benefits such as lower maintenance costs, improved battery utilisation, or safer operation.

b. *Trip Mode & Purpose Analysis:* ML-based analysis of travel behaviour, trip patterns, and trip purposes can provide useful information for vehicle deployment and service planning [140], [141]. These applications are particularly relevant for understanding how micromobility is used within broader travel behaviour, although behavioural inference alone does not demonstrate improvements in service efficiency or user satisfaction.

c. *User Safety Concerns:* ML methods have been used to identify factors associated with e-bike crash injury severity [142], assess cyclist road-safety conditions [143], and examine built-environment effects on cycling safety [144]. These analyses can support risk identification and prioritisation, but their value for safety improvement ultimately depends on whether subsequent interventions reduce actual crash risk.

d. *Infrastructure Improvements:* Data-driven and ML-based approaches can help identify high-risk locations and support the assessment of routes or infrastructure [145]. Such information can guide planning decisions, although the effectiveness of the resulting infrastructure or routing interventions requires evaluation under real operating conditions.

e. *Deployment Considerations:* Practical deployment of ML models in micromobility often requires operation on edge or embedded platforms. Lightweight neural architectures [138], [146], [147] and model-compression techniques such as pruning and quantisation [148] have therefore been explored for resource-constrained applications [53]. Deployment feasibility should additionally be assessed in terms of target-device latency, memory and energy requirements, and task-specific failure behaviour.

Predictive performance should be distinguished from downstream operational and safety outcomes, which depend on how model outputs are integrated into real-world decision-making. These outcomes are also influenced by data quality, computational resources, and the privacy and security requirements associated with mobility trajectories, user information, and sensor data.

VII. Research Directions & Challenges

Our study reviewed recent micromobility datasets, ML techniques, and their applications. The reviewed literature reveals limitations in data coverage, model evaluation, and application-level evidence that constrain the generalisability and practical use of current approaches. These challenges are discussed from the perspectives of datasets, techniques, and applications.

A. Datasets

A key limitation is the temporal and geographical concentration of available micromobility datasets. Among the 21 datasets presented in Fig. 3, 12 span two years or less, while 18 are associated with a single city or location, 2 cover multiple geographical areas, and 1 has unspecified geographical coverage. Among the 95 included studies presented in the *Supplementary Material*, 69 used a single-city or single-area setting, 20 covered multiple locations, and 6 had unreported or inapplicable locations. These counts describe geographical coverage. Only two studies explicitly evaluated cross-city transfer, including one that used target-city pilot data. These characteristics limit long-term and geographical generalisation. In the short term, dataset publishers and operators should improve reporting and data comparability, while longer-term progress requires comparable longitudinal datasets across cities and operators.

Data also remain fragmented across vehicle types, sensing modalities, and contextual layers. Existing work has begun to combine heterogeneous spatial relationships and contextual information for micromobility forecasting [100], showing that

TABLE IV
APPLICATIONS.

Application	Methods used	References
Personal mobility inattentive driving monitoring system	Short-time Fourier Transform, Wavelet Transform, CNN	[61]
Accident prevention on E-bikes for micromobility rider	CNN (object detection), Optical Flow, Object Tracking using CV	[71]
Bicycle-based collision prevention system using pedestrian trajectory prediction	CNN (object detection), Object Tracking using CV, TTC using depth camera	[89]
Object-localisation and classification for resource-constrained platforms such as micromobility	CNN (Novel Cell-wise segmentation)	[51]
Shared mobility demand prediction	ARIMA, STGCN, Conv-LSTM, GRU, RNN, LSTM, GCN, LR, RF, MLP, etc	[15]–[17], [67], [90], [108]–[118]
Shared mobility destination prediction	Conv-LSTM, GCN, RNN, LSTM, GRU, CNN, XGB, ARIMA, etc	[64], [66], [68], [91], [120]–[127]
E-mobility energy consumption prediction	RF, GB, ANN, kNN, MLR, LGBM, XGB, etc	[18]–[20]
Shared mobility route planning with constraints	LR, K-means, SVM, XGB, MLP, LSTM, etc	[62], [79], [135]

this direction is under-explored rather than absent. Future datasets should better align GPS trajectories, inertial or vibration signals, images, infrastructure attributes, weather, and public transport information within reusable data structures.

A further micromobility-specific challenge is the limited transferability of datasets developed for other mobility domains because of different sensing perspectives and motion dynamics. Autonomous-driving image datasets, for example, differ from micromobility data in camera placement, vehicle motion, and operating environment. Dedicated micromobility datasets should therefore document sensing position, camera configuration, road environment, and recording conditions, while longer-term efforts should expand coverage across devices, cities, and infrastructure settings.

B. Techniques

A central technical challenge is modelling micromobility spatiotemporal dynamics across different spatial structures and temporal scales. Model performance can depend strongly on the prediction target, dataset, and graph construction, while multi-graph approaches have begun to represent heterogeneous spatial relationships explicitly [98], [100]. Comparability can be improved by evaluating simpler temporal and tree-based baselines under consistent inputs, data splits, and forecasting horizons, and by reporting graph and attention ablations.

Generalisation is challenged by differences across cities, operators, seasons, and devices. Evaluation in multiple cities does not demonstrate transfer to an unseen city or operator when each location is trained and tested separately [100]. Generalisation also varies across riders. In [61], mean within-rider accuracy was 91.82%, compared with 43.07% when a rider was held out. Strong personalised performance therefore did not carry over to an unseen rider in that study. Changes in weather, infrastructure, policy, fleet operation, and user behaviour may require model monitoring and updating [75]. Short-term robustness tests should use chronological splits, held-out locations, and missing inputs, followed by broader cross-city and cross-operator evaluation.

Multimodal and multi-representation modelling is also under-explored rather than absent. Existing studies combine complementary signal representations for rider-attentiveness monitoring [61] and multiple spatial graphs for scooter-demand forecasting [100]. Future evaluation should address missing inputs, asynchronous sampling, and information leakage through modality and graph ablations and by fitting data-driven preprocessing using training data only. Broader integration with infrastructure and public transport data will require longer-term data-sharing arrangements.

Finally, resource-constrained learning is particularly relevant to micromobility safety applications requiring on-device or near-real-time inference. Lightweight lane-recognition models have already been investigated [53], but deployment feasibility also depends on target hardware, numerical precision, memory use, energy consumption, and end-to-end latency. Longer-term field studies are needed to assess reliability under changing road, weather, and operating conditions.

C. Applications

A central application-level challenge is the gap between predictive performance and system-level outcomes. Many studies focus on forecasting or classification accuracy, while equitable access, public transport integration, operating costs, and service reliability require decision-level evaluation.

Fairness-aware demand prediction has already incorporated spatial disparities into learning objectives [149], while more recent work published after the review period has combined cross-modal graph learning with equity-aware prediction [150]. In micromobility, ML can support fairness by identifying spatial disparities in demand and service availability, incorporating fairness constraints into allocation or rebalancing, and examining whether errors are systematically larger in underserved areas. However, similar prediction errors do not necessarily imply equitable access because observed demand may itself reflect unequal supply, affordability, or connectivity.

Public transport integration is another under-explored direction. ML can combine micromobility demand with public transport usage and contextual information to support first- and last-mile forecasting and vehicle allocation. Recent work published after the review period has integrated subway usage with shared micromobility demand forecasting [151]. Evaluation should extend beyond forecasting accuracy to outcomes such as vehicle availability near transport stops, unmet demand, transfer opportunities, and accessibility across population groups.

Privacy is particularly important because micromobility datasets can contain fine-grained trajectories, timestamps, and

behavioural information. Recent work published after the review period has investigated federated demand prediction without directly pooling raw data [152]. Federated learning does not by itself guarantee privacy, so evaluation should specify the threat model, shared information, privacy mechanisms, and trade-offs among privacy, predictive utility, and communication cost.

Operational and economic decision-making also remains under-explored. Relevant studies have examined incentive-based rebalancing, dynamic pricing, and prediction-informed rebalancing [111], [153], [154]. These approaches provide different levels of evidence, ranging from observed user responses to optimisation and simulation under modelled assumptions. Short-term evaluation should report operational indicators such as vehicle availability, unmet requests, rebalancing distance, utilisation, revenue, and cost under defined constraints. Longer-term studies should assess whether pricing, incentives, rebalancing, and infrastructure interventions produce sustained changes in access, mode choice, emissions, and safety.

Overall, future micromobility applications should be evaluated not only by model accuracy but also by whether they improve the intended service, operational, or societal outcome.

VIII. Conclusion

This systematic review examined 95 studies on micromobility datasets, ML techniques, and applications, including demand prediction, trip destination forecasting, energy management, route planning, and rider safety. The reviewed literature shows that the suitability and reported performance of ML methods depend strongly on the available data, modelling assumptions, and evaluation settings. Differences in spatial and temporal coverage, input features, data splits, aggregation levels, and prediction horizons therefore limit direct comparison across studies. Evidence of geographical generalisation also remains limited. Although several studies were conducted across multiple cities or geographical areas, only two explicitly evaluated cross-city transfer or generalisation, including one that used target-city pilot data. Evaluation in multiple locations should therefore not be interpreted as evidence of transfer to an unseen city or operator when models are trained and tested separately within each location. Improvements in predictive performance also do not necessarily translate into better operational, safety, or societal outcomes. Lower forecasting or classification error alone does not demonstrate improved vehicle availability, reduced rebalancing costs, more equitable access, or improved rider safety. Future work should therefore adopt more comparable evaluation protocols, test robustness and transfer across cities and operators, and assess whether model-informed decisions deliver measurable practical benefits under realistic operating conditions.

This review still has several limitations. It mainly focuses on open-access datasets, while private datasets may contain additional information that is not represented in the reviewed resources. Moreover, while the review provides technical comparisons of datasets, models, and applications, it does not systematically examine the effects of policy, regulation, user acceptance, or broader institutional conditions on micromobility deployment. Operations-oriented decision-making problems, including pricing, incentives, and operator key performance indicators, are also less consistently represented in the reviewed technical literature. The search applied publication-date restrictions without additional search-field restrictions, but the exact database-specific syntax used during the original searches was not retained, which limits complete replication of the search procedure. Finally, although large language models and generative artificial intelligence have recently attracted substantial attention, their use in micromobility-focused ML studies remains relatively sparse and heterogeneous. They are therefore not treated as a core technique category in this review and remain a direction for future work.

Acknowledgement

This publication has emanated from research conducted with financial support from Taighde Éireann — Research Ireland under Grant Nos. *21/FFP-P/10266* and *SFI/12/RC/2289_P2*, and from Dublin City University through the ECIU Seed Programme 2025 under the E-SAMoD project.

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Sen Yan (Graduate Student Member, IEEE) received his B.Eng. degree with first-class honours in Internet of Things Engineering from Shandong University in 2018, his M.Sc. degree with first-class honours in Computer Science from Trinity College Dublin, the University of Dublin, in 2020, and his Ph.D. degree from the School of Electronic Engineering, Dublin City University, in 2025. His research focuses on data-driven approaches to intelligent transportation systems, with broader interests in machine learning, data analytics, image processing, computer vision, and environmental applications.



Chinmaya Kaundanya is a researcher at the School of Computing at Dublin City University. His research focuses on implementing computer vision deep neural network model compression techniques and studying the challenges of deploying them on low-spec hardware platforms, especially for micromobility applications. His research mainly includes different neural network model pruning and quantisation techniques and various low-spec microcontroller units. His work aims to improve the computational efficiency and practical deployability of deep learning models for resource-constrained intelligent systems.



Noel E. O'Connor (Senior Member, IEEE) is a Full Professor with the School of Electronic Engineering, Dublin City University. He is the Director of Rinn Artificial Intelligence, one of seven research centres formed as part of Research Ireland's enhanced national research network. His research focuses on multimedia content analysis using machine learning and AI, with particular interests in computer vision, multimodal data analysis, and intelligent sensing. These methods are applied across domains including security and safety, autonomous vehicles, medical imaging, ambient assisted living, multimedia content-based retrieval, smart cities, precision agriculture, and environmental monitoring.



Suzanne Little is a Professor in the School of Computing at Dublin City University. She received the Ph.D. degree from the University of Queensland, Australia, in 2006. Her expertise is in video analysis, semantic search and data integration, and her current research includes projects examining bias in deep learning models for computer vision, safety in micromobility and personal transportation, improved medical image analysis, biomedical data, and water desalination. Her work brings together artificial intelligence, data analytics, and computer vision to address challenges across a range of complex real-world and multidisciplinary application domains, with particular emphasis on socially relevant problems.



Mingming Liu (Senior Member, IEEE) received the B.Eng. degree with first-class honours in electronic engineering from the National University of Ireland Maynooth, Ireland, in 2011, and the Ph.D. degree in control engineering and decision science from the Hamilton Institute at the same university in 2015. He is currently an Associate Professor with the School of Electronic Engineering, Dublin City University (DCU), Dublin, Ireland, and a Principal Investigator with Rinn Artificial Intelligence at DCU. His research interests include control, optimisation, and machine learning, with applications to intelligent transportation systems, electric vehicles, the Internet of Things, smart grids, and smart cities.