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# Spatial lock-in and a utilisation trap constrain sustainable scaling of shared micromobility

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# Spatial lock-in and a utilisation trap constrain sustainable scaling of shared micromobility


## Abstract

Shared micromobility services (SMMs) are increasingly promoted as a scalable pathway to urban transport decarbonisation, yet widespread growth stagnation and market exit raise doubts about their capacity to scale across cities. Using high-resolution time-series operational data from 64 cities in the United States, Australia, and New Zealand between 2019 and 2025, we show that SMMs growth is driven primarily by fleet expansion, whereas per-vehicle utilisation remains low in most cities and scales weakly with city size. Utilisation also emerges as an early signal of long-term viability, with divergence between surviving and closed systems emerging within the first three quarters after launch. Spatially, the SMMs activity remains persistently locked into urban centres, with strong core dominance still evident after five years of operation. We further show that both the extent of SMMs scaling (survival *versus* closure) and its intensity trajectories are highly predictable from widely available built-environment indicators. These findings suggest that the promise of SMMs is constrained by persistent operational and spatial barriers, and provide a basis for more targeted decisions on where and how cities support deployment.


## Main

Shared micromobility services (SMMs) are short-term, shared-use mobility services that provide lightweight electric or pedal-powered vehicles for users to rent for on-demand trips[1]. In recent years, these have been rapidly adopted by cities globally as a complement to public transport[1–3], and are widely viewed as an opportunity for transport decarbonisation that can reduce reliance on private cars, mitigate congestion, and lower urban emissions[4–6]. At the same time, SMMs are increasingly framed as a scalable urban mobility solution, and the sector is projected to become a US$119.9 billion global market by 2030[7]. Yet whether SMMs can achieve sustained growth and long-term persistence across cities remains unclear. For instance, in Munich, the share of SMMs in total trips remained below 0.1% in 2019[6], while in Paris, it was 0.8%-1.9% in the same year[8]. By contrast, scenario modelling for those two cities projected ridership shares as high as 15%–21%[9,10].

In most cities, SMMs are not delivered as a government-funded service but through a permit-based market, with providers operating under a municipal permit system and regulatory oversight[11]. As a new regulated industry with novel technology, consumer preferences, and supply economics, the challenge is long-term market viability. In practice, services are often scaled up with an incomplete understanding of local supply–demand dynamics, leading to misallocated fleets and pricing that erode viability[12]. For example, in 2019, several operators withdrew shared-scooter services from multiple North American cities after reassessing market performance, in which early scale-up had

outpaced durable demand[13–15]. More importantly, whether SMMs' scale is not only a business question but an urban one, because host cities incur fixed governance and set-up costs even when operators can rapidly retrench. Small- to medium-sized cities often spend on the order of ~US$200k per year on pilot administration, permitting, enforcement, and basic parking and marking setu[16–18]. Beyond these direct expenditures, implementation typically unfolds through a prolonged governance pipeline, including policy design, contracting, pilot test, phased transition to a long-term programme, all of which incur substantial administrative and opportunity costs[19,20]. But even these costs capture only part of what cities bear when SMMs fail to scale. Because uptake depends on urban conditions such as cycling infrastructure, bay density, and access distance, which are shaped by municipal street design and management[19,21], cities are not only regulators but also co-providers of this transport service. If SMMs remain weakly used, spatially concentrated or short-lived, their expected mobility and sustainability benefits may not be realised, even where cities have committed governance effort and supporting infrastructure.

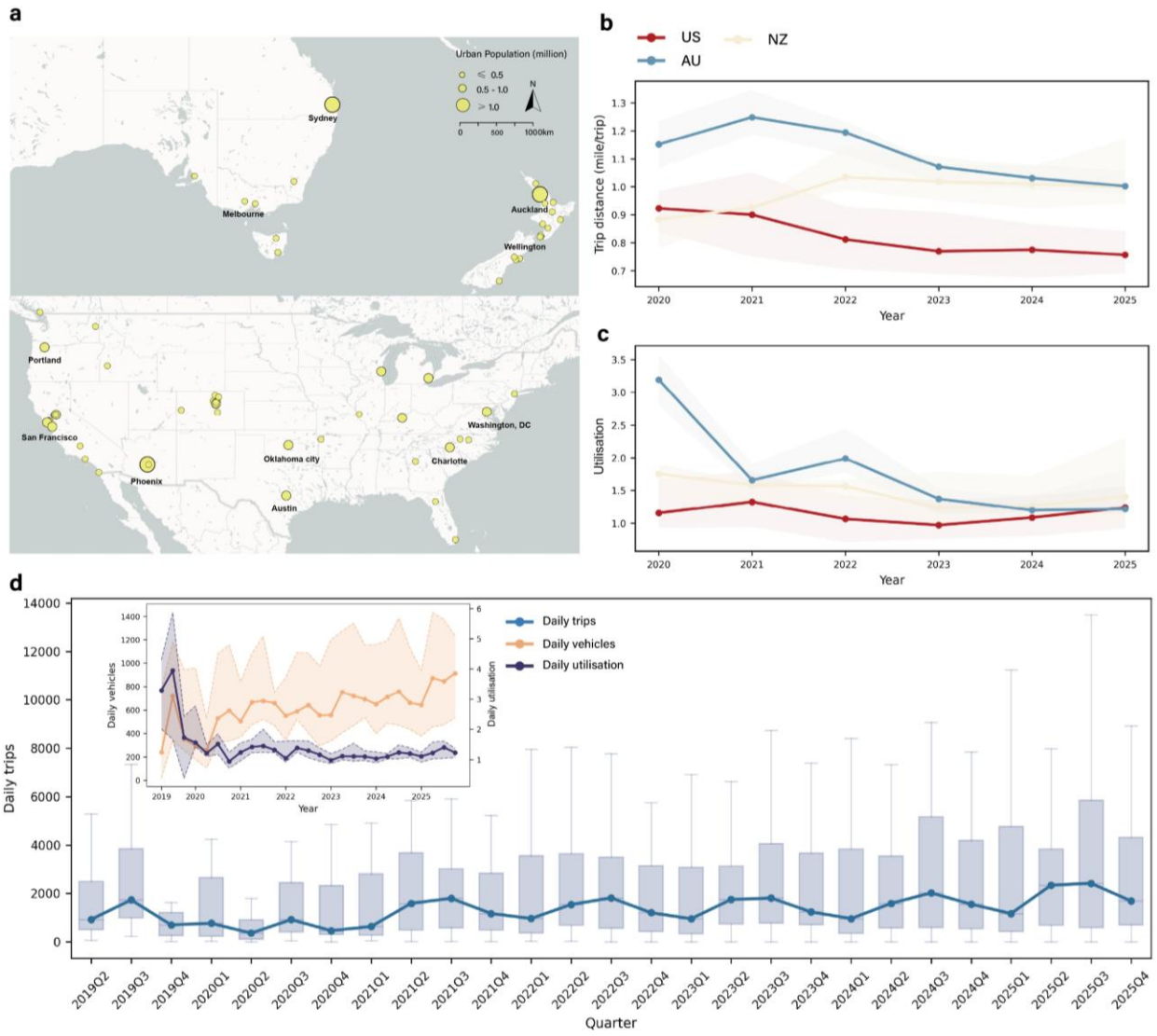
Despite growing policy and market interest, we still know little about how SMMs actually evolve across cities after their implementation as mobility service facilities. Cross-city evidence remains especially limited on how schemes persist and scale, why some exit before maturing, and which early signals can inform decisions on deployment, continuation, and expansion. We assembled a 64-city study cohort in the United States (US), Australia (AU), and New Zealand (NZ) covering cities that have introduced electrified SMMs (dockless e-scooters and e-bikes), and compiled street-segment-level operational records from 2019 to 2025. The cohort includes services that remain in service as well as those that subsequently ceased operations. In our analysis, we first describe how SMMs demand, supply and utilisation scale over time after implementation. Second, we trace how ride intensity and service footprints evolve across space and time beyond initial deployment cores. Third, we adopt a deliberately simple and parsimonious modelling framework, analogous to using population size in urban science to reveal baseline regularities in human activity[22]. We test whether a small set of widely available built environment (BE) indicators can predict whether a city is likely to sustain or close SMMs and anticipate future spatiotemporal evolution of ride intensity.

## Results

### Growth in SMM is supply-led while utilisation remains stable

In Fig. 1, we characterise the spatiotemporal evolution of SMMs from 2019 to 2025 across the US, AU, and NZ using a consistent set of operational indicators. Specifically, we define demand as daily trips, supply as daily deployed vehicles, and utilisation as daily trips per vehicle, and further describe trip-level service characteristics using trip distance.

**Fig. 1:** SMMs' temporal supply and demand trajectories change across countries




**a**, Geographic locations and population ranges of study cities. **b-c,** Annual changes in SMMs median trip distance and utilisation (trips per-vehicle) in the US, AU, and NZ. **b**, Annual trends in median trip distance across countries, 2020–2025. **c**, Annual trends in median utilisation across countries, 2020–2025. **d**, Quarterly changes in SMMs, 2019-2025, based on across-city quarterly median of daily trips, daily vehicles, and daily utilisation; shaded bands indicate 95% bootstrap confidence intervals for the across-city quarterly median. Map and administrative boundary visualised from Mapbox. In panels b-c, country-level annual series are summarised from city-level metrics using the across-city median after trimming the upper and lower 2.5% of city values within each year (central 95%), shaded bands show the interquartile range across cities (25th–75th percentiles); the observations for 2019 are excluded due to incomplete temporal coverage, to ensure consistent statistical comparability across years.

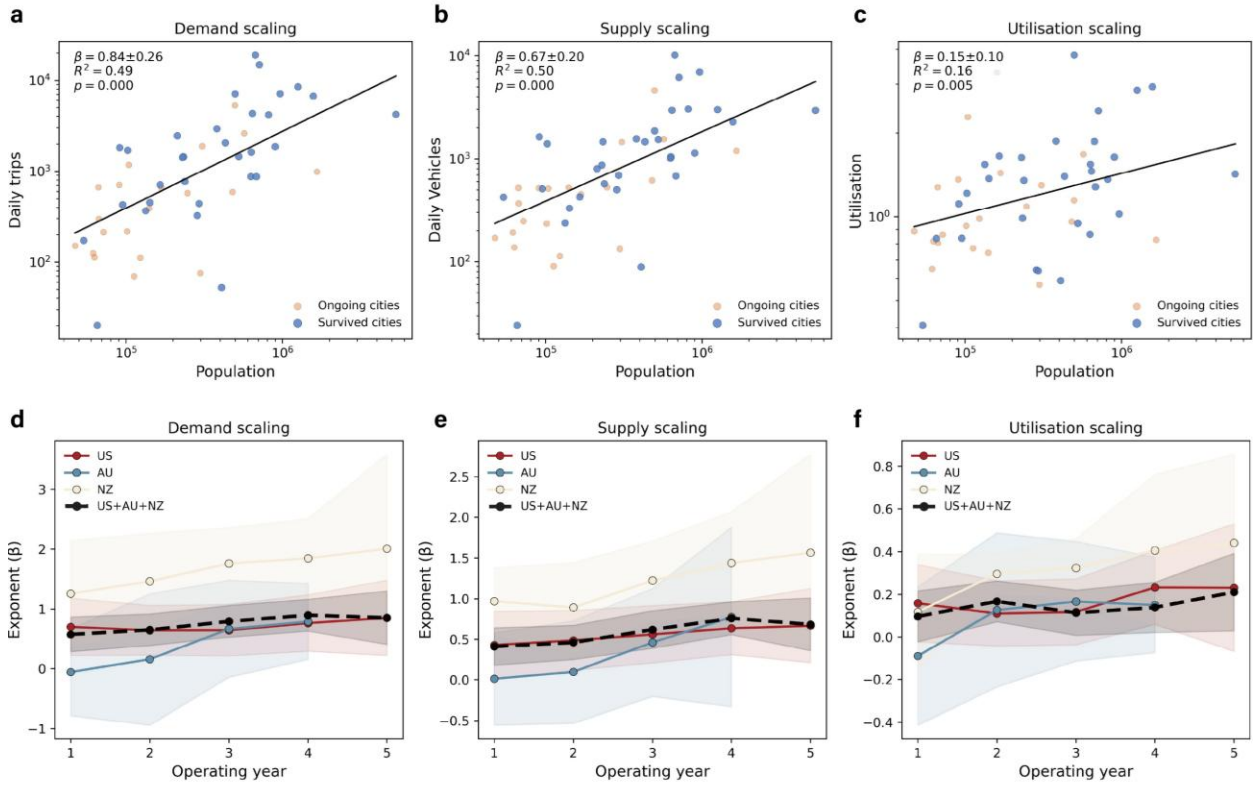
Fig. 1a reveals that the majority of the analysed cities are small to medium-sized, with urban populations below one million, except for Sydney, Phoenix, Auckland, and Brisbane. Fig. 1b–c illustrates aggregated median national trends, revealing temporal structure with distinct regional dynamics. In the US and AU, SMMs usage is characterised by an initially high level followed by gradual stabilisation and decline. In contrast, NZ had early growth followed by moderation. Despite these differences, since 2023, trip distance and utilisation have largely stabilised, with NZ and AU covering at higher levels than the US. By 2025, trip distance is ~1.0 miles in NZ and AU *versus* 0.76 miles in the US, while utilisation is broadly similar across countries (1.21–1.30 utilisation in NZ and AU and 1.24 in the US), consistent with SMMs being used mainly for short-distance access.

Fig. 1d provides a more granular depiction of system-wide dynamics across countries, showing that the observed growth in total trips follows a seasonal pattern, peaking around Q3 and declining before and after (supplementary Fig. S1 shows quarterly demand changes over the years). Importantly, this expansion is driven predominantly by the supply side, namely the steady increase in deployed vehicles, rather than by rising vehicle-level utilisation efficiency. Median daily utilisation as a proxy for utilisation remains low, reaching only around 1.40 trips even during peak Q3 seasons in 2025, down from 3.94 in 2019, which is approximately a 2.8-fold reduction. Having said what we have about uncertainty, the stabilisation of utilisation is, nevertheless, evidence of a global industry discovering how to operate efficiently. But as we show below, this has not prevented adoption and expansion problems.

**City size scales SMM demand and supply more strongly than vehicle-level utilisation**

Next, Fig. 2 scaling models reveal how SMMs' demand, supply, and utilisation scale vary with city size, and how these scaling relationships evolve over the operation.

**Fig. 2**: SMMs scaling in demand and supply across countries




**a,** Demand scaling across cities, log–log relationship between population and annual median daily trips. **b,** Supply scaling across cities, log–log relationship between population and annual median daily vehicles. **c,** Utilisation scaling across cities, log–log relationship between population and annual median daily utilisation. **d,** Demand scaling over time, the estimated scaling exponent $\beta$ for demand is plotted against operating year (years since launch) across countries. **e,** Supply scaling over time, the estimated scaling exponent $\beta$ for supply is plotted against operating year across countries. **f,** Utilisation scaling over time, the estimated scaling exponent $\beta$ for utilisation is plotted against operating year across countries. For panels a–c, scaling is estimated using each system's annual median operating performance from 2021 onwards to minimise pandemic-related distortions. Note that the analysis focuses on services with continuous operations (survived and ongoing cities), services that later ceased (closed cities) are excluded because their observations are truncated at shutdown.

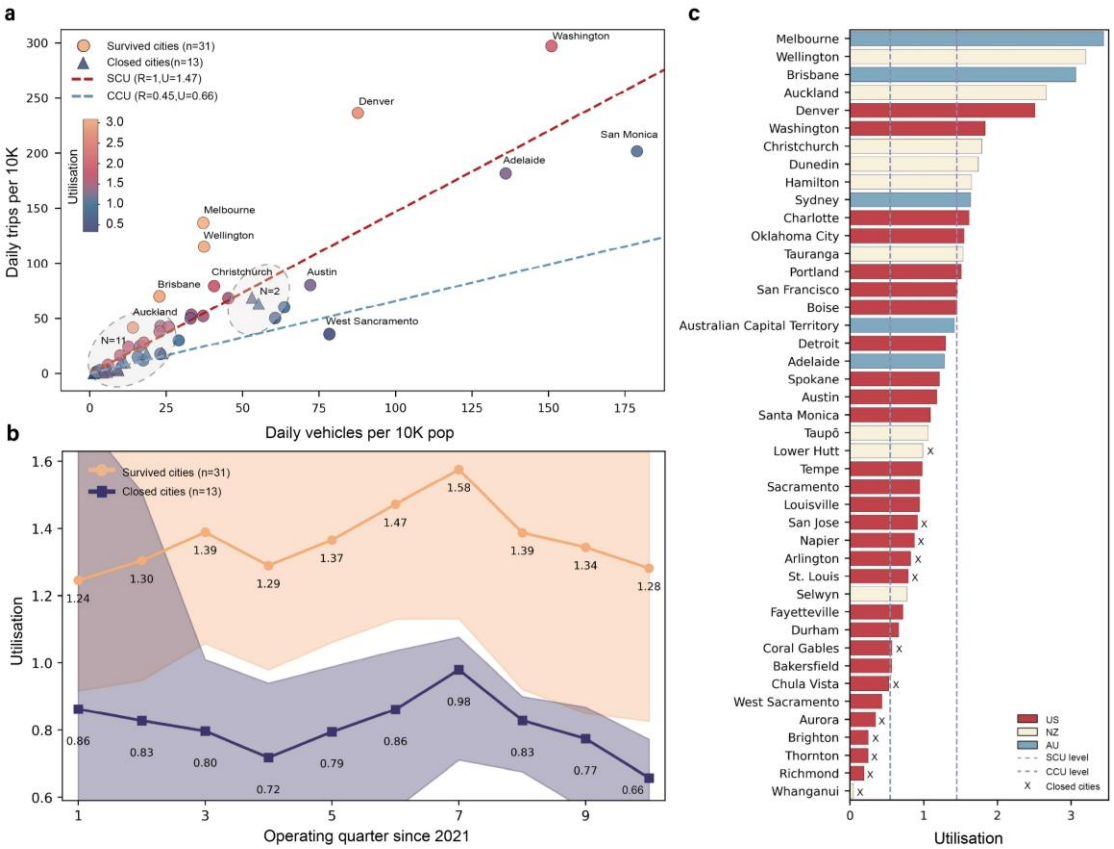
Fig. 2a–c shows clear cross-sectional scaling of both demand and supply with population. Daily trips scale with population at an exponent not significantly different from 1 ($\beta$ = 0.84 ± 0.26), which is consistent with suppliers facing similar conditions across cities in terms of reaching similar use penetration., with a lower exponent of $\beta$ = 0.67 ± 0.20. Deployed vehicles have a lower scaling exponent ($\beta$ = 0.67 ± 0.20), which is consistent with economies of scale in operation. By contrast, utilisation exhibits only weak size-dependence ($\beta$ = 0.15 ± 0.10 and a low $R^2$), which implies that larger systems expand primarily by deploying more vehicles rather than by increasing

per-vehicle use and may also indicate, as noted, relatively ubiquitous economics of the industry. Fig. 2d–f shows that, in the pooled all-country sample, the demand, supply, and utilisation exponents all increase gradually with operating years, although the magnitude of change is modest. The demand exponent (all countries) rising towards 1.0 reveals market-penetration maturity over the years (in later years, demand rises cross-sectionally in line with population). The supply exponent (all countries) around 0.5 implies economies of scale in provision, with the slight rise over time probably indicating increased market penetration rather than a fall in efficiency. NZ's scaling trend is markedly different from the other countries. Utilisation scales sub-linearly as with the other countries (growing less than per capita across city size), but demand and supply rise with population above per-capita in NZ cities. This is of interest, meaning that something about NZ cities and this regulated industry in that country results in larger cities growing larger SMM industries over this period.

**Early SMM trajectories can predict survival and closure**

We further compare the gap in utilisation efficiency between cities that survived SMM systems and those that did not. This metric is highly policy and operational viability can directly capture how effectively fleet supply is translated into realised trip demand. Fig. 3 shows the city-level contrast in utilisation between survived and closed systems and their evolution over operating time. We find that the divergence does not emerge late in the lifecycle—it is already evident early on, largely separating the two groups within the first three operating quarters and then persisting thereafter.

**Fig. 3** SMMs utilisation in survived and closed cities




**a,** Relationship between daily supply (vehicles per 10K population) and daily demand (daily trips per 10K population). Colour $U$ encodes utilisation, while $R$ is median utilisation in survived cities. **b,** Utilisation trajectories by operating quarter since 2021 (defining each system's first post-2021 observation as operating quarter 1) shaded bands indicating interquartile range (25th–75th percentiles) across cities within each group. **c,** Distribution of SMM utilisation across countries.

In Fig. 3a, we quantify the utilisation gap using the survived city utilisation (SCU), $R = 1, U = 1.47$; closed city utilisation (CCU), $R = 0.45, U = 0.66$ . In the population normalised supply–demand space, most cities fall within a common band of roughly 75 vehicles and 150 trips per 10K population. In contrast, closed cities cluster at lower levels, around 25 vehicles and 50 trips per 10K population. Only a few cities lie outside these typical ranges, including Denver, Washington, Adelaide and Santa Monica.

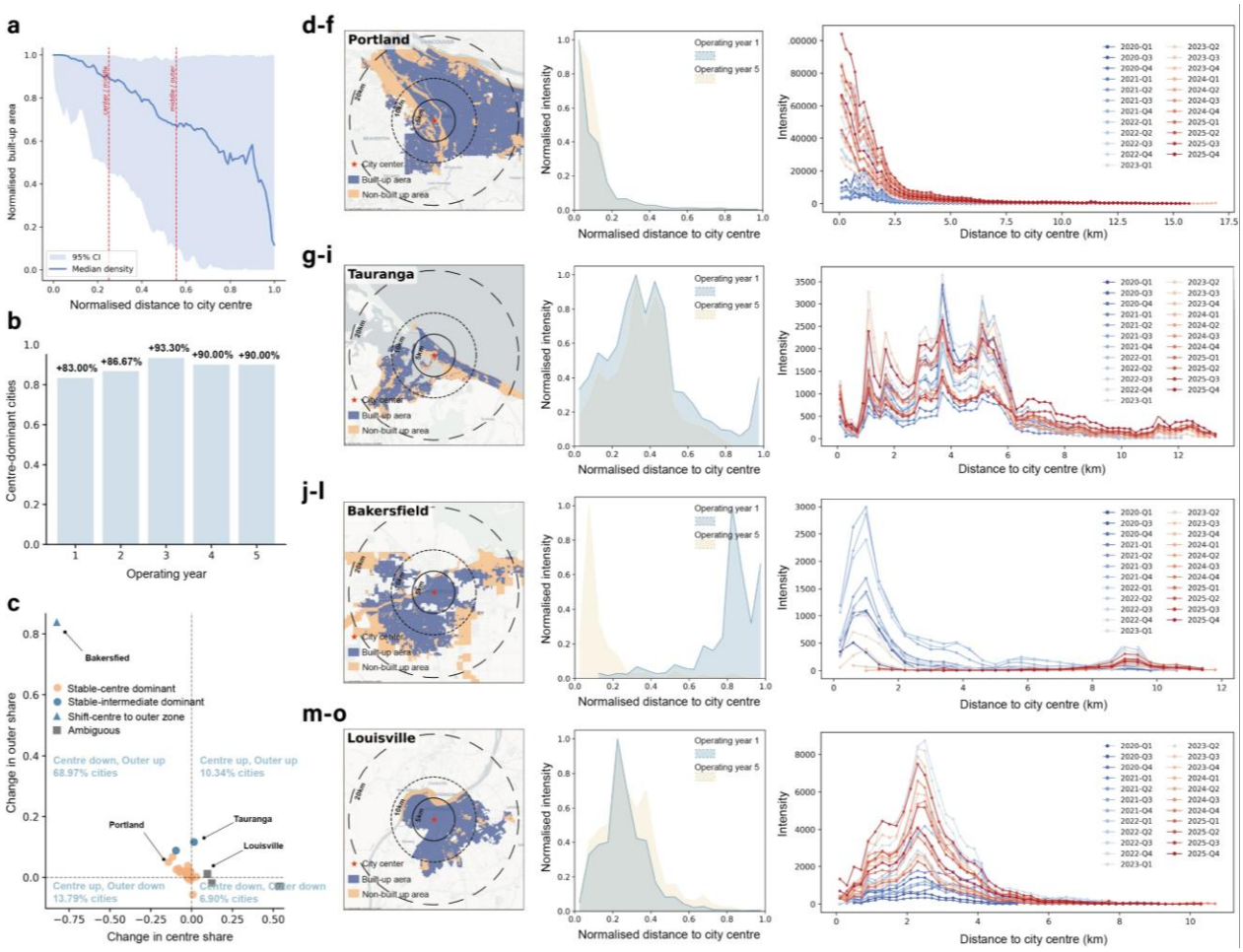
Building on this contrast, Fig. 3b follows post-2021 utilisation trajectories aligned by operating quarter to examine when the survived and closed separation emerges. The two groups share similar quarter-to-quarter rises and dips, but their levels separate early. The gap is largely established within the first three operating quarters, and the interquartile ranges (25th–75th percentiles) show little overlap thereafter. Closed cities seldom reach $U = 1$, So, remaining below this level after three quarters provides a strong empirical signal that a system is unlikely to converge towards survived city performance. In Fig. 3c, cities are used to contextualise this separation across

countries. The US shows the clearest split, with most closed services occurring alongside a small set of high-utilisation cities. NZ and AU are tended toward higher utilisation overall, and no closed cities are observed in AU in this sample. This early divergence was further supported by a survival-based sensitivity analysis, in which lower mean utilisation over the first three operating quarters predicted earlier exit and a higher subsequent risk of system exit (see Supplementary Fig. S2 and Supplementary Table S1)

## SMM systems find it hard to break out of the city centre

Fig. 4 examines how SMM spatial demand is distributed spatially and how they evolve in cities able to sustain the service. We used a normalised distance metric when classifying cities into distinct spatial patterns to account for the heterogeneity of urban shapes. Across the survived cities, SMM demand remains highly concentrated in central urban areas, reaching a "stable-centre" pattern.

**Fig. 4** Spatial demand evolution patterns of SMMs ride intensity



**a,** Radial profiles of normalised built-up area and distance intensity. **b,** Share of centre-dominant city-years across operating years. **c,** Change in normalised ride intensity (operating year 5 minus operating year 1) by pattern type. **d-f,** Stable-centre dominant. **g-i,** Stable-intermediate dominant. **j-l,** shift from centre to outer zone. **m-o,** Ambiguous (no clearly dominant zone). In panels **d–o**, we show representative cities for each dominated type. For each city, we present (left) the built-up footprint with concentric distance bands, (intermediate) normalised radial ride intensity profiles in operating years 1 and 5, and (right) the corresponding unnormalised quarterly radial profiles in absolute units.

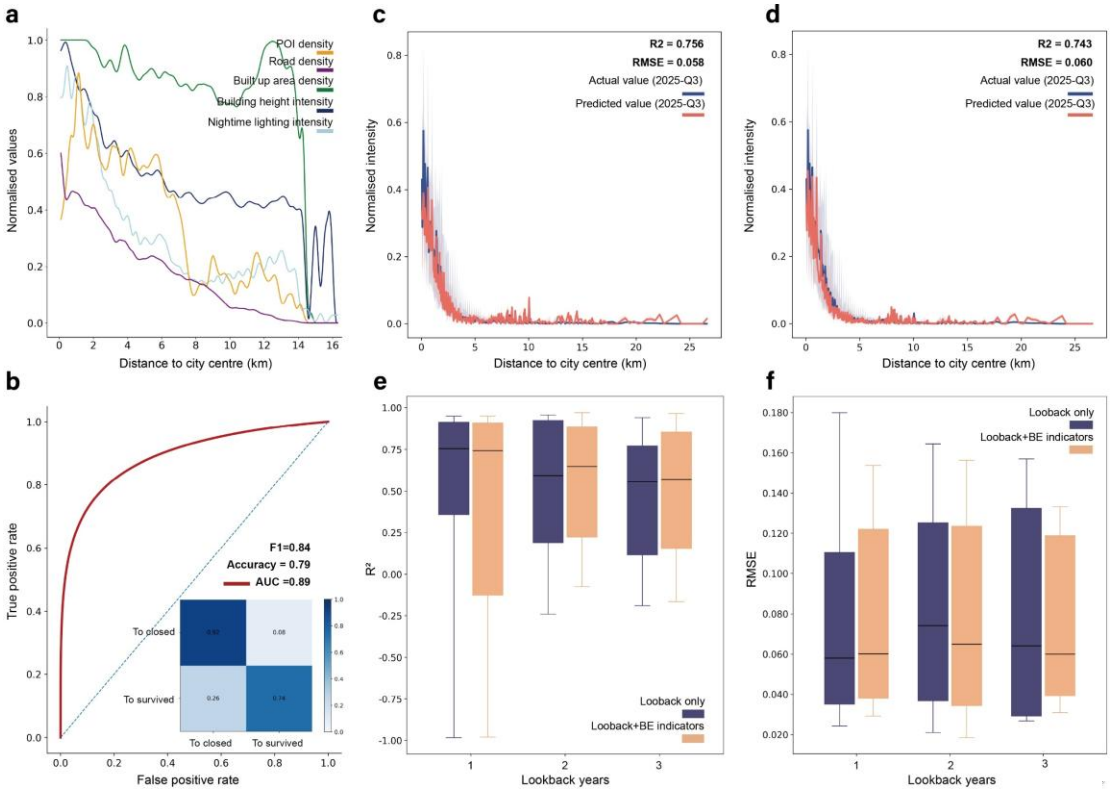
Fig. 4a focuses on cities with survived SMM, which we find to provide longer and more stable time series in like-for-like comparison. For each operating year since 2021, we construct a radial intensity profile by aggregating spatial ride intensity. Using Jenks natural breaks on the pooled radial distributions, we define three concentric zones: centre (0–0.25), intermediate (0.25–0.56), and outer (0.56–1). We classify the dominant zone for each city-year as the zone accounting for more than 50% of the total intensity.

In Fig. 4b, the share of centre-dominant cities in city-years is already high in operating year 1 (83%). It increases further by operating year 5 (90%), indicating that persistent core concentration slightly strengthens over time. This pattern is robust to alternative threshold definitions, with around half of cities persist concentration in the urban centre even under a much stricter 80% threshold (supplementary Fig. S3). To examine whether rebalancing occurs despite this, we plot cities in a four-quadrant space in Fig. 4c, where the x-axis is the change in centre share, and the y-axis is the change in outer share (year 5 minus year 1). Although ~69% of cities exhibit simultaneous decreases in centre share and increases in outer share, these shifts are typically insufficient to cross the >50% dominance threshold. So, the dominant zone remains the centre in most cases. Notably, Bakersfield is the only city that transitions from centre-dominant to outer-dominant, and a small number of cities (e.g., Louisville) are ambiguous in this sense, with no dominant zone in both years. Further, Fig. 4d–f corroborates this pattern; apart from Bakersfield, most cities show growth concentrated within their year 1 served footprint, consistent with intensification within existing service areas rather than substantive expansion into the outer zone.

## Common BE indicators can predict SMMs' persistence

Fig. 5 tests the potential of using common and globally available BE indicators to predict SMM systems that survived *versus* those that closed, and for forecasting spatial ride intensity by using the historical trajectory along with BE indicators.

**Fig 5.** SMMs development assessment and ride intensity prediction




**a**, BE "urban curves", includes ring-aggregated, distance-to-centre profiles (normalised) derived from open datasets, Washington D.C. as an example. **b**, Persistence classification using logistic regression trained on labelled survival *versus* closed cities, with BE indicators as predictors; held-out test performance is evaluated using Area Under the Curve (AUC) and F1 score. **c**, Forecast performance evaluation using only one-year lookback operational history. **d**, Forecast performance evaluation using one-year lookback operational history combined with BE indicators. **e**, $R^2$ (coefficient of determination) performance across different lookback windows, comparing models with and without BE indicators. **f**, RMSE (root mean squared error) performance across different lookback windows, comparing models with and without BE indicators. In panels c–f, performance metrics are summarised as the median across cities.

Fig.5a shows how we encode urban form into comparable features. Using the city centre as a reference, we aggregate open BE descriptor layers into concentric distance bands to obtain normalised urban curves capturing core-to-periphery gradients in activity and morphology. Fig. 5b uses these BE indicators to predict subsequent system outcomes. We fit a binary logistic regression on cities with known labels (survived *versus* closed status), using BE covariates as inputs. The test results (AUC = 0.89; F1 = 0.84) indicate that widely available BE information alone provides a strong signal for whether a system is likely to converge toward survived operation or instead exit (supplementary Fig. S4 includes threshold selection and feature effects).

In Fig. 5c–d, we move beyond persistence classification to trajectory prediction of SMMs' ride intensity. We train an LSTM to forecast ride intensity in 2025 Q3, which is the seasonal peak in the operating records, by varying (i) the lookback window of historical operational data (up to one year) and (ii) whether BE indicators are included as additional inputs, and we compare predictive performance accordingly. The results show that using only the city's one-year operational history yields the strongest forecasts, outperforming alternatives in both $R^2$ and RMSE. We then extend this test in Fig. 5e–f by allowing up to three years of historical lookback as input. Even in this setting, the one-year lookback remains consistently optimal, indicating that more historical data does not necessarily translate into better predictive performance. Together, these findings support the feasibility of forecasting spatial ride intensity using a parsimonious, data-light, planning-oriented approach to capturing the most informative recent dynamics.

## Discussion

SMMs growth appears to be driven more by fleet expansion and service rollout than by strong gains in daily per-vehicle utilisation. This matters not only for operational performance, but also for decarbonisation, because when vehicles are used infrequently, life-cycle emissions can erode or even offset the emissions savings expected from mode substitution[23]. More fundamentally, utilisation remains limited in many cities and scales only weakly with city size, such that a tenfold increase in population corresponds to only ~1.41×, far from supporting an intuitive "bigger is more efficient" expectation, which reinforces recent critiques of the policy assumption that simply expanding system size increases performance[24]. Against this broader pattern, cross-country heterogeneity remains substantial that AU and NZ showing more high-performing survived systems and the US exhibiting a more polarised pattern. One possible explanation for the observed cross-country heterogeneity is variation in governance and regulatory consistency. The city-led permitting, parking, and operating requirements in the US and wide cross-city variation in rules[25,26], whereas AU and NZ more often set requirements for operators through standardised state or national-level frameworks to structure local rollout, potentially reducing institutional uncertainty and supporting more predictable operational performance[27,28].

Utilisation is also a practical indicator of whether SMM scaling is likely to be sustained or end in closure. Utilisation in closed SMM cities is about 45% of survived SMM cities and rarely exceeds a pragmatic benchmark of $U = 1$ across subsequent quarters once implemented. Crucially, the separation between survival and non-survival trajectories emerges early, with the gap typically established within the first three operating quarters after implementation, suggesting strong early lock-in in system performance. This finding provides empirical support for the common use of a one-year evaluation window in pilot governance[29,30]. In practice, however, some programmes evolve into multi-year trials. For example, England's rental e-scooter trials launched in 2020 and are currently scheduled to run until 2028[20]. Our study here highlights a simple early warning signal that utilisation trajectories typically separate within the first few operating quarters. A persistent

failure to reach or approach $U = 1$ should trigger earlier adjustment of rules and operations, such as service area design, parking, deployment and rebalancing, pricing, and speed management[26,31], rather than waiting for performance to improve naturally with additional supply.

We also indicate that SMMs face a fundamental spatial limitation as a scalable decarbonisation pathway, as their expansion remains strongly concentrated in urban cores rather than extending more broadly across the city. Prior work had consistently identified distance to the city centre as a key determinant of use, reflecting denser demand, more supportive infrastructure, and lower operational costs for retrieval and management[32,33]. Based on our multi-city, cross-country evidence, we believe that core locking is not merely a spatial reflection of demand density. Still, more likely a self-reinforcing equilibrium shaped by demand density, infrastructure supply, and operating costs, and operators eventually tending to deploy in the core to reduce recovery and rebalancing costs. The higher accessibility and security of the core further amplify demand, leading to continuous accumulation of resources and usage in the core, which may further reinforce pre-existing inequalities in access and use across social groups[34]. If SMMs are expected to complement public transport and displace private car trips over time[2,35,36]. These findings suggest that market-led expansion alone may be insufficient to extend those benefits beyond already advantaged central areas.

In addition, we contribute a transferable, low-data decision support approach that goes beyond single-city operational forecasting[37,38]. Using widely available BE indicators and standard modelling approaches, we provide a low-barrier, transferable toolkit for two complementary tasks. First, we jointly predict whether a city's SMMs is likely to survive. Second, for near-term trajectory forecasting, we show that quarterly ride intensity is best predicted using a city's own recent operating history, with longer historical records adding limited additional predictive value. This suggests that SMM trajectories are shaped primarily by the current operating state rather than deep historical dependence, consistent with a short-memory, path-dependent growth process that resonates with a stochastic growth perspective, in which divergence emerges through the cumulative carry-over of recent changes rather than direct dependence on distant initial conditions[39]. This also helps explain why early operational performance is so informative for long-term persistence that small early differences in utilisation may be propagated over successive periods into substantially different system trajectories. From a governance perspective, it reinforces the idea that transport operators and policymakers across cities should rely on more on forecasting grounded in recent operating performance and spatial evidence when introducing SMMs.

We acknowledge that this study has limitations and scope for extension. First, our main analyses characterise system evolution using annual aggregated measures, but we do not yet resolve finer temporal structure at the quarterly or within-day level (e.g., peak periods *versus* nighttime), limiting our ability to isolate seasonal effects, diurnal patterns, or short-term policy adjustments

on trips and demand. Second, we assess SMM as a city-level service provision rather than isolating mode-specific effects. Although all cities in our sample include e-scooters, and some also include e-bikes, future work could examine whether utilisation and spatial expansion vary systematically by service composition. Third, while we document robust utilisation differences and predictability between survived and closed systems, we do not directly identify the causal mechanisms behind different outcomes, for example, variations in regulation, market structure, pricing, and infrastructure provision. Future research could apply mechanism decomposition, quasi-experimental and case-study designs to test the key drivers.

## Methods

### SMMs operational data

We compiled quarterly SMM operational statistics for 64 cities from the Ride Report from 2019-2025[40]. In these cities, licensed operators report fleet and trip records as part of the local permitting process. Ride Report then anonymises, aggregates, and publishes these records for social supervision. As a result, the statistics reflect system-wide operational logs across permitted operators within each city, rather than a crowdsourced and conventional bicycling datasets, thereby reducing self-selection and sampling bias in data coverage[41]. As SMMs' services are typically permitted and regulated at the municipal level, where operators are licensed to serve a defined municipal service area[25,26], we excluded data outside each city's municipal administrative boundary. Municipal administrative boundaries were derived from OpenStreetMap (OSM)[42], and population data were obtained from the national statistical agencies of the corresponding countries and matched to the same administrative units.

### Definition of city operation status

However, the operating history varies by city (Supplementary Fig. S5 shows the start of the operating year). Thus, we classified the city-level SMM system's operational status into three categories. Survived cities (n = 31) are those with continuous operation for at least five post-2021 operating years and still active by the end of 2025. The five-year threshold was adopted because it spans a typical recapitalisation window, given the 3–5-year service life of vehicle fleets[43], and also commonly used in prior e-cooter studies to characterise the sustained supply and demand[12]. Ongoing cities (n = 20) remain in operation by the end of 2025 but have fewer than five post-2021 operating years observed. Closed cities (n = 13) are those that operated at some point after 2021 but ceased operations by the end of 2025. We use 2021 as the common starting point to minimise COVID-era distortions and to harmonise operating time across services that began in 2019–2020.

### SMMs spatial ride intensity

To reveal how SMMs ride intensity varies from the city centre towards the urban periphery, we adopt a concentric buffer-ring approach that has been widely used in studies of urban spatial structure and dynamics[44,45]. Specifically, we construct a sequence of concentric rings centred on

the city downtown, with each ring $R_i$ defined as the annular area between two successive radii (supplementary Fig. S6 and Table S2 includes buffer rings construction).

For each SMM's trajectory $j$, we compute the length of the trajectory segment lying within the ring. $R_i$, denoted $L_{ij}^{\text{inter}}$, and weight it by the usage count $c_j$, representing the number of observed trips associated with the trajectory $j$. All trajectory segments located within restricted zones (no-ride and no-parking areas) are excluded before this calculation to avoid confounding ride intensity estimates (supplementary Fig. S7-S8 and Table S3-4 include restricted zones). The SMMs ride intensity in the ring $i$ is then defined as in equation (1).

$$\text{Ride intensity}_i = \frac{\sum_{j \in \mathcal{J}} L_{ij}^{\text{inter}} c_j}{A_i^{\text{city}}} \quad (1)$$

where $\mathcal{J}$ denotes the set of all trips and $A_i^{\text{city}}$is the area of the urban footprint intersecting the ring $R_i$. This formulation yields a density-like measure of SMMs activity, capturing usage-weighted travelled length per unit urban area and enabling direct comparison across rings and across cities (supplementary Fig. S9 show spatial demo).

**BE indicators**

Following prior SMMs road-network studies, we first removed high-speed arterial roads that are generally unsuitable for micromobility travel (motorway, trunk, primary, secondary, tertiary, and their link variants) [46,47]. Using road network data downloaded from OSM, we then derived two road-based measures: (i) bikelane network, representing dedicated cycling facilities, defined as segments explicitly tagged for bicycle use; and (ii) sidewalk network, representing pedestrian walkways along city roads.

In addition, we assembled four of the most widely used BE datasets in micromobility studies, including land use (Sentinel-2, 10 m resolution)[48], nighttime lights (VIIRS, 500 m resolution)[49], building height (GBH2020, 150 m resolution)[50], and points of interest (OSM POIs). Together, these datasets capture functional land-use patterns, human activity intensity, built-form density, and destination attractiveness, which strongly shape short-distance and first/last-mile travel behaviour[51–54].

While other BE indicators (e.g., urban morphology and urban design) and socio-demographic factors (e.g., education level and demographic composition) may also influence SMMs' usage[51,55,56], the datasets selected here represent the most commonly discussed dimensions in urban and transport research and, critically, are available as globally consistent and harmonised datasets. Then, all BE indicators were projected onto the same set of concentric buffer rings and summarised within the urban footprint intersecting each ring (supplementary equations S1-S10 and Fig.S10-14 include definition and spatial distribution).

## Statistical analysis

### *Scaling law for SMMs demand, supply and utilisation*

We modelled city-level SMMs operating performance as a power function of city population, fitted using ordinary least squares in log–log form. For each outcome $Y$—daily trips (demand), daily active vehicles (supply), and daily trips per-vehicle (utilisation), we assume a scaling relationship as in equation (2).

$$Y = Y_0 \, P^{\beta} \tag{2}$$

Where $P$ is the city population, $Y_0$ is a normalisation constant, and $\beta$ is the scaling exponent. We estimate $\beta$ by fitting the natural-log specification using equation (2a).

$$ln\ Y = ln\ Y_0 + \beta ln\ P + \xi \tag{2a}$$

Where $\xi$ is the error term. By convention, $\beta < 1$ indicates sublinear scaling (less-than-proportional increase with population), $\beta = 1$ indicates linear scaling (proportional increase), and $\beta > 1$ indicates superlinear scaling (more-than-proportional increase).

### *Logistic regression of city operation status*

We modelled city-level SMM operation status as a binary outcome and tested whether globally available BE metrics contain a predictive signal for subsequent persistence. We restrict this classification to cities with known end states, coding survived cities as $y_c = 1$ and exited cities as $y_c = 0$. Let $\mathrm{Z}_c$ denote the vector of BE predictors for the city $c$, derived from built environment metrics. We fit a logistic regression using equation (3).

$$\log\left(\frac{p_c}{1-p_c}\right) = \alpha + \mathrm{Z}_c^{\top}\theta \tag{3}$$

Where $p_c = Pr\ (y_c = 1 \mid Z_c)$, $\alpha$ is the intercept, and $\theta$ are coefficients estimated by maximum likelihood. Predictors are scaled consistently before estimation to ensure comparability across covariates. Model performance is assessed out-of-sample and summarised using the F1 score and AUC. With confusion-matrix counts $\{TP, TN, FP, FN\}$, as in equation (4).

$$\mathrm{F1} = \frac{2\mathrm{Precision}\cdot\mathrm{Recall}}{\mathrm{Precision}+\mathrm{Recall}}, \mathrm{Precision} = \frac{TP}{TP+FP}, \mathrm{Recall} = \frac{TP}{TP+FN} \tag{4}$$

We report AUC as a threshold-free measure of discriminative performance, while Accuracy and F1 provide complementary threshold-based summaries; F1 is particularly informative under unequal class sizes because it balances precision and recall.

### *LSTM prediction of SMMs ride intensity*

To examine the temporal dynamics and predictability of SMMs' ride intensity, we used LSTM networks to model ring-level ride intensity time series. For each city $c$ and ring $r$, and quarter $t$, let $y_{c,r,t}$ denote observed intensity. For each city $c$, ring $r$, and quarter $t$, let $y_{c,r,t}$ denote the observed ride intensity. The forecasting task is a one-year-ahead, multi-step prediction, in which the model takes the previous $L$ quarters as input and outputs forecasts for the subsequent $H = 4$ quarters (i.e., $t + 1, \dots, t + 4$). We test lookback windows corresponding to 1–3 years of historical information, $L \in \{4,8,12\}$ quarters.

In the baseline specification, the LSTM uses only the historical intensity sequence, as in equation (5).

$$\hat{\mathbf{y}}_{c,r,t+1:t+H} = f_{\mathrm{LSTM}}(\mathbf{y}_{c,r,t-L:t}) \tag{5}$$

Where $\mathbf{y}_{c,r,t-L+1:t}$ denotes the observed intensity sequence over the previous $L$ quarters and $\hat{\mathbf{y}}_{c,r,t+1:t+H}$ denotes the predicted sequence over the subsequent $H$ quarters.

To test whether the BE indicator adds explanatory power beyond temporal persistence, we estimate otherwise identical models augmented with ring-level BE covariates, as in equation (6).

$$\hat{\mathbf{y}}_{c,r,t+1:t+H} = f_{\mathrm{LSTM}}(\mathbf{y}_{c,r,t-L:t}, \mathbf{X}_{c,r}) \tag{6}$$

Where $\mathrm{X}_{c,r}$ denotes BE characteristics aggregated to the same buffer ring and treated as static covariates over the forecasting window. To limit dimensionality, $\mathrm{X}_{c,r}$ includes a parsimonious subset of variables guided by the linear associations with intensity.

## Data availability

All data used in this study are publicly available. Shared micromobility operational data were obtained from the Ride Report public data portal (https://public.ridereport.com/). The population data sources include Census Reporter (https://www.censusreporter.org) for the United States, Australian Bureau of Statistics (https://www.abs.gov.au) for Australian cities, and Stats NZ (https://www.stats.govt.nz) for New Zealand cities. Municipal administrative boundaries, street network data, and points of interest were extracted from OpenStreetMap (https://www.openstreetmap.org/). Land use and land cover information were derived from the Sentinel-2 10-m resolution global land cover dataset available via the ArcGIS Living Atlas (https://livingatlas.arcgis.com/landcover/). Nighttime light intensity data were obtained from the VIIRS annual nighttime lights dataset provided by the Earth Observation Group (https://eogdata.mines.edu/nighttime_light/annual/v20/). Building height data were sourced from the Global Building Height 2020 (GBH2020) dataset available on Figshare (https://figshare.com/articles/dataset/2020_150__/25729248/6).

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