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Evaluation of Sustainable Shared Mobility Initiatives in Rudersdal Municipality

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Abstract

This paper evaluates shared mobility usage patterns and public transport integration in Rudersdal, a suburban municipality 20 km north of Copenhagen, within the European project GEMINI. Using one year of trip data from shared mobility operators, alongside user survey data, the study examines temporal and spatial demand patterns, user segmentation by usage intensity, and the relationship between shared mobility and public transport. E-bike demand is significantly weather-dependent and seasonal, while carsharing exhibits greater year-round stability. Weekday demand shows pronounced commuting peaks driven by frequent users, while weekend usage is more evenly distributed and leisure-oriented. Spatially, trips concentrate around mobility hubs, public transport stations, residential areas, and employment or academic centres. Frequent users make shorter, routine trips along stable commuting corridors, while occasional users display more dispersed behaviour. Nearly all trips start and endpoints fall within 300 metres of a public transport stop. Age and alternative mode preferences are the principal predictors of intermodal behaviour. The findings demonstrate that shared mobility can function effectively in suburban settings when supported by strategically placed mobility hubs, complementing rather than substituting public transport.

1 Introduction

The transport sector accounts for a substantial share of emissions, and achieving climate targets requires a fundamental restructuring of mobility planning. Shared mobility has emerged as an important tool in this restructuring, offering on-demand vehicle access without the costs and externalities of private ownership (Shaheen et al., 2016). When well integrated with public transport, shared mobility can extend the reach of transit networks, address first- and last-mile gaps, and reduce dependency on private cars.

However, the evidence base for shared mobility is heavily skewed towards dense urban environments. Suburban and peri-urban municipalities, characterised by lower population densities, dispersed residential patterns, higher car ownership rates, and less frequent public transport, present a qualitatively different operating context. The applicability of urban shared mobility findings to these settings cannot be assumed, and the conditions under which shared mobility services achieve meaningful adoption and public transport integration in suburban contexts are not well established (Liao and Correia, 2022; Bruning et al., 2025).

This paper addresses this gap through an empirical analysis of a Mobility Living Lab 2 (MLL2) in Rudersdal, Denmark, as a part of the EU-funded GEMINI project[1]. MLL2, coordinated by the Capital Region of Denmark, was the first of its kind to operate in Rudersdal, a municipality with a passenger car ratio of 66.83% in January 2025, compared to 24.13% in the City of Copenhagen and a national average of 46.46% (Statistics Denmark, 2025). Three shared mobility operators were introduced within a multimodal mobility hub: Dott (shared e-bikes), GreenMobility(free-floating e-carsharing), and Kinto (station-based carsharing). The study covers the full first year of operations (22 August 2024 to 31 July 2025).

In this paper we focus on three research questions: (1) How do shared mobility demand and trip characteristics vary across temporal and spatial dimensions? (2) What differences in trip characteristics can be observed across user segments defined by usage intensity? (3) To what extent and under which conditions does shared mobility complement or connect to public transport?

The paper is structured as follows. Section 2 reviews relevant literature on shared mobility patterns, user segmentation, and public transport integration. Section 3 describes the study area and data sources. Section 4 outlines the methods applied. Section 5 presents the empirical results. Sections 6 and 7 discuss the findings and draw conclusions.

2 Background

2.1 Integration with Public Transport

The integration of shared mobility with public transport is essential for promoting intermodal travel, especially for longer journeys and in lower-density contexts (Liao and Correia, 2022; ShareDiMobiHub, 2024). Shared micromobility can play a key role as a first- and last-mile connector. However, achieving seamless integration requires coordinated infrastructure, digital platforms, and pricing across modes (Oeschger et al., 2020; Bruning et al., 2025).

Mobility hubs are increasingly used to operationalise this integration. When strategically positioned, mobility hubs can encourage multimodal travel behaviour and improve system coverage (Nikitas et al., 2025; Czarnetzki and Siek, 2023). Research suggests that frequent hub users are more likely to reduce car ownership and adopt sustainable travel habits (Czarnetzki and Siek, 2023). In suburban contexts, hybrid solutions combining physical and virtual hubs have been found most effective, balancing vehicle availability with spatial flexibility (Bruning et al., 2025).

[1] Grant No. 101103801

2.2 Usage Patterns and User Segmentation

Temporal analyses of shared mobility consistently reveal distinct patterns across time scales. At the yearly level, micromobility demand is strongly correlated with temperature and weather conditions (Eren and Uz, 2020). Carsharing exhibits greater resilience to seasonal variation, reflecting the protection from weather that cars afford. At the weekly and daily level, a clear weekday-weekend duality is well-established: weekday demand is characterised by morning and evening commuting peaks, while weekend demand tends to be more evenly distributed throughout the afternoon and evening, consistent with leisure-oriented use (Dziecielski et al., 2024; Jo et al., 2024).

Spatially, shared mobility demand concentrates near transit hubs, employment centres, universities, and residential areas with good cycling infrastructure (Dziecielski et al., 2024; Jo et al., 2024). User profiles typically skew towards younger, higher-educated, and more environmentally conscious individuals who are accustomed to public transport and cycling (Liao and Correia, 2022; Shaheen et al., 2016).

User segmentation by usage intensity reveals a characteristic pattern across operators: a majority of users make only one or a few trips (occasional users), while a small minority of heavy users account for a disproportionate share of total trip volume (Baumgarte et al., 2021). These two groups exhibit qualitatively different temporal, spatial, and modal behaviour, with important implications for service design and marketing.

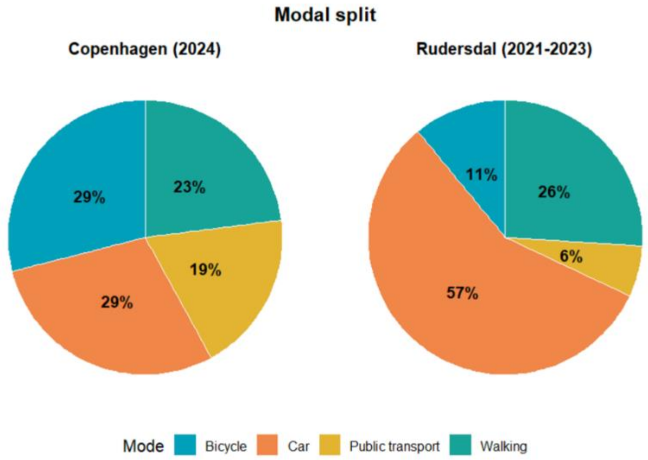
While the evidence base for urban shared mobility is substantial, suburban and peri-urban deployments remain underrepresented in the literature. This paper contributes directly to filling this gap.

3 Study Area and Data

3.1 Rudersdal

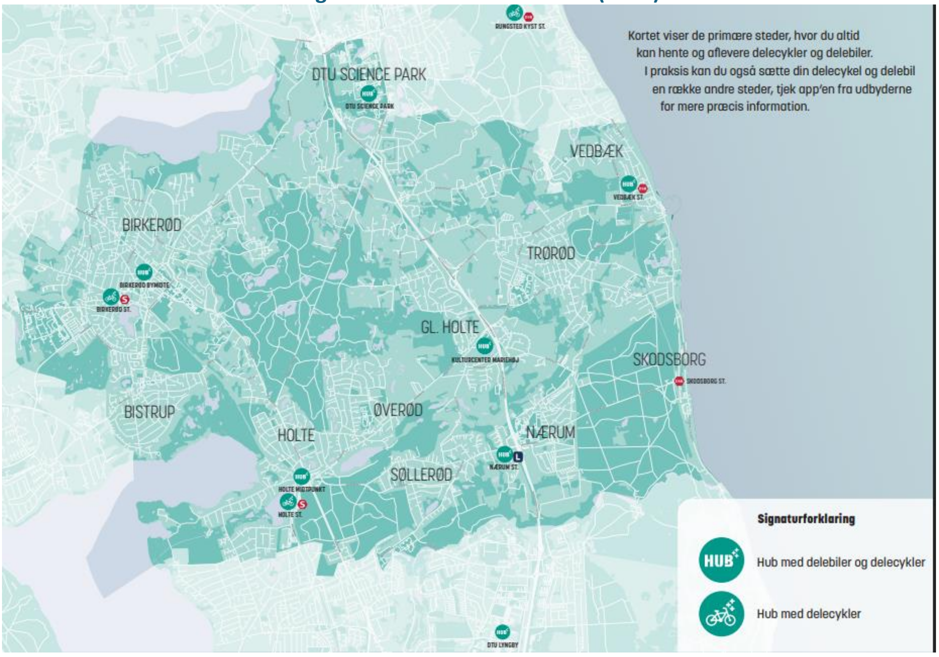
Rudersdal is connected to Copenhagen by one regional train line, two S-train lines and one Bus Rapid Transit (BRT) line.. However, public transport services within the municipality between individual towns are infrequent and poorly accessible, making internal mobility largely car-dependent. The modal split for trips to, from, and within Rudersdal (2021–2023) shows 57% of trips made by car, 26% on foot, 11% by bicycle, and only 6% by public transport. This contrasts sharply with Copenhagen, where the equivalent shares in 2024 were 29% car, 23% walking, 29% cycling, and 19% public transport (DTU Center for Transport Analytics, 2024; Kobenhavn Kommune, 2025).

Figure 1 - Modal split for Copenhagen in 2024 (left); and modal split for Rudersdal between 2021 and 2023 (right). Data extracted from DTU Center for Transport Analytics (2024) and København Kommune (2025).



The MLL2 established a network of mobility hubs at 6 strategically chosen locations. Three further hubs were established outside Rudersdal. Hub locations were selected based on input from local stakeholders, analysis of public transport data, traffic counts, and demographic studies (Pek et al., 2024).

Figure 2 - Locations of the hubs in Rudersdal. Image extracted from Pék et al. (2024).



3.2 Shared Operators

Dott has a micromobility fleet of over 250.000 vehicles EU-wide, including 200 shared electric bikes in this project. Its business model centres on an app-based system combining virtual and physical hubs: 14 physical hubs were established in the study area, complemented by over 200 virtual hubs displayed in the mobile application. During the study period, the virtual hub network was expanded by 20–30% to improve service coverage. Users can access vehicles through subscriptions or per-trip rentals.

GreenMobility is a fully electric free-floating carsharing operator from Denmark. Ten physical hubs were established under the GEMINI project, but vehicles can also be parked in GreenMobility's free-floating zones in Copenhagen and the Capital Region. The initial fleet of 20 electric cars was expanded to 60 during the study period in response to growing demand.

Kinto Share, a sub-brand of Toyota, provides hybrid Toyota models at fixed station-based hubs under a round-trip model: users must return the vehicle to the same hub from which it was collected. Six hubs were established in the study area. Reservations are made via the Kinto app; vehicles can be rented by the hour, day, or week.

3.3 Trip Data

The core dataset consists of anonymised trip records provided by each operator, covering the period from 22 August 2024 to 31 July 2025. Each record contains a unique trip identifier, an anonymised user identifier, a vehicle identifier, local start and end timestamps, and spatial data for trip origins and destinations (geographic coordinates for Dott and GreenMobility; hub identifiers for Kinto).

After data processing and cleaning, the retained datasets comprise 18,464 Dott trips (96.4% retention) by 4,937 users; 19,390 GreenMobility trips (89.0% retention) by 4,200 users; and 672 Kinto trips (97.8% retention) by 162 users.

3.4 User Survey Data

Operators administered two user survey waves. The first survey collected information on location, user satisfaction (0–5 scale), connection to public transport (yes/no), and suggestions for service improvement. The second survey expanded to include trip purpose, alternative transport mode if the shared vehicle had been unavailable, frequency of vehicle unavailability, and demographic characteristics (age, gender). For Dott, wave 1 collected 605 responses (Sept 2024–Mar 2025) and 198 in wave 2 (Mar–May 2025). For GreenMobility, wave 1 collected 562 responses (Aug 2024–Mar 2025) and 442 in wave 2 (Mar–Sept 2025). Kinto surveys received only 9 and 10 responses per wave respectively and were excluded from all survey-based analyses due to insufficient sample size.

3.5 External Data

Public transport infrastructure data, namely stop and station coordinates for Rudersdal Municipality and the Capital Region, were obtained from Rejseplanen Labs[2]. Travel time estimates for alternative transport modes (walking, public transport, and driving) were retrieved via the Google Maps Directions API. Because the API does not accept historical date queries, all trips were simulated using a reference week in December 2025 while preserving the original day of week and hour of departure for each trip. This approach enables estimation of public transport frequency and traffic conditions, though December conditions may differ from conditions during the actual trips.

4 Methods

4.1 User Segmentation

Users were segmented into four groups based on their total number of completed trips: Low (1 trip), Medium (2–5 trips), High (6–20 trips), and Heavy use (more than 20 trips). This segmentation, consistent with approaches used in recent shared mobility research (Baumgarte et al., 2021; Dziecielski et al., 2024), enables exploration of behavioural differences between occasional and frequent users in terms of trip timing, duration, spatial distribution, and public transport connectivity.

4.2 Temporal Analysis

Temporal patterns were examined at three scales. Annually, monthly trip volumes were plotted against average temperature data from the Danish Meteorological Institute, and Pearson analysis was used to quantify the strength and statistical significance of any association (significance $\alpha=0.05$). At the weekly scale, the percentage of total trips on each day of the week was plotted by user segment to identify weekday–weekend differences across user groups. At the daily scale, trip counts were aggregated by start hour and plotted separately for weekdays and weekends, and further disaggregated by user segment, to identify intra-day demand patterns. Trip duration was also analysed: mean duration and standard deviation were calculated by operator and user segment, and trips were assigned to duration categories defined separately for each operator to reflect their distinct service models.

4.3 Spatial Analysis

Origins and destinations of each trip were assigned to one of the GEMINI physical hubs or to a broader geographic zone, using reverse geocoding via the OpenStreetMap service and polygon-based spatial classification. The spatial analysis encompassed four components. First, a bidirectional flow network diagram was constructed to identify the main movement corridors and overall connectivity structure between

[2] https://labs.rejseplanen.dk/hc/en-us

locations. Second, station usage intensity was assessed by plotting the number of unique users against the trips-per-user ratio for each hub and zone, to distinguish between broad-based and concentrated demand patterns. Third, the daily vehicle balance at each location was computed as the difference between arrivals and departures, and the number of days with a deficit or surplus was tallied to identify systematic imbalances. Fourth, origin-destination matrices were computed by user segment and day type to examine spatial variation in travel behaviour.

4.4 Public Transport Proximity Analysis

Geographic coordinates were projected into a metric coordinate reference system (EPSG:25832) to enable accurate distance calculations. For each trip, binary indicators recorded whether the origin and destination fell within five distance thresholds (100, 200, 300, 400, and 500 m) of the nearest public transport stop and S-train station. Aggregated percentages were computed for all trips and disaggregated by hub and zone to identify spatial variation in public transport proximity.

4.5 Travel Time Comparison

For each trip with distinct origin and destination coordinates (trips returning to the same location were excluded), travel time estimates were retrieved for three modes: walking, public transport, and driving. The analysis focused on: (a) the mean time difference between shared mobility and each alternative mode across trip duration categories; (b) the percentage of trips for which shared mobility was faster than each alternative; and (c) the hourly distribution of cases where shared mobility outperformed public transport, to identify temporal patterns in competitive advantage.

4.6 Modelling Public Transport Connectivity

Survey data from Dott (wave 2, n = 198) and GreenMobility (wave 2, n = 442) were used to model whether a trip was connected to public transport using two complementary methods. First, a classification tree identified non-linear relationships and interactions among predictors, with the decision rules visualised to highlight distinct user segments. Second, a logistic regression model was estimated using the same predictors, age, gender, trip rating, trip purpose, and the user's stated alternative transport mode, and results were interpreted using odds ratios and p-values (significance α=0.05). Model performance was assessed using 10-fold cross-validation with Area Under the ROC Curve (AUC) as the evaluation metric.

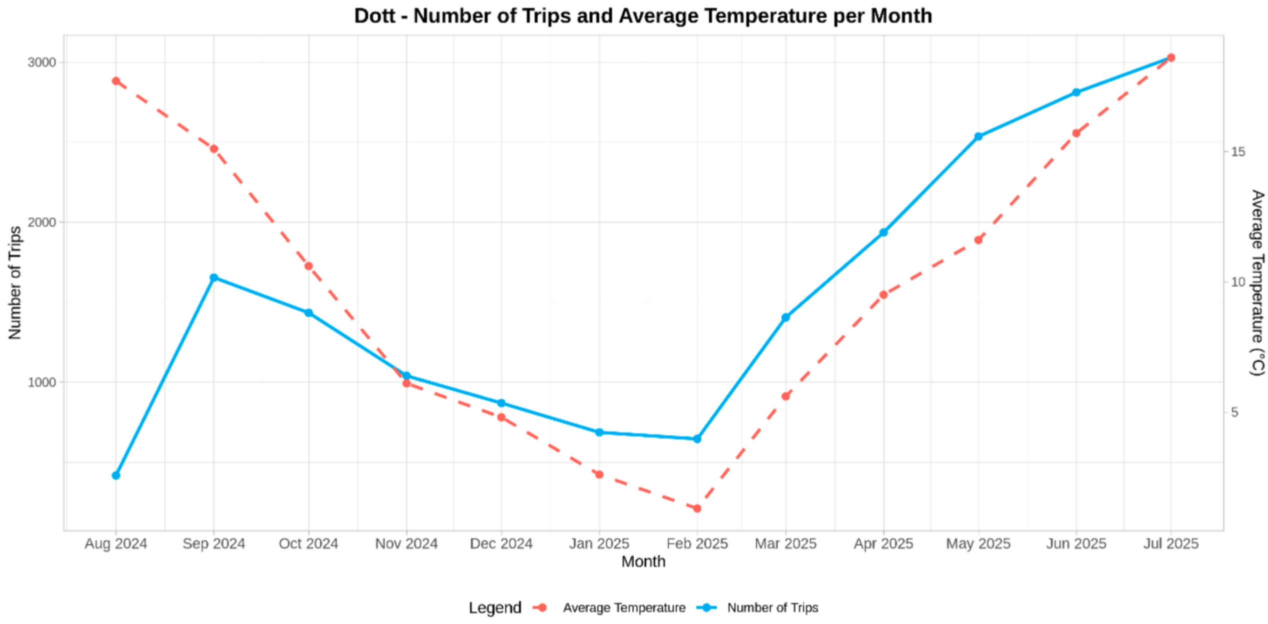
5 Results

5.1 Yearly Trends

Since the implementation of mobility hubs in August 2024, a sustained upward trend in the adoption of all three shared mobility services has been observed. This growth is evident in both trip volumes and operational expansions: GreenMobility tripled its initial fleet from 20 to 60 electric cars in response to growing demand, and Dott expanded its virtual hub network by 20–30% to improve coverage.

Dott shows the strongest seasonal signal. Monthly trip volumes follow a trajectory closely mirroring average monthly temperatures (Pearson r = 0.58, p = 0.047). This relationship confirms that shared e-bike usage in Rudersdal is highly sensitive to weather conditions, consistent with evidence from comparable European deployments (Eren and Uz, 2020; Dziecielski et al., 2024).

Figure 3 - Total monthly trips and average monthly temperature for Dott in Rudersdal during the study period (August 2024 – July 2025). Temperature data was extracted from the weather archive from the Danish Meteorological Institute (n.d.).



GreenMobility exhibits considerably greater year-round stability (r = 0.06, p = 0.85). A mild seasonal dip is visible between December and February, but overall usage remains relatively consistent. A notable exception is a sharp spike in May–June 2025, coinciding with planned S-train infrastructure maintenance works. Kinto operates at lower absolute volumes but shows gradual growth throughout the study year (r = 0.09, p = 0.78). The absence of any seasonal relationship likely reflects the station-based round-trip model, which primarily serves users with specific, planned mobility needs that are independent of weather conditions.

5.2 User Segmentation

Users across all three operators were classified into four segments based on total trip volume. The distribution is consistent: roughly 50–51% of all users fall into the Low use category (1 trip), 35% are Medium users (2–5 trips), 10–11% are High users (6–20 trips), and 2.6–4.2% are Heavy users (more than 20 trips).

Despite their small share of the user base, Heavy users generate a disproportionate amount of total trips. For GreenMobility, Heavy users (3.79% of users) account for 45.27% of all trips (mean: 55.2, max: 272). For Dott, Heavy users (2.55%) account for 31.25% of trips (mean: 45.8, max: 270). For Kinto, Heavy users (4.20%) account for 44.20% of trips (mean: 49.5, max: 154). Across all operators, the mean is consistently higher than the median within the Heavy use segment, confirming the presence of a small number of exceptional outlier users who drive up the group average.

Low use users, though numerically dominant, generate only 10.7–13.6% of total trips. Their behaviour — one-off or infrequent engagement — suggests that they are primarily exploratory or occasional users who have not yet integrated shared mobility into their routine. Converting them into more frequent users represents the most significant opportunity for expanding system-wide ridership.

5.3 Trip Duration

Trip duration reflects fundamental differences in the service model of each operator. For Dott, 95.1% of trips fall between 0 and 30 minutes (mean 12.3 min). Heavy users average 10.3 minutes per trip with relatively low variance, reflecting routine, repetitive commuting patterns. Low users average 17.4 minutes and show a higher standard deviation, consistent with exploratory or leisure-oriented trips.

For GreenMobility, 84.3% of trips last under one hour (mean 89.2 min, standard deviation 316 min — indicating high variability). Heavy users show the shortest mean duration (69.9 min) and 88.4% of trips fall under 1 hour, while Low users show the longest mean duration (128 min). This pattern — where frequent users make shorter, more purposeful trips and occasional users make longer, more diverse journeys — holds across all three operators and is consistent with findings from other shared mobility contexts (Jo et al., 2024; Baumgarte et al., 2021).

Kinto's round-trip model produces a markedly different profile: only 28.1% of trips last less than two hours, 55.2% fall between 2 and 10 hours, and 16.7% exceed 10 hours. The overall mean of 11.7 hours reflects an extended rental pattern more consistent with day-trip or professional use than with the short, functional trips characteristic of the other two operators.

5.4 Weekly and Daily Temporal Patterns

Weekly analysis reveals a clear functional duality that is consistent across all three operators. Heavy users peak on weekdays (Monday–Friday) and show a pronounced drop at weekends. This pattern is strongly consistent with the interpretation that Heavy users primarily use shared mobility as a commuting tool for professional or educational purposes.

Table 1 - Descriptive statistics of number of users, number of trips, and the distribution (%) of users and trips by user segment and service (Dott, GreenMobility (GM) and Kinto)

	User segment	Low Use (1)	Medium Use (2-5)	High Use (6-20)	Heavy Use (>20)	Total
Dott	Number of users	2514	1754	543	126	4937
	Number of trips	2514	4821	5359	5770	18464
	Percentage of users	50.92%	35.53%	11.00%	2.55%	100%
	Percentage of trips	13.62%	26.11%	29.02%	31.25%	100%
GM	Number of users	2132	1465	444	159	4200
	Number of trips	2132	4024	4456	8778	19390
	Percentage of users	50.76%	34.88%	10.57%	3.79%	100%
	Percentage of trips	11.00%	20.75%	22.98%	45.27%	100%
Kinto	Number of users	72	51	14	6	143
	Number of trips	72	150	153	297	672
	Percentage of users	50.35%	35.66%	9.79%	4.20%	100%
	Percentage of trips	10.71%	22.32%	22.77%	44.20%	100%

Low and Medium users display the opposite pattern: maximum activity on Fridays and Saturdays, often nearly doubling their Monday trip share. This leisure and weekend orientation among occasional users suggests that they perceive shared mobility primarily as a supplementary option for non-routine situations rather than as a daily transport mode.

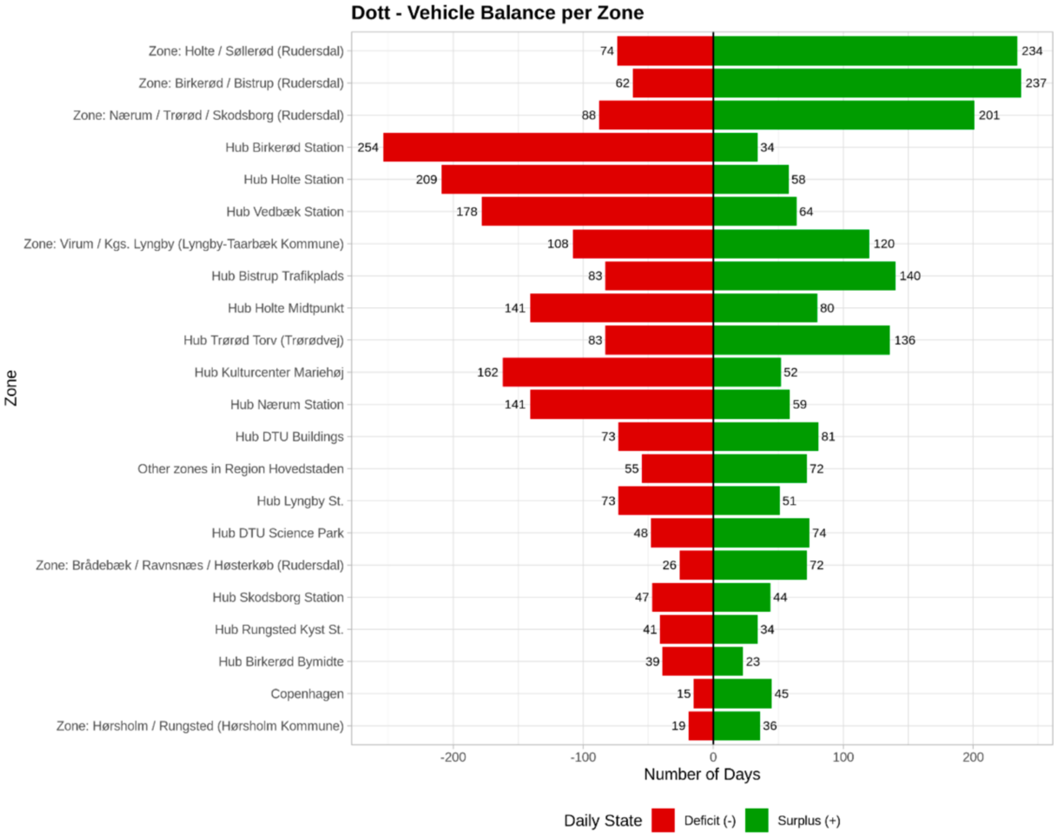
Hourly analysis confirms the weekday–weekend duality at an intra-day level. On weekdays, both Dott and GreenMobility show two distinct peaks: a moderate morning peak between 07:00 and 09:00 and a more pronounced afternoon peak between 15:00 and 18:00. These peaks are driven principally by Heavy users. On weekends, the morning peak disappears entirely; demand for Dott builds from approximately 14:00 and persists into the evening, with a notable secondary spike between 00:00 and 03:00 on weekend nights, reflecting nocturnal leisure and social mobility. GreenMobility's weekend pattern is similar but without the late-night spike, reflecting the additional steps involved in locating and accessing a car compared to an e-bike. Kinto, operating under a round-trip model, shows a sharp weekday morning peak at 08:00 (vehicle pick-ups) and a return peak between 15:00 and 17:00, consistent with half-day rentals.

5.5 Spatial Patterns

For Dott, 61.98% of all trips involve at least one physical hub as either origin (30.36%), destination (19.28%) or both (12.34%). This asymmetry reveals an imbalance in the system: shared e-bikes are predominantly used for outbound journeys from transit hubs into residential areas. The bidirectional flow analysis confirms that the strongest spatial interactions occur along corridors linking public transport station hubs with adjacent residential zones.

Vehicle balance data quantifies the operational consequences of this directionality. Birkerod Station registered net vehicle deficits on 254 out of the approximately 344 operating days, and Holte Station on 209 days. Conversely, the Birkerod/Bistrup and Holte/Sollerod residential zones showed surpluses on 237 and 234 days respectively. This highlights the necessity of proactive rebalancing to maintain first-/last-mile connectivity.

Figure 4 - Dott's daily vehicle balance by location. This divergent bar chart shows the number of days each location experienced a vehicle deficit (red) and a vehicle surplus (green).



Station usage intensity analysis shows that residential zones (Holte/Sollerod, Birkerod/Bistrup) exhibit the highest trips-per-user ratios (approximately 3.2), indicating strong user loyalty and routine behaviour. Station hubs (Birkerod Station: 2.6 trips/user) are used intensively but attract a more transient user population than residential zones. More distant locations such as Rungsted Kyst Station show low loyalty ratios (approximately 1.5), reflecting predominantly occasional use. As user frequency increases, spatial activity becomes more focused: Heavy users concentrate almost exclusively on the main commuting corridors, while Low users show dispersed patterns spread across the entire network.

For GreenMobility, all 19,390 recorded trips involve at least one GEMINI project hub. However, only 15.95% of journeys take place exclusively between two Rudersdal hubs; the remaining trips connected Rudersdal with the broader GreenMobility operating zone. The dominant spatial flows are between the Copenhagen — the highest-volume corridor in the GreenMobility network.

GreenMobility vehicle balances are more symmetric than Dott, with most hubs alternating between slight deficits and surpluses from day to day. This reflects the bidirectional nature of commuting flows — roughly equal numbers of journeys inbound and outbound on any given day — and reduces the need for systematic rebalancing. The highest variability is observed in Copenhagen and North Copenhagen zones, reflecting the stochastic nature of demand from first-time and occasional users.

For Kinto, the round-trip model eliminates origin-destination flow analysis. DTU Science Park shows an exceptional trips-per-user ratio exceeding 10, though driven by a single outlier user (154 trips out of a 672-trip and 162-users dataset). Holte Midtpunkt and Birkerod Bymidte attract the most unique users (approximately 40 each) with lower recurrence ratios, functioning as general-purpose entry points into the service. Vedbaek Station shows a balanced profile with a trips-per-user ratio (approximately 6), indicating a stable group of regular users.

5.6 Public Transport Proximity

Proximity analysis confirms a strong spatial relationship between shared mobility trips and public transport infrastructure. Considering all public transport stops in the area, 87.3% of Dott trips and 88.8% of GreenMobility trips have both their origin and destination within 100 m of a public transport stop. The high proximity values reflect the strategic placement of mobility hubs near transit nodes, and the relatively dense network of bus stops in Rudersdal.

When restricting the analysis to S-train stations proximity is lower, since only a subset of hubs isco-located with S-train stops. Within 100 m of an S-train station, only 10.5% of GreenMobility trips and 31.8% of Dott trips qualify; at 500 m, these figures rise to 42.7% and 48.6%. This variation across hubs reflects the fact that some GEMINI hubs were placed near bus or regional rail stops rather than S-train stations and highlights that S-train connectivity is not universal across the hub network.

Table 2 - Percentage of trips with both origin and destination within specific proximity ranges to public transport stops and S-train stations for GreenMobility and Dott

	All public transport stops		S-Train stations	
Distance range (m)	GreenMobility	Dott	GreenMobility	Dott
100	88.82%	87.34%	10.49%	31.78%
200	97.98%	97.20%	18.06%	35.60%
300	99.76%	99.76%	21.69%	40.23%
400	100.00%	99.94%	34.73%	46.83%
500	100.00%	99.96%	42.71%	48.57%

5.7 Travel Time Comparisons

Travel time comparisons show that shared mobility is most competitive relative to public transport for short trips, where waiting and transfer times inflate journey times. For Dott, e-bikes outperform public transport in 78.4% of Short trips (0–10 min, mean saving 7.4 min) and 61.6% of Medium trips (10–30 min, mean saving 6.2 min) an advantage most pronounced in the early morning hours (00:00–04:00) when public transport frequencies are low or services are not operating. For trips exceeding 30 minutes, the balance reverses: public transport is faster in 73.7% of Long and 96.9% of Prolonged trips, with mean savings of 8.2 and 41.8 minutes respectively. These findings position e-bikes primarily as short-distance trip facilitators and first-/last-mile connectors, rather than as a general-purpose alternative to public transport for all trip distances.

For GreenMobility, short car rentals (0–1 hour) outperform public transport in 81.4% of cases, with an average saving of 11.5 minutes. This substantial advantage is explained in large part by the 70.5% of public transport alternatives that require at least one transfer — a common feature of cross-municipal suburban commutes. For rentals exceeding one hour, GreenMobility is faster in only 7.1% of Medium trips and 0.1% of

Long trips; for prolonged rentals (>10 hours), public transport is categorically faster, indicating that these bookings involve extended parking of the vehicle rather than continuous travel.

Compared to driving, shared mobility is consistently slower. For Dott, private cars are faster in 93.1% of Short trips, though the mean time difference is only 2.5 minutes — suggesting that for the very shortest journeys, e-bikes are a near-equivalent alternative to driving when parking time and urban congestion are factored in. For GreenMobility, private driving is faster in 92.1% of short rentals, with a mean advantage of approximately 10 minutes. This advantage reflects the additional time involved in locating an available shared car, completing the booking process, and returning it after use.

5.8 Modelling Public Transport Connectivity

Among Dott survey respondents in wave 2, 58% (114 of 198) reported connecting their shared e-bike trip with a public transport, compared to 30% (131 of 442) for GreenMobility. These figures establish that intermodal behaviour is already prevalent in both services, making it meaningful to examine which factors predict it.

For Dott, the classification tree identifies age as the dominant predictor of public transport connectivity. Users under 23 have a 70% probability of connecting their trip with public transport — consistent with the high representation of students and young commuters in the Dott user base, who are likely using the bike for last-mile access to train or bus services. The logistic regression confirms these effects: each additional year of age reduces the odds of public transport connectivity by 2.4% ($p = 0.041$), and leisure trips show 68.6% lower odds than educational trips (p not significant at conventional thresholds). The cross-validated AUC of 0.621 indicates moderate discriminative power — above random chance but limited, reflecting the inherent difficulty of predicting individual intermodal behaviour from survey data alone.

For GreenMobility, the classification tree places the user's habitual alternative transport mode as the first split. Users who would have walked or cycled if GreenMobility were unavailable form a small but highly connected segment of multimodal travellers who incorporate shared carsharing into journeys that otherwise involve active modes and transit. The remaining users — those who would have taken a private car, taxi, or public transport as a standalone alternative, or would not have made the trip at all — show much lower connectivity probabilities. The logistic regression confirms that all motorised alternatives are associated with substantially reduced odds of public transport connection compared to the walking/cycling reference group: private cars show an 86.3% reduction, taxis an 80.3% reduction, standalone public transport a 78.6% reduction, and not traveling a 74.8% reduction (all $p < 0.05$). The AUC of 0.517 indicates limited but non-random discriminative ability, likely constrained by the high class imbalance (311 No vs. 131 Yes) and the relatively coarse predictors available in the survey.

6 Discussion

The results collectively demonstrate that shared mobility can achieve meaningful integration with public transport in a suburban context. The evidence from Rudersdal is encouraging: within just one year, a system that did not previously exist has established a loyal base of frequent commuting users , while simultaneously attracting a much larger pool of occasional users who engage with the service for leisure and non-routine travel.

The pronounced segmentation between frequent and occasional users has important implications for operational management and marketing. Frequent users generate the majority of trips and follow predictable temporal and spatial patterns; understanding and stabilising their commuting routines is critical for system viability.

The travel time comparisons reveal a clear positioning for shared mobility in the suburban transport hierarchy. Shared e-bikes and carsharing are fastest for short trips — where public transport waiting and transfer times are disproportionately costly relative to total journey time — but public transport is faster for longer journeys. This positioning is well-suited to first- and last-mile roles, where shared modes can bridge the gap between residential areas and transit stops, extending the effective catchment area of public transport services. The very small time disadvantage of e-bikes relative to driving for the shortest trips (approximately 2.5 minutes) further suggests that e-bikes are a viable car substitute in this distance band, particularly when parking time and cost are taken into account.

The intermodal behaviour analysis highlights two distinct user profiles with high connectivity potential. For Dott, the key target group is young users — particularly students and young professionals — who are already inclined to combine e-bike use with train or bus travel. This group would benefit from integrated journey planning tools and combined ticketing that reduce the cognitive and transactional friction of multimodal trips. For GreenMobility, the highest-connectivity users are those who normally choose active travel modes; their intermodal behaviour suggests that they perceive shared carsharing as an extension of a multimodal lifestyle rather than as a car substitute. Conversely, GreenMobility users who normally drive or take taxis show very low public transport connectivity, indicating that they are primarily using shared carsharing as a car substitute rather than as a public transport complement. Targeted incentives — such as discounted rates for trips that demonstrably end at public transport stops — could shift behaviour in this group.

Several limitations should be acknowledged. The absence of a unified dataset linking individual public transport and shared mobility journeys prevents direct, trip-level observation of intermodal behaviour; the proximity and survey analyses provide convergent but indirect evidence. Survey response rates (ranging from approximately 4% to 8% of total trips depending on wave and operator) introduce potential self-selection bias. The analysis covers a single municipality over one year, which may limit generalisability to other suburban contexts with different infrastructure, demographics, or transport supply. Future work should extend the analysis to a second year of operation to assess whether early adoption trends are sustained and should explore integrated Mobility as a Service platforms that could provide richer data on complete intermodal journey chains.

7 Conclusion

This paper has presented a comprehensive empirical evaluation of shared mobility usage patterns, user segmentation, and public transport integration in Rudersdal during the first year of GEMINI MLL2 operations (August 2024–July 2025). The analysis draws on operational trip data from three operators covering 38,526 trips by more than 9,000 unique users, supplemented by user survey data and external travel time and proximity analyses.

The principal empirical findings are as follows. First, shared e-bike demand is strongly weather- and season-dependent, with a significant positive correlation with monthly average temperature, while both carsharing operators exhibit year-round stability.

Second, user segmentation by trip frequency reveals a consistent pattern across all three operators: a small minority of Heavy users (2.6–4.2% of the user base) generates 31–45% of total trips, with concentrated weekday commuting patterns, short trip durations, and stable spatial routines. The majority of users are occasional users who engage with the service for leisure and non-routine travel, predominantly at weekends. These two groups have distinct operational and marketing implications that should be addressed separately.

Third, shared mobility in Rudersdal is spatially anchored to mobility hubs and shows strong proximity to public transport infrastructure: over 99% of Dott and GreenMobility trips have both start and endpoints within 300 m of a public transport stop. Travel time comparisons confirm that shared mobility is most competitive relative to public transport for short trips, where it often outperforms transit by several minutes, while public transport is faster for longer journeys. This positions shared mobility firmly in a first- and last-mile complementary role rather than as a direct competitor to transit. Survey-based models identify younger age and habitual active-mode use as the primary predictors of intermodal behaviour, pointing to specific target groups for multimodal marketing and integrated ticketing initiatives.

Taken together, the results support two policy-relevant conclusions. Mobility hubs near public transport stops can be effective anchors for suburban shared mobility, as evidenced by the concentration of demand and the high proximity to transit across both bike-sharing and carsharing. Proactive vehicle rebalancing is essential for sustaining service reliability, particularly for the one-directional Dott network.

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