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Switching to smaller vehicles in freight and service trips: comparing usage patterns of internal combustion fleets and cargo bikes/light electric vehicles

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Abstract

Commercial freight operations heavily burden urban areas through congestion, noise, and emissions. Alternative vehicles such as cargo bikes (CBs) and light electric vehicles (LEVs) can mitigate these impacts, yet their adoption remains slow and largely confined to niche applications. Many business sectors continue to rely on conventional vehicles (ConVs), while economic pressures and uncertainty about which trips are substitutable further hinder the transition. This study investigates CB and LEV usage in a long-term trial involving 42 German companies and 91 use cases over 12 months, using GPS trajectory data from both trial vehicles (CBs/LEVs) and ConVs. Around 100,000 km of CB and LEV mileage, alongside data from ConVs, were recorded, enabling the derivation of operational metrics such as daily mileage, trip chain lengths, stops per day, and vehicle-specific catchment areas, thereby enabling a detailed assessment of spatial coverage and local concentration. The study aims to identify the operational and spatial conditions under which usage patterns align across vehicle types. Results show that while ConVs exhibit dispersed operating patterns, distinct segments of conventional trip chains overlap with the observed capabilities of CBs and LEVs. These overlapping segments are characterized by high stop density and short, local operational ranges. Substitution potential is greatest for trip chains with limited spatial coverage, many stops, and stable, repetitive tasks, regardless of business sector. The study provides rare insights into real-world usage profiles of CBs and LEVs, and offers a practical basis for identifying substitution opportunities beyond niche applications.

Keywords: Urban freight transport; cargo bikes; light electric vehicles; fleet usage profiles; spatial coverage

1 Introduction

Commercial freight and service operations constitute a major source of traffic-related externalities in urban areas, contributing to congestion, air pollution, noise, and the occupation of public space. Several studies have shown that alternative vehicles such as cargo bikes (CBs) and light electric vehicles (LEVs) can mitigate these impacts and contribute to more sustainable urban logistics (Ehrenberger et al., 2022; Gruber, 2024; Seiffert et al., 2025). Although earlier momentum around climate action initially accelerated interest, the diffusion of cargo bikes and LEVs still remains slow and largely confined to niche applications (Menge et al., 2024; Rudolph & Gruber, 2017; Sherriff et al., 2023). Since climate protection rarely drives fleet restructuring, any shift towards CBs/LEVs in city logistics must maintain efficiency, economic viability, service quality, and employee acceptance without compromising any of these factors. Therefore, a key practical challenge lies in identifying which existing commercial trips and trip chains are suitable for such a transition. While parcel and courier companies increasingly deploy CBs in urban areas, many other business sectors including crafts, maintenance, and service, continue to rely predominantly on conventional vehicles (ConVs) such as vans. This persistence is notable even in contexts where operational conditions such as short trip distances, high stop densities, and recurring usage patterns (particularly in dense urban environments) would appear well suited for alternative vehicles (Conway et al., 2017; Schliwa et al., 2015; Tipagornwong & Figliozzi, 2014). This limited diffusion cannot be explained by operational constraints alone. Recent economic pressures and rising operational costs have further slowed fleet transitions, reinforcing existing vehicle dependencies thereby stabilising established routines and path-dependent decision-making (Schreyögg & Sydow, 2011). Shifting from ConVs to CBs therefore requires not a simple vehicle substitution but the adaptation of operational routines and the development of new organizational capabilities (Gruber et al., 2026; Su et al., 2023). Companies often lack clarity regarding both the operational feasibility of CBs/LEVs and the scope of organizational change required to undertake a change process (Gruber et al., 2024). They are also exposed to

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external pressures that challenge conventional fleet structures, such as changes to infrastructure focused on cycles or an increased demand for cycle-based business models (Dalla Chiara et al., 2023). The persistence of ConVs does not primarily reflect a general resistance to innovation. Rather, many firms face uncertainty regarding which concrete trip patterns, service routines, or spatial contexts can be shifted without compromising reliability, employee acceptance, or economic viability. In contrast to prevailing practices, recent studies indicate that CBs can be integrated into business operations not only in logistics but also in diverse fields such as services and public organizations (Kania & Assmann, 2024). These developments highlight the potential of CBs and draw attention to intermediate solutions, such as urban micro hubs, which facilitate the use of CBs as alternatives for smaller catchment areas and short-distance operations (Conway et al., 2017; Gruber & Narayanan, 2019; Transport for London, 2023). Also, progressing technological improvements such as enhanced safety features, better ergonomics, and more efficient driving systems, enhance the attractiveness and operational viability of CBs, thereby strengthening their potential to compete with ConVs for commercial use (Carracedo & Mostofi, 2022).

Despite these insights, existing empirical research based on real-world data comparing usage patterns between ConVs and CBs/LEVs remains fragmented. Existing studies address selected aspects of CB performance, often relying small samples, or mode-specific datasets (Dalla Chiara et al., 2023). Comparisons frequently draw on simulated ConV routes rather than empirical data, or focus exclusively on van-only GPS analyses (Colonna et al., 2025; Greaves & Figliozzi, 2008; Kale AI, 2023). Further, studies indicate substantial theoretical potential for replacing ConVs with CBs/LEVs, particularly in terms of time efficiency and emissions, yet remain based on stylised assumptions or passenger travel data (Ehrenberger et al., 2022; Ritzer et al., 2023). Only a few studies draw on real-world GPS data from both, showing systematic differences in spatial movement and service times, with advantages for CBs in dense urban environments (Conway et al., 2017; Gruber et al., 2014; Schrader et al., 2024). However, these analyses are typically limited to few operators, narrow delivery contexts, or specific performance metrics. Consequently, systematic, cross-sectoral, real-world comparisons of usage patterns, and operational characteristics across different business sectors remain largely absent. There is still limited empirical evidence on where, how, and under which organizational and spatial conditions ConV trips can realistically be substituted or reconfigured within mixed commercial fleets.

This study addresses this gap by analysing vehicle tracking data from a long-term trial scheme involving CBs, LEVs, and ConVs across multiple business sectors. Drawing on this longitudinal context, the study illustrates fleet restructuring through the integration of CBs and LEVs, using a fleet-level perspective to analyze transformation processes and usage patterns. The core objective is to identify the operational and spatial conditions under which the usage profiles of ConVs align with those of CBs and LEVs and to determine the substitution potential of these overlaps while maintaining operational feasibility.

2 Data & Methods

2.1 Study design, sample and data sources

Table 1: Dataset overview

Dimension	Vehicle type	Dataset 1 (All)	Dataset 2 (Sample)
Total vehicle-days	CBs/LEVs	5,455	2,482
	ConVs	7,256	5,258
Tracked days per vehicle	CBs/LEVs	1–351, mean: 59.9	3–351, mean: 57.7
	ConVs	2–287, mean: 59.0	2–287, mean: 63.3
Total distance	CBs/LEVs	97,347 km	44,612 km
	ConVs	471,829 km	343,589 km
GPS tracking systems	CBs/LEVs	MovingLab, PowUnity, ONO Motion	MovingLab, PowUnity
	ConVs	MovingLab	MovingLab
Data used for the following Section	-	Section 3.1–3.2	Section 3.3–3.4

This study analyses GPS trajectory data from the long-term field trial *Ich entlaste Städte 2* (Germany), in which companies tested CBs and LEVs under real operational conditions. Most participating companies were accompanied for 12 months, some even for up to 23 months. The overall project lasted from 12/2021 to 01/2026, while the field tests ran from 06/2023 to 08/2025 across two generations of testers. The test fleet included 38 CBs and nine LEVs, all of which were regularly serviced. CBs are further differentiated between compact, more agile two-wheeled Long John CBs and three- or four-wheeled, heavy-duty CBs. Companies were provided with a mean of 2.1 test vehicles per company. The empirical basis covers 42 companies and 91 use cases (i.e., vehicle integrations) across multiple business contexts.

GPS tracking (CBs/LEVs, i.e. alternative vehicles): For the 91 use cases, GPS data were collected using two tracking solutions, predominantly (i) the DLR MovingLab smartphone- and GPS-tracking device-based system

(DLR, 2026) and (ii) permanently installed trackers (PowUnity and ONO Motion), complemented by proprietary systems for selected vehicles. In total, 47 vehicles were recorded, resulting in 5,455 vehicle-days.

GPS tracking (ConVs, i.e. conventional vehicles): For benchmarking, GPS data from companies' pre-existing internal combustion fleets were also collected via DLR MovingLab. The overall dataset includes 123 ConVs with a total of 7,256 tracked vehicle-days. Because not all recordings represent substitutable operations, subsequent analyses use a filtered 'reference fleet' approach.

Context and validation information: Quantitative data were complemented by qualitative data from interviews and company own recordings to identify causes of non-use (e.g., staff absences, equipment issues) and to collect information on conventional vehicles suitable as operationally feasible reference vehicles. This included details on transported goods and task requirements relative to the tested cargo bikes and LEVs. Table 1 offers a concise overview of the study's primary characteristics, as allocated to the used datasets.

2.2 Data processing and parameter construction

To ensure the plausibility of the data and enable the construction of analytical parameters for subsequent analysis, raw GPS data from the different data sources were first cleaned, which included comparing start and end points, distances traveled, and odometer readings. After source-specific cleaning, the individual datasets were merged. Conflicts from multiple recordings were resolved and erroneous points and unrealistic jumps were removed. For analytical purpose, key performance metrics were derived from the cleaned GPS dataset including the number of vehicle-days, mileage, usage days per week, and the proportion of net use time relative to potential availability. The characteristics of the tours, including the trip chain lengths or stops per day, reflect operational usage throughout the day. Spatially, the distance of stops to the operating site, the proportion of stops within 5/10 km radii, and catchment areas are also considered. For catchment areas, GPS trajectories were converted into points spaced 200 m apart for each vehicle. After a buffer of 300 m was calculated around the points, polygons were created and their areas computed per vehicle, representing each vehicle's operational extent. Finally, several operational dimensions were defined to describe vehicle use and availability, focusing on organizational, procedural, and fleet-related factors (see Table 2).

Table 2: Operational dimensions

Dimension	Description
Onboarding period	The time between the initial introduction meeting and the handover of the vehicle.
Time-to-first-use	Time from handover until first operational week or usage period.
Gross utilization period	Total time a CB/LEV is available, i.e. provision period.
Net utilization period	Sum of all usage periods within gross utilization period.
Week with vehicle usage	Week with at least 1 day of movement data.
Established usage period	Continuous weeks of vehicle use, representing established usage patterns in which the vehicle is employed consistently over multiple weeks. Short interruptions, such as planned holidays or sick-leave of employees, are not considered breaks in usage, whereas longer gaps (e.g., vehicle maintenance or damage) are treated as interruptions.
Use case	The specific integration scenario of a vehicle within an organization over a certain period of time.
Reference vehicle	ConVs that have been identified as "in competition" with the CBs or LEVs, that is, serving similar areas, performing potentially transferable tasks or transporting comparable goods, and/or having shared driver assignments. Only these vehicles and their trips are included in substitution-focused analyses.
Operating site	The location where a vehicle is stationed for a specific operational purpose. This is often the company headquarters, but can also be another site outside the headquarter, e.g., at a customer location, garage, or an external operational site.

2.3 Comparability framework (comparison of the use of CBs/LEVs and ConVs)

To enable meaningful comparisons between alternative and conventional vehicles, this study adopts an approach that focuses on overlaps in operational and spatial usage patterns. The underlying assumption is that the potential for substitution between CBs/LEVs and ConVs does not necessarily emerge in mean values, but rather in shared usage patterns. Thus, comparability is understood as the degree of overlap in the operational and spatial usage of vehicles rather than full equivalence across all metrics.

Two analytical populations are distinguished (see Table 1). First, the entire set of use cases is employed to characterize the overall operational usage patterns of all three categories of alternative vehicles (Long John CBs, heavy-duty CBs and LEVs). Second, an analytical sample is created for consistent, substitution-oriented comparisons of CBs/LEVs with CVs. This sample reduction follows the 'reference fleet' logic (see Table 2). Due to limited data from some companies, the sample is restricted to those with sufficient data for both conventional and alternative vehicle types, ensuring a consistent comparison. Thus, comparability is assessed along four analytical levels: (1) longitudinal uptake and usage continuity of CBs/LEVs, (2) operational usage profiles of CBs/LEVs by vehicle subtype, (3) comparative operational profiles of CBs/LEVs and ConVs, and (4) comparative spatial patterns of operations. We evaluate operational compatibility using distributional overlap across key usage metrics (see Section 2.2), such as trip chain length, total fleet mileage, utilization, and stop density. Spatial compatibility is examined using distance-based indicators and vehicle-specific catchment areas. To ensure robustness and comparability across heterogeneous tracking systems and observation periods, the analyses rely on normalized indicators (e.g., per day) and distributional reporting (e.g., median, or quantile). Relevant overlaps may exist only for specific trip types, distance ranges, or spatial configurations, which are examined in detail in subsequent comparative chapters.

3 Results

3.1 Longitudinal uptake and usage continuity of CBs/LEVs

The trial is unique in its long-term design, accompanying companies over an extended period and culminated in 91 distinct use cases. This enabled us to observe the longitudinal uptake of alternative vehicle integration in terms of continuity, as well as breakdowns and instances of non-usage. First, the duration of the onboarding phase can serve as an indicator of how clearly specified and prepared the use cases for alternative vehicles are, reflecting overall organizational and employee readiness. With a median duration of 13 weeks, a broad variety of onboarding phases were detected, with some organizations demonstrating agile and flexible decision-making processes, while others adhere to more bureaucratic procedures that prolong the preparation period. The onboarding duration can be indicative of organizational engagement, the clarity of planned use cases, and the level of preparation necessary for effective integration into everyday operations. Furthermore, examining the testing period itself, trial vehicles were available for an average of 39 weeks per use case. This resulted in a total gross utilization period of 3,568 weeks across all participants (see Table 3). In 58 out of 91 use cases, we recorded at least minimal continuous usage (at least one day per week). A total of 148 usage periods were identified, ranging one to 1.7 periods per use case. The totality of usage periods for a given organization constitutes its net utilization period, which amounted to 1,769 weeks across all participants, approximately 50% of the gross utilization period. Within the designated net utilization period, 74% of the recorded mileage was observed. These findings underscore the complexity of interpreting annualized performance metrics without distinguishing between gross and net utilization.

Examining the time until first established usage, a total of 36% of the observed use cases were implemented at week 0, with deployment continuing up to 99 weeks. The remaining use cases were established thereafter. After a period of about three months, an additional 35% of the vehicles achieved continuous usage. The final 29% were established by week 33. On average, establishments occurred after 2.0 weeks for LEVs, 5.2 weeks for heavy-duty CBs, and 7.5 weeks for Long John CBs. Heavy-duty CBs often supported predefined logistical use cases, resulting in faster and more predictable integration scenarios. In contrast, Long John CBs were often introduced to companies with limited cargo bike experience, resulting in longer establishment times or non-adoption.

The intensity and continuity of vehicle use over the observation period is illustrated by Fig. 5 in the Appendix. It shows how many days each use case is used per week during the first 52 weeks, on a scale ranging from 0 days (blue) to 7 days (dark red). Overall, vehicle usage is highly inconsistent, and when disaggregated by business sector, an equivalent diverse picture emerges. Public organizations, as an example of a non-logistics sector, exhibited the shortest average trial duration (34 weeks), whereas logistics providers showed the longest trial periods, averaging 50 weeks. Also, trial interruptions or early terminations occurred less frequently among logistics providers than among companies in non-logistic sectors. The most frequent reasons for temporary non-use, which serve as indicators of intermittency, were vehicle damage (n=31) and technical problems (n=14). A notable finding of the study was that companies with a limited number of usage days frequently experienced earlier termination of the trial than anticipated. In contrast, certain companies extended the testing period beyond 52 weeks. This decision was influenced by various factors, including the complexity of the establishment process or the development of a practical and viable use case, which took multiple weeks to consolidate after the initiation of the trial.

3.2 Operational usage profiles of CBs/LEVs

This section provides an overview of the operational characteristics of CBs/LEVs used during the trial period. Table 3 presents descriptive statistics for three groups: the full population of the two CB subtypes (Long John CBs and heavy-duty CBs), LEVs, the total population of CBs/LEVs, the analytical sample of CBs/LEVs, and the corresponding sample of ConVs. While all groups are included for transparency, this section's analytical focus is on the full population of CBs/LEVs. To explore usage profiles within the alternative vehicle fleet and capture the heterogeneity observed, Fig. 1 summarizes the operational usage distributions across the three tested vehicle subtypes. Rather than relying on averages alone, the distributions describe the observed operational profiles of the CBs/LEVs in terms of daily intensity, time structure, trip organization and operational speed.

Table 3: Descriptive overview of alternative and conventional vehicles

Parameter	Long John CBs (All)	Heavy-duty CBs (All)	LEVs (All)	CBs/LEVs (All)	CBs/LEVs (Sample)	ConVs (Sample)
Organizations	27	21	15	42	25	25
Use cases	32	41	18	91	43	83
Vehicle type	4	8	7	18	17	-
Gross utilization period (weeks)	1,322	1,569	677	3,568	1,681	-
No. of weeks w/ vehicle usage	576	789	404	1,769	913	1,502
Utilization rate (%)	44	50	60	50	54	-
No. of days with vehicle usage	1,345	2,642	1,468	5,455	2,482	5,258
Total mileage (km)	26,810	45,472	25,065	97,347	44,612	343,589
Daily mileage (mean, km)	20.0	17.3	17.1	17.9	18.3	65.3
No. of trip chains	1,559	2,944	2,042	6,545	3,280	7,574
Trip chains per day (mean)	1.27	1.32	1.46	1.35	1.37	1.4
Trip chain length (mean, km)	13.30	10.60	11.60	11.40	13.5	44.8
No. of stops	5,454	8,646	4,339	18,439	9,290	22.045
Stops per day (mean)	5.0	6.1	4.2	5.2	4.9	4.8
Distance stop to operation site (mean, km)	4.2	3.6	7.0	4.7	6.1	20.1
Stops within 5 km of operation site (%)	80	88	58	79	68	26
Stops within 10 km of operation site (%)	92	94	73	88	80	50

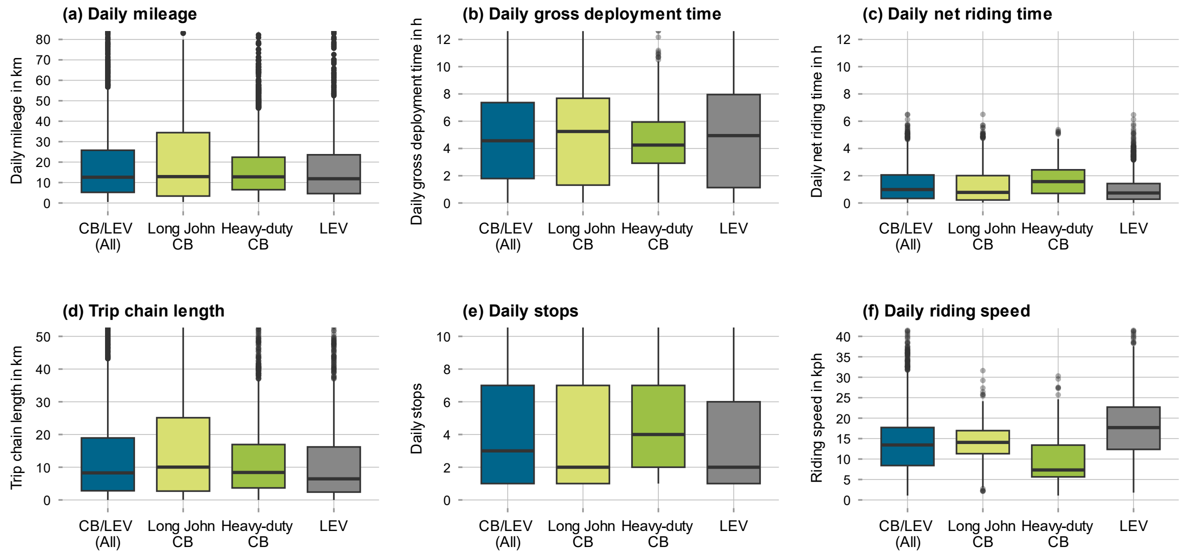

Fig. 1: Distribution of six operational parameters of alternative vehicles by subtype (a) – (f)

Across all subtypes, **daily mileage** is concentrated in a moderate range, while substantial day-to-day variability remains visible. The distributions suggest that the alternative vehicles were typically used for short- to medium-range urban operations of typically 5 to 25 km daily. At the same time, differences between the vehicle subtypes become visible in the spread of the distributions: heavy-duty CBs show a more compact range of daily mileage, whereas Long John CBs exhibit a broader spread with more low-intensity days as well as a wider upper range. This pattern is consistent with a more routinised deployment of heavy-duty CBs in pre-defined logistics-oriented applications, while Long John CBs have been used across a broader range of more flexible and demand-driven contexts. LEVs fall within a comparable overall mileage range, indicating that their everyday use was not fundamentally different in scale, even though they represent a distinct vehicle category. Looking at the time structure of use, it becomes evident that in all vehicle subtypes, **gross deployment time** per day clearly exceeds **net riding time** (e.g., the median of gross deployment time for all test vehicles is 4.6 hours, which is more than four-times the median of net riding time). This indicates that the alternative vehicles were embedded in work processes and services rather than used as pure freight transport vehicles. Vehicle-days typically consisted not only of riding, but also of substantial time spent on tasks performed at destinations. This interpretation is consistent with the composition of the sample, which includes many service-oriented and craft-based applications. At the same time, the distributions show that gross deployment time often extends across a substantial part of a typical

8-hour working day, while shorter task-based deployments are also observable. Here again, heavy-duty CBs appear somewhat more compact in their distribution, suggesting a more standardized operational embedding. Trip organization is comparatively stable across classes. **Trip chain lengths** remain within a relatively compact range, with heavy-duty CBs typically showing the highest values in this parameter. Furthermore, the distribution of tours per day is strongly concentrated around one tour, indicating that many vehicle-days are structured around a single dominant depot-to-depot chain rather than multiple separate tours. This is reflected in **daily stop** patterns: with a median of three stops per day, vehicle use is usually organized into tours that connect multiple delivery or service points. These stop patterns are similar for Long John CBs and LEVs and remain at a lower level than those of heavy-duty CBs, which generally serve a higher number of stops. Across all vehicle subtypes, however, stop counts vary widely, ranging from one stop at the first quartile to seven at the third quartile. This wide dispersion reflects the diversity of use cases and business sectors represented, spanning from occasional service-oriented trips to logistics-intensive operations. Observed **riding speed** over the course of the day further differentiates the observed usage patterns, but should be interpreted as a descriptive profile indicator rather than a performance metric. LEVs show higher observed speeds than CBs, which is plausible given their higher technical maximum speeds (of mostly 45 kph and up to 80 kph). However, the difference is not fundamental in operational terms: visually, the gap between LEVs and CBs is of a similar order of magnitude as the difference between the more agile single-track Long John CBs and the larger and heavier two-track heavy-duty CBs, despite the latter two sharing the same legal e-assist limit of up to 25 kph. This suggests that observed speed reflects not only technical vehicle characteristics, but also route conditions, maneuverability, operational organization and the broader task context in which the vehicles are used.

Taken together, the distributions define consistent sets of operational usage profiles for the trialed alternative vehicle categories: CBs and LEVs are typically used in short- to medium-range, work-process-integrated vehicle-days with moderate daily mileage, one dominant daily tour, and substantial non-riding time. The following section uses these empirical observations as the benchmark for assessing where conventional fleet activities align with observed CB and LEV usage profiles.

3.3 Comparison and overlap of reference vehicle's usage profiles

This section is based on the sample of 25 organizations with sufficient data and comparable framework conditions (see Section 2.3), capturing tasks in which ConVs and CBs/LEVs directly substitute or compete in fulfilling similar operational tasks. To ensure a reliable comparison, only ConVs labeled as 'reference fleet' were selected. For comparability, we apply the same parameters as used for the analysis in Section 3.2 and conduct an analogous comparison for the sample presented in Fig. 2. Concerning **daily mileage**, as expected, ConVs are used for longer distances, also resulting in longer trip chain lengths and higher observed riding speeds, which is consistent with their stronger motorization. In terms of this parameter, there appears to be overlap only in short-range segments among existing and newly introduced alternative vehicles. CBs/LEVs in this sample exhibit in general a more compact distribution. Most days, the daily mileage does not exceed 25 km. However, a few extreme days reach up to 54 km, which is close to the lower range of ConVs (median: 45 km). This shows that while there is some overlap, it is limited. In terms of **gross deployment time**, there is some more similarity: ConVs are used for a median of 7.3 hours per day, whereas CBs/LEVs are used for a median of 4.1 hours per day. Due to the longer distances, the gross time appears higher. Interestingly, despite the difference in mileage and gross deployment time, there is large overlap of actual **net riding time** between conventional and alternative vehicles, suggesting that the core riding activity is largely independent of vehicle type and that they are integrated into similar operational routines. Similar to daily mileage, **trip chain lengths** also vary, largely reflecting the fact that most vehicle-days consist of a single tour, as observed across the full population. In contrast, detected **daily stop** support that conventional and alternative vehicles can be integrated into operational routines in a similar way. The median number of stops per day is three for both groups. The sample mainly consists of service and craft use cases, with relatively few logistics or last-mile delivery vehicles. For the logistic use cases, stop counts are substantially higher (median 6, mean 9.5), whereas non-logistics use cases exhibit fewer stops (median 2, mean 3.3), reflecting the specific composition of the sample. With respect to the observed **daily riding speed**, ConVs demonstrate significantly higher velocities. Nonetheless, the upper whisker of the CBs/LEVs distribution (36 kph) exhibits slight overlap with the median of ConVs. This finding suggests that in certain dense operational areas, where operating speeds are generally lower, usage patterns may exhibit similarity among different vehicle types.

These findings suggest that vehicle-days for both vehicle types often exhibit similar usage patterns and trip chain structures despite the difference in the spatial extent of the trip chain lengths. In other words, although ConVs cover longer distances, the organization of work processes underlying both types of vehicles appears comparable. These processes are structured around a clearly defined set of service locations or delivery points per tour. This structural similarity suggests that tasks and operational logics largely remain unchanged. Differences in daily mileage therefore appear as a consequence of the reorganization of travel, in which CBs/LEVs are deployed primarily for short-range trips while ConVs continue to serve longer-distance tasks, as reflected in the observed mileage distributions.

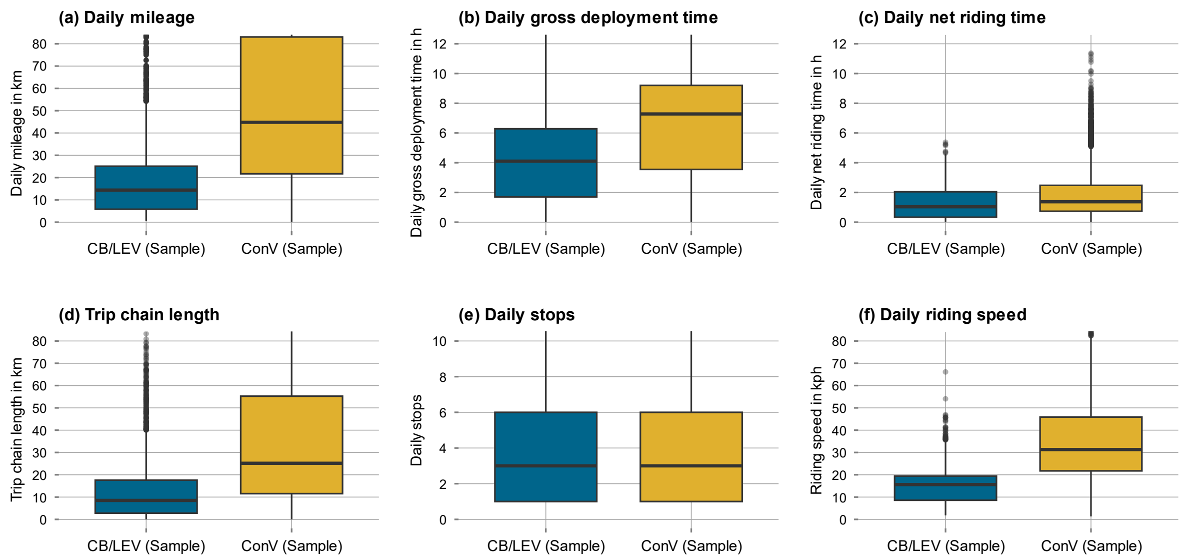

Fig. 2: Distribution of six operational parameters of CBs/LEVs (sample) and ConVs (sample) (a) – (f)

To explore this further, we now select three operational parameters (daily mileage, riding time, and riding speed) to examine potential overlaps between ConVs and the different subtypes of CBs and LEVs. Fig. 3 presents these as empirical cumulative distribution functions (ECDFs). First, the **daily mileage** distributions illustrate on how many usage days each mileage value was reached. Steep curves indicate that the mileage is mostly in a narrow range on most days (homogeneous usage), while flat curves indicate heterogeneous usage. All curves of CBs and LEVs are steep: In 75% of all usage days, the vehicles remain below a mileage of 25 km. Heavy-duty CBs and Long John CBs show similar mileage distributions, particularly from the median onwards. Conversely, on one-quarter of the day's ConVs are utilized, their distance traveled is less than 25 km. Moreover, ConVs exhibit a greater daily mileage, suggesting that they are utilized for extended distances. In this regard, alternative vehicles are unable to compete. A relevant overlap exists in the short- and mid-range mileage segment: while most usage days of alternative vehicles fall below 20 km, this distance range still accounts for roughly one quarter of conventional vehicle usage days, indicating potential substitution opportunities. In terms of **daily net riding time**, a more differentiated picture emerges. Despite their different vehicle designs, Long John CBs and LEVs exhibit very similar riding time distributions. For both vehicle subtypes, the majority of usage days are characterized by comparatively short riding times: around 50% of all usage days involve less than two hours of riding time, and almost all usage days remain below three hours. This pattern is consistent with their predominant non-logistic use cases, such as service-related and craft-oriented trips, which typically involve fewer trips per day, longer stop durations, and more sporadic usage. The usage profile of heavy-duty CBs is in contrast characterized by longer riding time, longer distances, lower travel speeds, and sustained operation. This is because these vehicles are mostly used for long logistics deployments. This shows that CBs in general are feasible not only for short distances but also for longer ones. Lastly, **daily riding speed** shows the most heterogeneous picture. On half of the days, the travel speed of ConVs is less than 30 kph. As expected, these vehicles exhibit a heterogeneous usage pattern, while CBs operate at a lower speed due to their maximum e-assistance of 25 kph. LEVs fall in between the two. In terms of travel speed, LEVs are most comparable to ConVs. Around one fifth of ConV usage days fall below 20 kph, indicating that LEVs clearly operate within the urban and suburban speed range. Their real speed is often not dramatically lower than that of a ConV. When comparing ConVs and CBs, there is substantial overlap in the lower range of riding speeds, particularly in areas where traffic-related slowdowns occur. The temporal advantages of ConVs are evident on only a limited number of days, primarily at higher riding speeds.

In summary, as expected, ConVs have substantially higher daily mileages, and higher travel speeds than alternative vehicles. However, in terms of net riding time, the difference is small. There seems to be meaningful overlap between conventional and alternative vehicles under certain conditions. CBs and LEVs have usage profiles comparable to those of ConVs for short- and mid-range trips, particularly at lower speeds and shorter riding times. These results suggest that alternative vehicles could replace conventional vehicles for many urban and suburban trips, especially those with limited distance, time, or speed requirements.

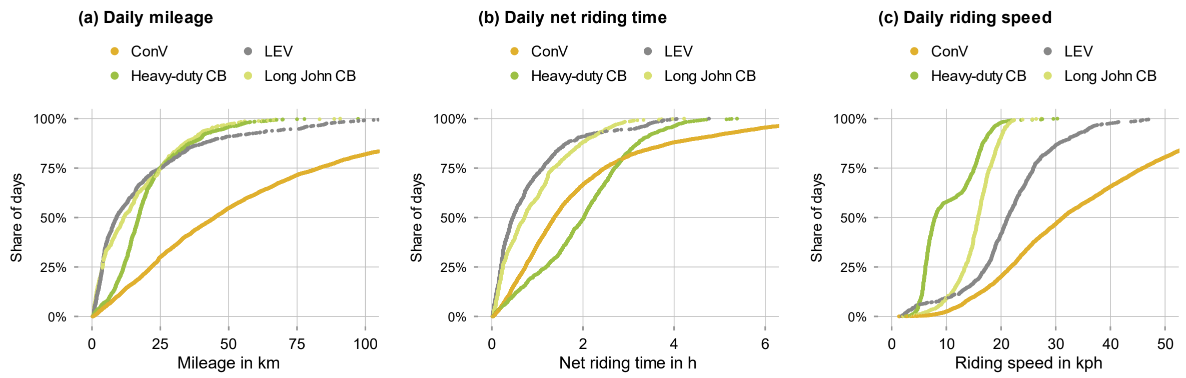

Fig. 3: ECDFs of three selected operational parameters of CBs/LEVs (sample) and ConVs (sample) (a) – (c)

3.4 *Spatial operating ranges and catchment areas*

Building on the operational profile comparison in Section 3.3, this section examines how CBs/LEVs and ConVs differ in the spatial organization of their activities. We combine operating-site proximity indicators with catchment areas to translate the previously observed scale differences into spatial reach and spatial concentration. Table 3 shows a pronounced contrast in how strongly daily activities are concentrated around the **operating site** (overnight vehicle storage or operational base). In the comparison sample, CBs/LEVs operate much closer to the operating site than ConVs: the mean distance of detected stops to the operating site is 6.1 km for CBs/LEVs versus 20.1 km for ConVs. Likewise, 68% of CB/LEV stops occur within a 5 km radius compared to 26% for ConVs, and ConVs still show that half of recorded stop activities occurs within 10 km of the operating site. Overall, these patterns indicate that CBs/LEVs are predominantly deployed in local operating ranges, whereas ConVs cover substantially broader service areas. At the same time, the ConV distributions reveal a substantial local segment: one quarter of ConV activity occurs within 5 km and half within 10 km of the operating site, indicating a local overlap segment that is, in principle, compatible with the typical operating ranges of CBs/LEVs. Within the trial fleet, proximity patterns also differentiate vehicle classes in a manner consistent with their operational design: CBs show the strongest local concentration, while LEVs exhibit intermediate proximity between CBs and ConVs. Heavy-duty CBs in particular operate within a very small radius, with 75% of all recorded stops occurring within 2.5 km (Fig. 4). Because some stops may be missed due to detection thresholds or tracking gaps, we treat absolute stop counts with caution. However, the strong differences in stop distance to the operating site and in the shares within 5 km and 10 km indicate robust contrasts in spatial operating ranges.

To complement Euclidean proximity indicators with a measure of spatial dispersion, we compute vehicle-specific **catchment areas** from GPS trajectories (see Section 2.2). Catchment areas represent observed operating areas over the available tracking windows and are therefore examined comparatively rather than as absolute service-area estimates. Fig. 4 plots catchment area against tracked mileage on a log–log scale. Two patterns emerge. First, ConVs span a much broader range: they accumulate higher tracked mileages and cover substantially larger catchment areas on average (mean: 285 km²), whereas the catchment area of CBs/LEVs is markedly smaller (mean: 70 km²), reflecting the ability of ConVs to serve more spatially dispersed operating areas.

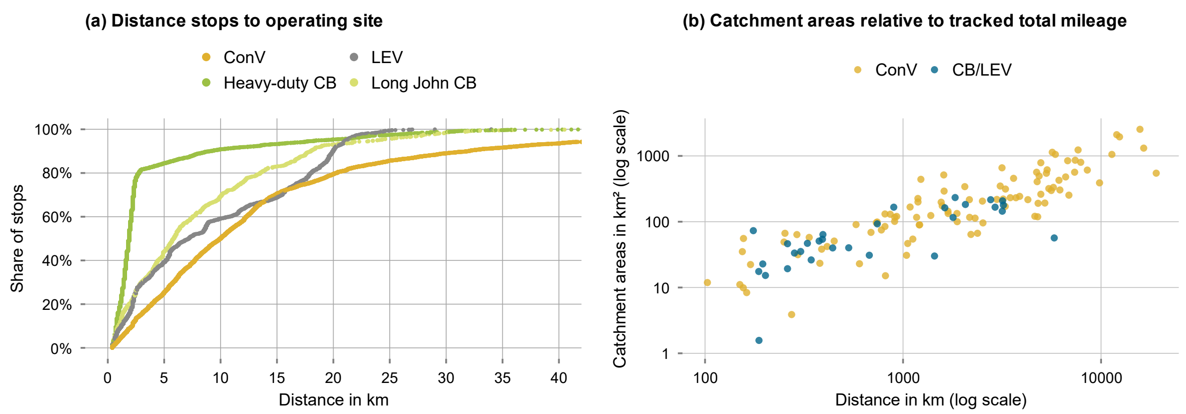

Fig. 4: (a) operating site proximity; (b) catchment areas

Second, and more relevant for substitution-oriented interpretation, the scatter shows strong variability in catchment area size at comparable mileage levels: for a given amount of travel, both compact and dispersed operating areas are observed. This indicates that spatial dispersion is a distinct operational dimension beyond mileage alone. In the mid-range segment, the point clouds of ConVs and CBs/LEVs overlap over a broad window, roughly spanning 150–3,500 km tracked mileage and 15–300 km² catchment area (see Fig. 4). A prominent cluster is visible around ~400 km tracked mileage and ~60 km² catchment area, indicating a frequently observed operating pattern with relatively compact catchment areas at moderate mileage levels. Taken together, catchment areas and proximity indicators reinforce the main insight from Section 3.3: while ConVs operate on a larger spatial scale overall, a relevant subset of conventional vehicle-days is characterized by local operating ranges and catchment areas that fall within the empirical range observed for CBs/LEVs. This spatial overlap segment provides a concrete entry point for substitution-oriented fleet restructuring.

4 Discussion

The study draws on a novel empirical dataset that includes long-term GPS tracking data of commercially used vehicles collected during a real-world trial scheme. Such a dataset remains rare in the field of commercial freight transport and enables a data-driven comparison of operational and spatial patterns. By providing detailed information on parameters representing certain usage patterns, the dataset enables an empirically grounded analysis of how different vehicle types are actually used in everyday operations across a broad range of business sectors, thereby addressing an important empirical gap in existing research.

Conceptually, the longitudinal design made it possible to track organizations over extended periods and to complement GPS data with qualitative information on vehicle deployment and operational context. Therefore, we were able to identify reference vehicles within existing fleets that perform comparable operations to those of newly introduced CBs or LEVs. This enables and enhances a direct comparison, a feature that is unique thus far. In addition, the differentiation between gross and net utilization periods offers a conceptual refinement: it allows a more accurate assessment of the operational performance of alternative vehicles in existing fleets once they have become established within organizational routines. Throughout the analysis, it became evident that substitution potential is segmented rather than sector-specific: overlaps between ConVs and CBs/LEVs emerges where trip chains are short to mid-range, spatially concentrated, and compatible with the usage profiles of existing fleets. By integrating operating-site proximity and catchment areas, the study adds a spatial dimension, demonstrating the limits of using mileage alone to evaluate the operational relevance of vehicle deployment. Spatial concentration emerges as an important characteristic for understanding where alternative vehicles can effectively complement conventional fleets. Theoretically, the findings also indicate that pre-existing organizational experience and knowledge of CB/LEV deployment inform subsequent operational decisions. Differences in readiness and prior familiarity with alternative vehicles appear to influence onboarding duration and continuity of use.

Several constraints should be acknowledged. Despite data cleaning, the harmonization of different data structures and GPS tracking systems may have introduced minor measurement uncertainties in operational metrics such as stop detection, which could affect comparability to a slight degree. Comparisons between conventional and alternative vehicles are also constrained by the complexity of real-world fleet deployment, mixed operational strategies, and organizations' varying willingness to participate in the trial. Finally, while the sample spans a broad range of sectors, it reflects a German trial context and therefore cannot be assumed to represent all commercial fleet settings.

5 Conclusion

This study compared the real-world operational and spatial usage patterns of conventional fleet vehicles and trialled CBs/LEVs in commercial freight and service contexts. The results show that CBs/LEVs are typically used in locally concentrated operations, whereas ConVs operate on a larger overall scale. At the same time, ConVs contain a relevant local and mid-range segment whose trip-chain and spatial characteristics overlap with the observed usage profiles of CBs/LEVs. Substitution potentials are therefore context-specific, emerging where operational, spatial, and organizational conditions align, as ConVs contain heterogeneous trip-chain segments rather than being uniformly non-substitutable. Those are most effective in short, frequent-stop trips, particularly in dense urban areas. Therefore operational feasibility and environmental benefits can be maximized by strategically targeting trips that allow for overlap between ConV and CBs/LEVs. Taken together, the study provides valuable, unique insights into vehicle usage patterns and substitution potentials, offering a solid foundation for future research and practical applications in sustainable urban freight and fleet planning.

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8 Appendix

Fig. 5: Intensity of weekly vehicle usage during the first 52 weeks