Journal of Cleaner Production 521 (2025) 146252

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Greenhouse gas emissions trends and fleet renewal of ride-hailing in Toronto, Canada

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HIGHLIGHTS

- Ride-hailing in Toronto increased in trips, distance, and emissions (2020–2023).
- Deadheading accounts for 33–37 % of the distance and remained constant (2022–2023).
- 43 % of drivers do less than 200 km/week, with nearly 44 % of deadheading (2020–2023).
- Electric vehicles have up to 46 % lower ownership costs for high-mileage drivers.
- Electrifying the top 20 % of high-mileage drivers cuts emissions by over 43 %.

ARTICLE INFO

Keywords:
Ride-hailing
Vehicle Emissions
Fleet Electrification
Total cost of ownership
Transportation Network Companies

ABSTRACT

This study examines the evolution of ride-hailing (RH) in Toronto, from January 2020 to December 2023, focusing on greenhouse gas (GHG) emissions, driver long-term operational patterns, and total cost of ownership (TCO) across electric, hybrid, and gasoline vehicles. Using descriptive analysis based on three years of data from 179 million trips, our findings indicate growth in RH trips, distances traveled, and GHG emissions, with deadheading rates remaining at 33-37 % over the past two years. By January 2023, the percentage of electric vehicles (EVs) in Toronto's private transportation company (PTC) fleet reached 2.3 %, slightly higher than Ontario's 1.7 %. Driver operational patterns significantly impact efficiency and emissions. We identified that 42.9 % of drivers operate less than 200 km/week, covering less than 200 km/week with a higher turnover rate and 43.9 % deadheading mileage. In contrast, 40.2 % of drivers exceed 400 km/week, work more than five days per week, and are more likely to remain in the business. This group shows higher efficiency, increased trip cancellations and multi-platform operation. Our TCO analysis focused on active drivers suggests EVs are more cost-competitive than hybrids and gasoline vehicles, with new models offering 7-46 % lower ownership costs.

1. Introduction

Ride-hailing (RH) is considered one of the most important innovations in transportation in the last ten years (Chan and Shaheen, 2012). Uber, one of the most predominant Transportation Network Companies (TNCs), is present in over 10,000 cities worldwide, completing 9.4 billion trips in 2023, with 6.8 million drivers and couriers (Uber, 2024). In the City of Toronto, from Sept 2016 to March 2019, RH has grown from 62.2 to 176 thousand daily trips, accounting for 5–8 % of total traffic in the downtown area (City of Toronto, Big Data Innovation Team, 2019). Even though RH is generally more convenient than transit options, there is scant evidence on how such systems have contributed to traffic congestion (Gregory et al., 2019), vehicle kilometers traveled (VKT), deadheading (driving without a passenger) (Wenzel et al., 2019; Sheldon and Dua, 2024; Saleh et al., 2024), and emissions (Sui et al., 2019; Tirachini, 2020).

As a result, there has been growing attention on ways to promote the adoption of electric vehicles (EVs) in RH platforms, with studies discussing different regulatory mechanisms (Z. Liu et al., 2022; Zhang and Liu, 2024), subsidies (Mo et al., 2020), charging costs (Chen et al., 2024), EV acceptance and drivers' intentions to stay in the business (Du et al., 2020; Sanguinetti and Kurani, 2020), and proposing improved distribution of charging stations (Moniot et al., 2022; Li et al., 2023; Popiolek et al., 2023). On the operator's side, TNCs are forming auto

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https://doi.org/10.1016/j.jclepro.2025.146252
Received 17 February 2025; Received in revised form 16 July 2025; Accepted 19 July 2025
Available online 28 July 2025

industry partnerships to supply EVs, providing financial incentives to drivers on their platforms, investing in or partnering for charging infrastructure, and conducting rider outreach and education (Peter Slowik et al., 2019).

Electrifying the fleet is considered the primary pathway to decrease vehicle emissions from the RH sector (Jenn, 2019; Taiebat et al., 2022). Particularly in the province of Ontario, Canada, where the majority of electricity generation is from renewable sources (Pereira and Posen, 2020), the electrification of the RH fleet could reduce overall GHG emissions by 91 % (Saleh et al., 2024).

Nonetheless, the existing literature highlights several research gaps. First, due to a short longitudinal dataset, studies fall short in providing a diagnosis of how emissions have been changing over time. Studies have often relied on sampled data (Sheldon and Dua, 2024), limited temporal coverage, or a single TNC (Jalali et al., 2017; Jenn, 2019; Sui et al., 2019; Saleh et al., 2024). There is a lack of studies that quantify how the RH sector recovered from the COVID-19 pandemic and how levels of deadheading have changed. Second, studies on electrification of RH systems often overlook the evolution of drivers' characteristics, such as their fleet, operation level, and the wide variation across different groups (e.g., full-time and part-time basis). Finally, due to the high volatility of drivers in these gig economies (Du et al., 2020), studies overlook the commitment periods of drivers.

To address these research gaps, the aim of this study is twofold. First, it examines the longitudinal GHG emissions in RH systems for all TNCs in Toronto from January 2020 to December 2023. We assessed the efficiency of RH trips over time, how patterns have changed, and how such efficiencies were related to different characteristics of drivers. Second, we examined the current profile of RH drivers, particularly vehicle category, mileage cohorts, turnover rate, and TCO, in light of electrification policy scenarios and discussed the barriers and opportunities to decarbonize the sector. We bring a novel dataset (RH trips from 2020 to 2023), which spans 179 million trips with over 181 thousand drivers, along with data on their current fleet.

This study contributes to the literature by capturing the trends in GHG emissions and driver operational characteristics over three years in light of electrification policies, given the scarcity of longitudinal studies capturing the evolving nature of RH impacts (Sheldon and Dua, 2024). We explored how the transition to cleaner vehicles is affected by such characteristics. Most studies provide snapshots of the situation at a specific point but fall short of addressing the changes due to external factors, regulatory shifts, or technological advancements (Sheldon and Dua, 2024).

2. Background and literature review

A body of literature examines emissions from RH systems and the role of electrification, but an analysis of how such systems have evolved is relatively unexplored. Some studies investigated the emission savings considering a comparison between RH and regular drivers' activity. For example, due to the higher mileage of an RH vehicle, Jenn (2019) and Tu et al. (2019) found that emission savings from EVs used in RH are 3–3.5 times greater than those from typical private vehicle use. Wenzel et al. (2019) found that vehicles used for RH in Austin are, on average, two miles per gallon more fuel-efficient than comparable light-duty vehicles registered in the city. This is largely attributed to the higher share of hybrid-electric vehicles (HEVs) and the limited presence of pickups and SUVs in the RH fleet. As a result, the RideAustin fleet is more efficient than the citywide average, helping to offset the additional energy consumption associated with deadheading.

Previous research has examined the operational patterns of RH drivers about varying efficiency levels (Sui et al., 2019; Tengilimoglu and Wadud, 2022; Saleh et al., 2024). Cook et al. (2018) assessed RH drivers' efficiency by gender, indicating around a 7 % gender earnings gap amongst drivers, which is attributed to experience on the platform (learning-by-doing), preferences regarding work location, and driving speed. Tengilimoglu and Wadud (2022) performed an analysis of mileage and time efficiency for the 200 busiest RideAustin drivers for at least six months, suggesting a difference of at least 30 % in mileage efficiency across drivers. Saleh et al. (2024) found that, on average, full-time drivers (more than 4 h/day) achieve three times the GHG savings per electrified vehicle compared to part-time drivers. Tu et al. (2019) found that RH drivers tend to have higher emission savings than taxi drivers in Chengdu (China), as they have more efficient parking strategies and a passenger-driver matching system, which results in shorter idle distances. Nonetheless, these studies lack a longitudinal perspective that could reveal how such operational characteristics and efficiency patterns evolve.

Studies also investigated the total cost of ownership (TCO) across different drivers' operational cohorts (Pavlenko et al., 2019; Taiebat et al., 2022). Pavlenko et al. (2019) found that US part-time drivers have around 90 % additional per-mile costs than full-time drivers, mainly because the initial expense of purchasing an EV is distributed over significantly fewer total miles traveled. Taiebat et al. (2022) suggested that both new and pre-owned EVs tend to offer cost savings for many drivers. They estimated that a USD 5700 purchase subsidy would make new EVs cost-competitive with internal combustion engine vehicles (ICEVs) for all drivers on the Lyft platform, assuming constant annual mileage and vehicle prices. In terms of operational cost analysis, Bauer et al. (2019) incorporated the spatial distribution of chargers and demonstrated that with a sparse network of three to four 50 kW chargers per square mile, EVs can deliver the same level of service as ICEVs at a lower cost. Bruchon et al. (2021) optimized fleet composition (mix of ICEVs, EVs, and HEVs) and operations to meet demand at the lowest possible cost, comparing results across a broad set of present-day and future scenarios in three cities. In most cases, the optimal fleet features a mix of vehicle technologies, with HEVs and EVs accounting for the majority of distance traveled, while ICEVs are primarily used to meet peak demand (Bruchon et al., 2021). However, while some studies explore TCO across different fuel types, few incorporate both driver characteristics and the role of accelerated depreciation associated with high-mileage usage—factors that are crucial for capturing the full economic implications for RH fleets.

3. Methods

To provide a diagnosis on how the RH system in the City of Toronto is changing over time, the following subsections describe the trip data, the key parameters of the system, and the method used to estimate vehicle emissions. Next, we present the main metrics used to characterize RH drivers' operations. Finally, we combined information on operations with vehicle market costs to generate the TCO, which is used to provide an estimate of savings for drivers over time when changing to an EV, HEV, or ICEV.

3.1. Data

The longitudinal analysis for Toronto RH relies primarily on three main data sets, namely, trip records, cruising data, and motor vehicle characteristics (Toronto, 2018), provided by the City of Toronto under a non-disclosure agreement with the University of Toronto. To analyze the evolution of RH fleet characteristics, we combined additional data on fuel and efficiency by vehicle make and model from the U.S. Environmental Protection Agency (EPA) fuel economy data (EPA, 2024), as well as the distribution of total passenger cars by fuel type in the province of Ontario (Government of Canada, 2022). Finally, to assess the growth of RH compared to other on-road vehicles, we used data from the Traffic Emission Prediction Scheme (TEPs) (Ganji et al., 2020), which relies on traffic count data to predict periodic and annual volumes in Toronto.

The RH trip dataset comprises 179.47 million trips with origin in the city of Toronto, from Jan-01-2020 to Dec-31-2023. It contains the following information: trip ID; driver anonymized identification; pickup and dropoff coordinates; distance traveled; speed; trip time; fare amount; transportation network company (e.g. Uber or Lyft); service provided (e.g. uberX, Lyft Standard, Uber Pool, Lyft Shared, uberXL, and so on); time and dates for the events of trip request; trip acceptance; driver arrival; passenger pick up and drop off; and reason for trip cancellation (in case the trip hasn't been completed). Mean trip speeds were estimated by the ratio between distance and time. Information on the number of passengers per trip is not available in the current dataset, except for shared services (Uber Pool, Lyft Shared).

The cruising data have 157.1 million events from 2020 to 2023, corresponding to the period when drivers are available to accept a ride and are cruising without passengers. It contains information on driver anonymized identification, cruising event ID, coordinates (start and end of cruising events), traveled distance, and date/time of cruising start and end. Finally, the RH fleet dataset contains data on driver anonymized IDs, vehicle models, make, and model year.

The preprocessing stage involved removing duplicate records, incomplete trips (requests that were cancelled), and adjusting unrealistic values for speed, interval time, or distance. Duplicate records occur when drivers have more than one TNC app in operation, resulting in statuses such as 'cruising in Uber' and 'passenger-trip in Lyft' during the same time. Finally, cruising records longer than 1 h were also removed, as they are more likely to represent drivers who forgot to turn off the app rather than unrealistic deadheading.

3.2. Trip activity

For our analysis, the RH trips were divided into three main segments or periods (Fig. 1). Period 1 (P1) represents when drivers are available on the platform and are waiting for a trip request; P2 occurs when the driver accepts a ride request and is driving to pick up the passenger; P3 refers to the segment with at least one passenger in the vehicle. Deadheading refers to the sum of P1 and P2. After the "Passenger Drop Off" event, the driver could either log off, become available on the platform again, or head to the next trip pick up (P2 stage) — in case they have accepted a next trip before the current dropoff event. We estimated the total mileage, deadheading, and efficiency according to the following expressions:

$$\boldsymbol{Total\ mileage} = \sum_{i=1}^{3} \boldsymbol{P_i}, \tag{1}$$

$$\boldsymbol{Dead\ heading} = \frac{\boldsymbol{P_1} + \boldsymbol{P_2}}{\boldsymbol{Total\ mileage}}, \tag{2}$$

$$\boldsymbol{Efficiency} = \frac{\boldsymbol{P_3}}{\boldsymbol{Total\ mileage}}. \tag{3}$$

To estimate the time and traveled distance in each of the three trip stages, we considered data on cruising start and end time, driver arrival/pickup time, passenger pick-up/dropoff, and speed, according to the following expressions:

$$time_{p1} = (CruisingStartTime - CruisingEndTime) \tag{4}$$

$$time_{p2} = (PassengerPickUpTime - TripAcceptanceTime) \tag{5}$$

$$time_{p3} = (PassengerDropoffTime - PassengerPickUpTime) \tag{6}$$

$$distance_{stage} = speed_{stage} * time_{stage} \tag{7}$$

where $stage = P1, P2, \text{or } P3$.

For shared trips with more than one passenger per trip, the time on P3 (passenger platform) is calculated by the difference between the last passenger drop-off and first passenger pick-up, while time on P2 (dispatch) is calculated by driver arrival time minus driver acceptance for the first passenger. Fig. 2 presents an example of a shared trip with three pick-up events.

3.3. Vehicle emissions

To estimate GHG exhaust emissions from every trip, we used information on total traveled distance in *VKT* (km), mean speed (km/h), and emission factor *EF* (g/km), according to the following expression:

$$E_{GHG} = VKT * EF(Speed) \tag{8}$$

where the E_{GHG} represents the GHG emissions (g), $EF(Speed)$ represents the emission factor as a function of the mean speed. EF data are derived from the Motor Vehicle Emission Simulator (MOVES), developed by the Environmental Protection Agency (EPA, 2023), considering conditions of urban restricted roads representative of Toronto, and the passenger car (PC) age distribution of the province of Ontario (Government of Canada, 2022), which includes gasoline, hybrid, and diesel powertrain. In this model, the running exhaust EFs vary with vehicle speed following speed bins from 5 to 67.5 mph (8.04–108.6 km/h), with increments of 5 mph (8.04 km/h).

3.4. Driver activity

To assess how RH driver activity has been changing, we investigated several characteristics of their operation. At the system level, we quantified the total number of drivers by week, their mileage every week, and the number of days in a week that it took to complete such mileage. In addition, we analyzed each driver's number of active days on the platform, total mileage during the P1, P2, and P3 stages, and their trip cancellation rate.[1]

To identify drivers who could still transition to a cleaner vehicle while working for TNCs, we classified them as active or inactive based on their trip records, due to the absence of status information from the TNCs. Drivers were considered "active" if they had completed at least one trip in the past three months (September to December 2023). This resulted in approximately 55 thousand active drivers as of December 31, 2023.

Finally, we used the *k-means* clustering method to classify them based on six operational characteristics: number of active days, VKT per active day, distance per trip, percentage of VKT in the P3 stage, and cancellation rate. The elbow method was adopted to define the optimal number of clusters. This approach is relevant for estimating the TCO of different drivers, as discussed in the following section.

3.5. Total cost of ownership

To analyze the transition to different vehicles based on costs, we utilized the TCO approach, considering different driver operations over distinct commitment periods. The method analyses the total amount of money drivers will spend on the vehicle over the time they own it. It takes into consideration the purchase price, operational costs, insurance, maintenance costs, and depreciation over the commitment period. We deployed the TCO analysis for three vehicle fuel types (Electric, Gasoline, and Hybrid) and two conditions (new and pre-owned). Vehicles were selected based on the most common make and model found in the RH active fleet in Toronto, which is the Tesla Model Y (2023) for electric, the Toyota Prius-Prime (2020) for hybrid, and the Honda Civic (2019) for gasoline. For new vehicles, we considered the model year of 2024. Finally, to provide a more consistent discussion based on the driver's actual operation, we removed inactive drivers, drivers with less than one month of operation, and those with less than 20 completed trips. The TCO is quantified in total CAD and estimated using the

[1] Cancellation rate = Trips canceled by driver/(Total trips completed + Trips canceled by driver).

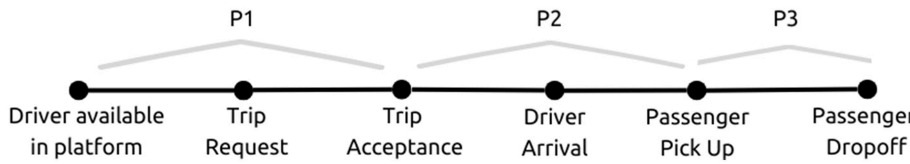

Fig. 1. Representation of ride-hailing trip stages.

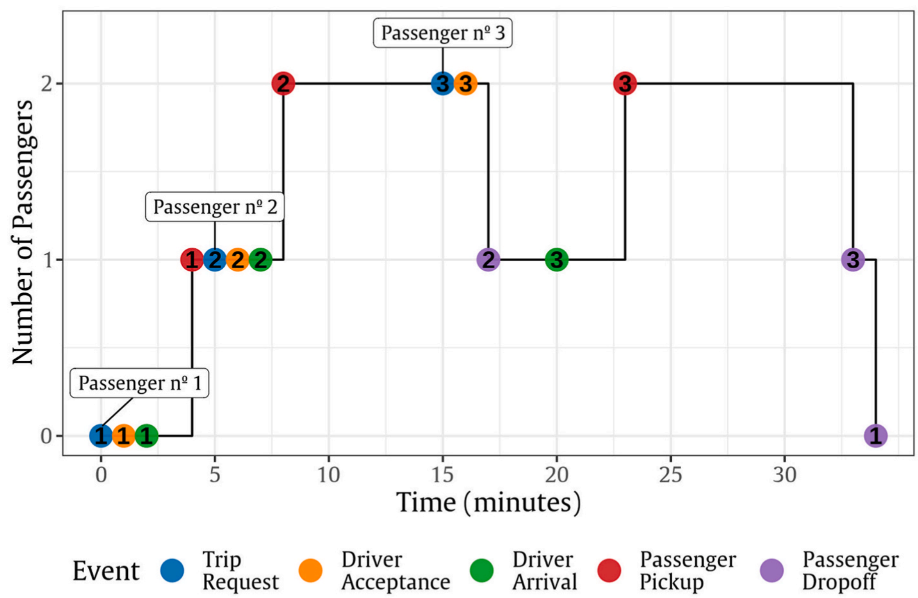

Fig. 2. Sequence of events of a shared trip with three pick-up events.

following expression:

$$TCO = Financing + Insurance + Operational + Maintenance - Depreciation \quad (9)$$

And

$$Depreciation = MRSP - VRV \quad (10)$$

where *MRSP* corresponds to the Manufacturer's Retail Suggested Price, and *VRV* represents the Vehicle Residual Value (the vehicle's value after depreciation). Given that cumulative mileage highly influences the TCO, we also utilized the Levelized Cost of Ownership (LCO), which is TCO per kilometer (CAD/km).

LCO can provide more comparable results between drivers working on a part-time (e.g. less than 35 h/week (Waheed et al., 2018)) and full-time basis. Finally, associated with TCO and LCO analysis, we used data on drivers' mean time in the business to estimate the probability of staying in TNCs during a given commitment period. This estimate is based on observed data on inactive drivers across different groups.

3.5.1. Purchase and insurance

The purchase prices of old vehicles were obtained from the Auto Trader database — one of the most commonly used platforms for trading vehicles in Canada (AutoTrader, 2024). For our analysis, we aggregated different prices of vehicles in the Toronto region and selected the median value as the representative price. For new vehicle prices, we obtained data from Honda (2024), Toyota (2024), and Tesla (2024) websites, considering the final price after taxes and eventual subsidies. The discount rate was considered to be 5 % of the total vehicle price based on the values adopted by other TCO studies (Taiebat et al., 2022; Woody et al., 2024), while financing costs adopted were 3 % of the total vehicle cost. Although insurance costs may depend on individual factors such as age, driving history, and gender (Woody et al., 2024), our annual insurance costs depended on the vehicle make and model year, and varied from 1767 (Pre-Owned Honda Civic) to 3260 CAD (New Tesla Model Y), according to the CAA (2024) online platform.

3.5.2. Operational costs

The operational costs refer to the expenses associated with the mileage driven by each driver. They rely on two main inputs, the fuel and/or energy price, and a driver's activity. For all fuel types, we used data on efficiency from the EPA (2024) fuel economy database, considering the condition of usage in the city. We adopted a cost of gasoline of 153.8 cents per liter, which is the mean price for January to April (2024) in the City of Toronto (Government of Canada, 2024). For electricity consumption in Toronto, as of July 2024, the off-peak price is 0.087 CAD/kWh, mid-day is 0.122 CAD/kWh, and on-peak is 0.286 CAD/kWh (Toronto Hydro, 2024). Although drivers can benefit from lower prices in off-peak periods, we considered the mid-peak costs for winter and summer as an average value. This would account for the effect of recharging during on-peak when needed, even though home-charging is usually done at off-peak times. In our analysis of hybrid vehicles, which uses both fuel and electricity costs, we followed the EPA fuel economy estimates (EPA, 2024), which uses only energy in the first 45 miles, and only gasoline after the first 45 miles.

To estimate the mileage for each driver during a given commitment period (in months), we used operational data on their daily mileage and the number of active days per month. We also considered additional mileage to incorporate their usage off the platform. The extra daily distance was 30 km, which is the average distance driven per day in the Greater Toronto Region for private vehicle owners (Transportation Tomorrow Survey, 2018). We apply this extra daily activity for 25 days a month. Therefore, the total mileage per driver during the m months of the commitment is given by

$$VKT_i = m * (Daily\ mileage_i * Days\ per\ month_i + 30 * 25) \quad (11)$$

where i refers to each driver.

3.5.3. Depreciation

Depreciation refers to the decrease of a vehicle's value over time and is estimated as the difference between the manufacturer-suggested retail price (MSRP) and vehicle's residual value (VRV) at the end of a specific period. It depends on vehicle mileage, current vehicle age, and number of years of commitment. Depreciation decay rates were obtained from the Car Edge online platform (Car Edge, 2024), which provides depreciation curves for over 200 models, considering different mileage bands and years of ownership. For each driver, we matched their annual mileage with the closest mileage band in the database to provide a more precise decay rate.

3.5.4. Maintenance

Maintenance services involve the costs of routine maintenance and repair. We obtained the average annual costs of maintenance for each vehicle type and condition from the AAA online platform (AAA, 2024). One limitation of this platform is its provision of cost estimates primarily for regular drivers, which tends to overlook the impact of the high mileage typically achieved by RH drivers. To address such a limitation, we used data from Taiebat et al. (2022) to generate weighted factors to adjust for the high mileage effect. The authors developed a mileage-weighted model that incorporates service & maintenance costs for BEV, HEV, and ICE for RH drivers in the U.S. We used the annual maintenance costs of regular drivers as a baseline price and multiplied it by the mileage weight factor. Table 1 shows the average price of maintenance for each vehicle type, as well as the weight factors used to incorporate the mileage effect.

The proposed TCO method has a few limitations. First, it assumes fixed rates over time, such as vehicle efficiency rate, purchase price, annual insurance, and fuel cost. Moreover, these values are associated with the current market for regular drivers in Toronto, who do not cover the same mileage as TNC drivers. Particularly for EVs, we adopted the mid-day energy price as a mean value considering home charging. Also, while studies have demonstrated that an EV battery can meet a commuter's daily needs in most cases (Tu et al., 2019), we do not assess any limitations related to battery range. In addition, the operational challenges to accessing charging stations in Toronto were not explored, such as the detour to charging, the variation of charging prices, and the possible effect of competition to access such services. Further studies are needed to simulate the sensitivity of the TCO parameters when assessing the cost of a vehicle transition.

4. Results and discussion

4.1. TNC evolution in Toronto

RH services have experienced significant growth in Toronto over time compared to other sources. Fig. 3 presents the growth in VKT as of 2018 for TNC in comparison with total traffic counts, using the Traffic Emission Prediction Scheme developed at the University of Toronto

Table 1
Annual service & maintenance (S & M) costs in CAD and mileage weight factors.

Variable	Characteristic	Electric	Hybrid	Gasoline
S & M Cost (Baseline)	New	33,73[1]	3976	3673
	Pre-Owned		5541	5427
Weight factor by mileage (thousand km/year)	1–49	1	1	1
	50–159	1.17	1.38	1.43
	160–240	1.24	1.45	1.5
	>240	1.28	1.53	1.58

[1]Data on maintenance cost was the same across EV conditions given that it has similar model years (2024 for new, and 2023 for pre-owned).

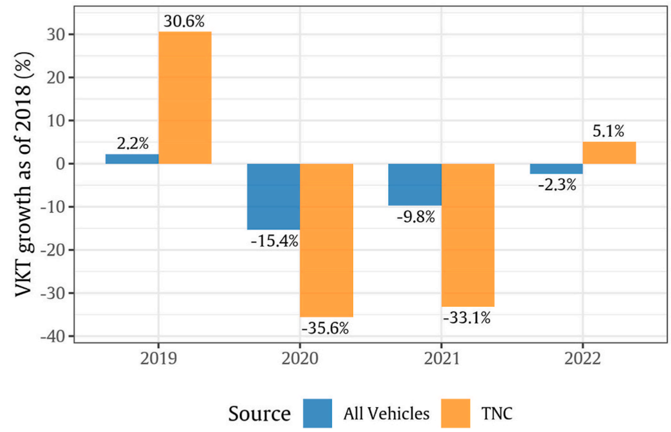

Fig. 3. VKT growth as of 2018 for TNC and other vehicles.

(Ganji et al., 2020). As of 2022, we found that RH accounts for 2.1 % of total vehicle emissions in Toronto. TNC mileage had the highest increase in 2019, followed by a sharp decline during the first year of the pandemic. The high drop in 2020 is attributed to decreased travel overall (Haider and Anwar, 2022), health concerns regarding shared spaces, and an increased preference for driving one's vehicle (Loa et al., 2020). However, after 2020, RH appears to be recovering at a faster rate than the rest of the traffic. This rapid recovery may be partly due to the flexibility with which TNCs can adapt to demand (J. Liu et al., 2024).

RH has experienced significant growth in Toronto over time. Fig. 4 presents the absolute number of trips per week (A), the relative number of trips compared to the first week of January 2020 across different Toronto wards (B), and the spatial distribution of trips for January 2020 and January 2023 (C). In Fig. 4B, we highlight the relative growth in black, as well as the ward with the highest increase in green (Scarborough Rouge Park) and the slowest in red (Toronto Center). While the data show that the total number of trips has reached pre-pandemic levels, this recovery was uneven across different neighborhoods of the city. Downtown areas were highly impacted by the increase in teleworking since the pandemic (PwC, 2021). In contrast, the demand in Scarborough-Rouge Park can be due to the association between the income of the population (higher than average) and TNC characteristics (relatively cheap trips over time, such as shared trips). The three most significant declines in trip numbers were observed in March 2020 (COVID-19 outbreak), December 2020 (Wave 2 of COVID-19 restrictions), and December 2021 (Wave 5 - Omicron outbreak) (Government of Canada, 2022) (see Figs. S1, S2, and S3 for detailed analysis by ward).

As a result of the increased number of trips, GHG emissions in Toronto have also returned to pre-pandemic levels. Fig. 5 displays the seven-day moving average GHG emissions according to the stage of the trip. Emissions from P1 events (cruising on the platform) appear to have decreased since the pre-pandemic period, while P2 and P3 events have slightly increased. Over the last two years, P1 and P2 events accounted for 33–37 % of total GHG emissions, while P3 represented 63–67 %. Similarly, in 2016–2017, deadheading rates were 45 % in the RH systems of Austin, Texas (Wenzel et al., 2019), and around 33–50 % for the busiest drivers (Tengilimoglu and Wadud, 2022). These results were also consistent with Henao and Marshall (2019), who estimated deadheading levels at 40 % in the city of Denver, U.S. Although extensive literature exists on optimization methods to reduce deadheading (Sheldon and Dua, 2024), there are still challenges in improving efficiency rates in the City of Toronto, as deadheading has stayed the same in the past two years (see Fig. S3–S6 for detailed analysis of deadheading by Ward).

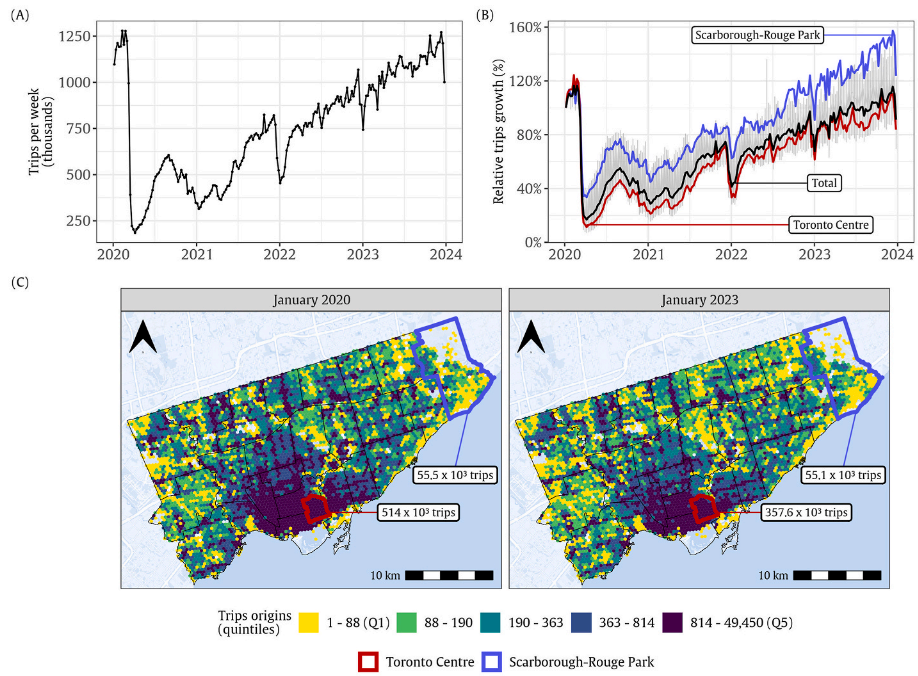

Fig. 4. (A) Number of trips per week in Toronto; (B) Relative trips growth per week by Toronto Wards, highlighting "Toronto Center" (red) and "Scarborough-Rouge Park" (purple); (C) Spatial distribution of trips origin by H3 resolution 9 (0.105 km^2) by quintiles in January (2020 and 2023). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

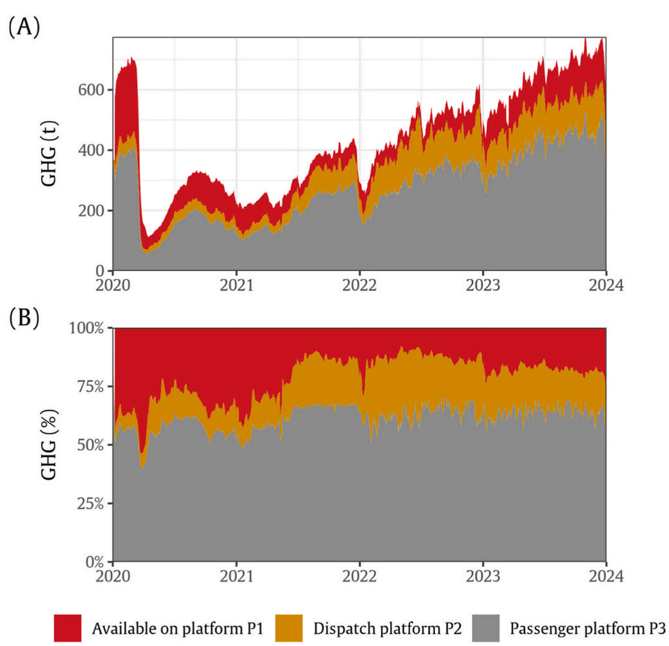

Fig. 5. Seven-day moving average of GHG emissions levels in tonnes (A) and relative trip stage (B), from Jan-1st-2020 to Dec-31-2023.

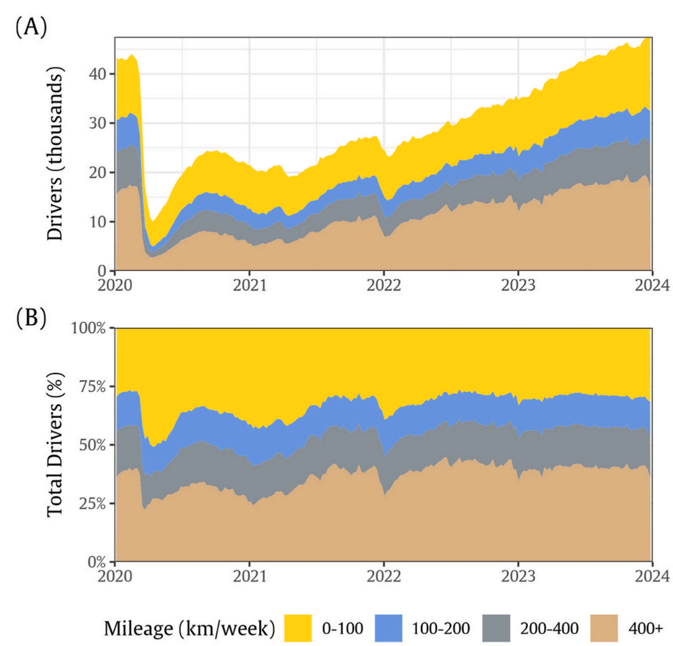

Fig. 6. Absolute (A) and relative (B) number of drivers per week according to mileage range.

4.2. Supply characteristics over time

To adjust for the demand, the number of active drivers in TNCs has grown accordingly, reaching 46,000 by the last week of December 2023. Fig. 6 illustrates the number and proportion of drivers by week, along with their respective weekly mileage over time. Approximately 30 % of drivers tend to operate at low weekly mileage (0–100 km per week), while around 40 % operate more than 400 km per week. During the COVID-19 outbreak, the proportion of low-mileage drivers increased to approximately 50 %, before decreasing to 30 % by the end of 2023.

Driver operations vary not only by their weekly mileage but also by the average number of days they operate each week. Fig. 7 illustrates the number of days per week required for different groups of drivers to achieve their weekly mileage. Drivers with low mileage typically complete their mileage in one or two days, whereas approximately 80 % of drivers who cover more than 400 km per week operate five or more days per week.

In terms of efficiency, varying levels of deadheading are observed

Fig. 7. Proportion of drivers by weekly mileage and days of operation per week.

based on the weekly mileage. Fig. 8 illustrates GHG emissions relative to different weekly mileage per driver. Although low-mileage drivers contribute less to overall emissions, they tend to be less efficient in minimizing deadheading events. Drivers covering more than 400 km per week manage deadheading events at a rate of 32 %, whereas low-mileage drivers operate with approximately 55 % of their distance traveled without passengers. The lower efficiency of low-mileage drivers can be attributed to several factors: (a) lack of experience in managing their driving hours, which includes the ability of selecting the best periods or optimal regions, as noted by Cook et al. (2018); (b) the fact that

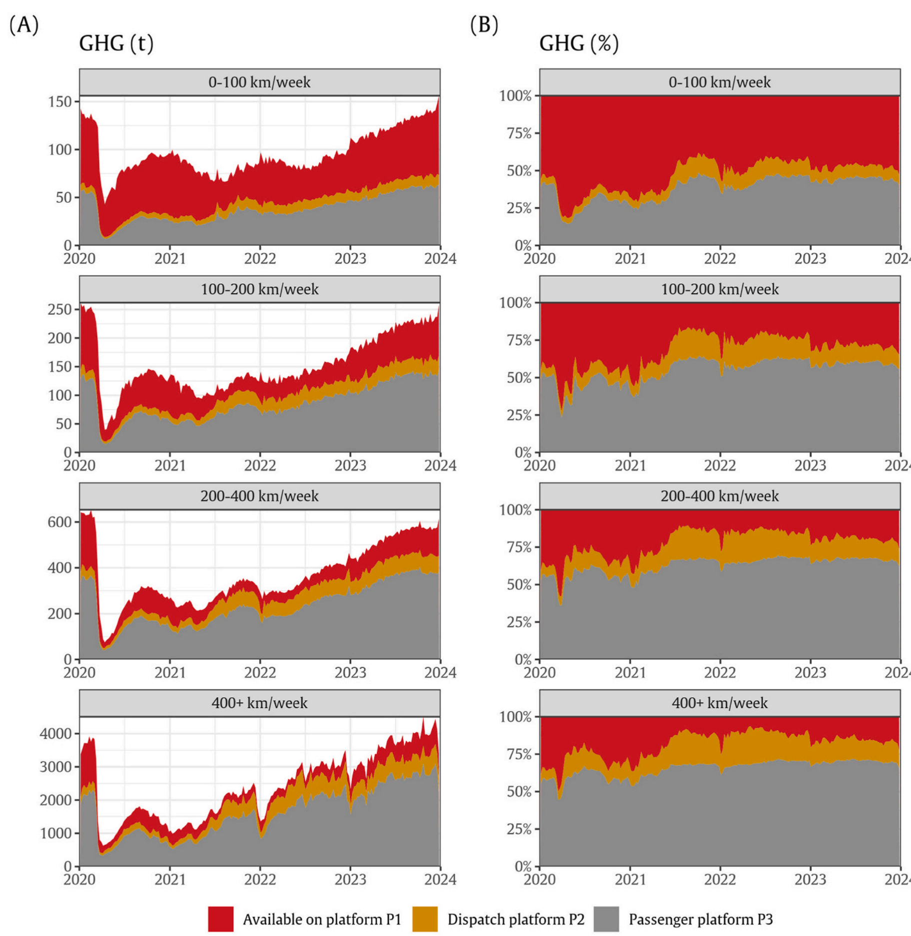

Fig. 8. Absolute (A) and relative (B) GHG emissions by drivers' mileage and trip stage.

some drivers engage in other gig economies, such as deliveries; or (c) their tendency to accept trips only if they align with their pre-existing routes. Despite variations in efficiency within groups, the results for the busiest drivers (400+ km weekly) align with the range reported by Tengilimoglu and Wadud (2022), which is 41–70 %, highlighting significant impacts on the overall efficiency of RH systems.

For short intervals, such as a day, we found that drivers operating for more than 4 h do not experience a significant gain in efficiency, and top performers do not maintain 100 % efficiency after 2 h (Fig. S1 shows the mean efficiency level according to the maximum number of working hours for the fleet and top performers, highlighting the daily mean efficiency across all drivers, and the top performers - drivers with the highest efficiency at different working hours). This is likely due to the dynamic pricing systems of TNCs, which rapidly adjust the supply by attracting drivers through surge prices or repelling them with unattractive rides, to maintain a steady "system-level" efficiency.

Since TNC offers a flexible driving schedule and low entry barriers, many drivers try the business. However, a smaller percentage remains in the business for longer periods. Fig. 9 shows the relative (A) and cumulative proportion (B) of drivers according to the number of months since becoming a RH driver (expressed as the first recorded trip). Results are shown according to their status as active or inactive as of December 31st, 2023. They indicate that around 10 % of active drivers have been in the system for over 47 months, and 55 % have been operating for less than a year. For inactive drivers, the mean time is 5 months, and around 75 % have left the system in less than 12 months of operation. These findings are similar to Hall and Krueger (2015), who assessed U.S. Uber drivers and argued that RH may serve as a bridge for drivers seeking alternative employment opportunities. Peticca-Harris et al. (2020) argue that drivers tend to work part-time and do not view ride-sourcing as a long-term career. In the context of decreasing GHG emissions, it poses a challenge when assessing the cost-benefit of replacing an ICE vehicle with an EV, given their low commitment period to pay off the investment.

RH companies have committed to decreasing their emissions not only in rides themselves but also for deliveries (Lyft, 2023; Uber, 2024). In this context, Fig. 10 evaluates how the TNC fleet is changing over time in Toronto according to fuel type (A) and whether these profiles differ from the Ontario Provincial fleet (B and C). It shows that the proportion of EVs in TNC has been growing, particularly since 2023. As of the last week of December 2023, the system had 4.5 % EVs. Compared with the most recent data available for Ontario (2024), TNCs had a slight advantage in EV participation, with 2.35 % compared to 1.2 %. HEVs were particularly present in TNC's system, with 12.5 % of the total fleet. It is being viewed as an alternative to EVs, as it is partially eligible for low-carbon incentives from TNCs (Canada, 2025) and has a smaller upfront price (Zhao et al., 2023). However, the growing trend of EVs to achieve zero tailpipe emissions has yet to be fully demonstrated (see Fig. S5 for detailed analysis on fleet evolution over time).

Since drivers operate under their own rules, each one has unique mileage, commitment time, and strategies for accepting or rejecting incoming trips. Therefore, their TCO values are individualized. However, to better illustrate how TCO values vary across drivers, we present the results in terms of two groups or clusters. These groups were defined based on the characteristics described in Fig. 11 — number of active days, daily trips, VKT per day, distance per trip, efficiency (percentage of VKT in P3), and cancellation rate. For visual analysis, we named the first cluster "Low Activity" due to their short engagement time and part-time-like operation. The second cluster, "High Activity", includes drivers more likely to stay longer in the business and complete more trips per day. The cancellation rate refers to the number of trips canceled by the driver compared to the number of completed trips. Although the results appear similar across clusters, more experienced drivers tend to have a higher cancellation rate. This behavior may be due to their tendency to operate under specific strategies, leading them to cancel trips that do not align with their approach (Popiolek et al., 2023).

4.3. Total cost of ownership

Although it has been demonstrated that the investment in EVs pays off much faster for RH drivers than for regular drivers (Taiebat et al., 2022), there are still uncertainties due to the wide range of operational characteristics among RH drivers. Table 2 presents the mean TCO for different vehicles and commitment periods, considering the two clusters previously defined. High-activity drivers were shown to have almost twice as much mileage as low-activity drivers. Such values were consistent with Burnham et al. (2021), who analyzed TCO for LDV under different driving distances. The results indicate that the TCO is proportionally higher for shorter periods due to higher annual upfront costs such as insurance, financing, and purchase. The depreciation and maintenance costs of a pre-owned vehicle highly influence the final TCO when compared to a new vehicle.

In terms of vehicle fuel type, the TCO for EVs was observed to be lowest, followed by hybrids and gasoline vehicles. These results are consistent with the findings of Woody et al. (2024), who developed a TCO model comparing five vehicle classes, three powertrains, and three EV ranges for U.S. cities. Given the fixed commitment periods proposed, we estimated the probability of drivers leaving the business. Although the TCO is proportionally smaller for more extended commitment periods, drivers are less likely to remain in the industry for such durations.

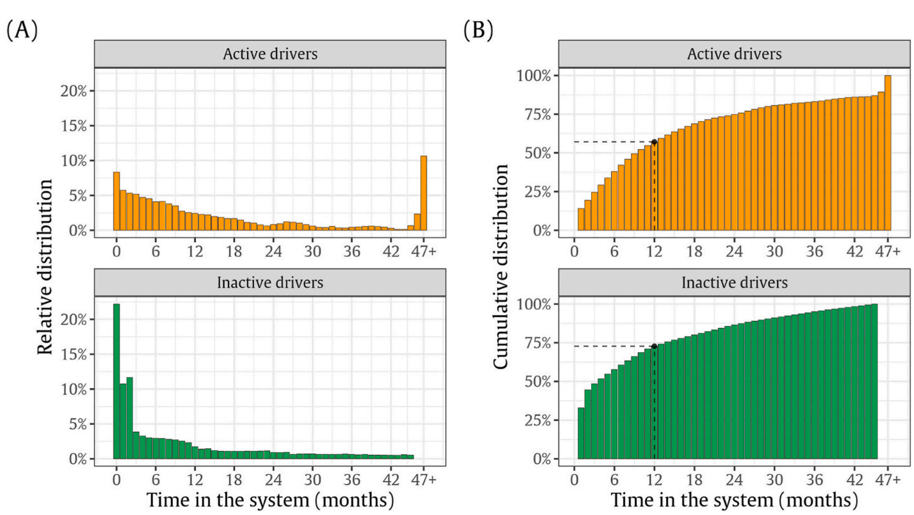

Fig. 9. Relative (A) and Cumulative (B) distribution of drivers by number of months in status in the platform.

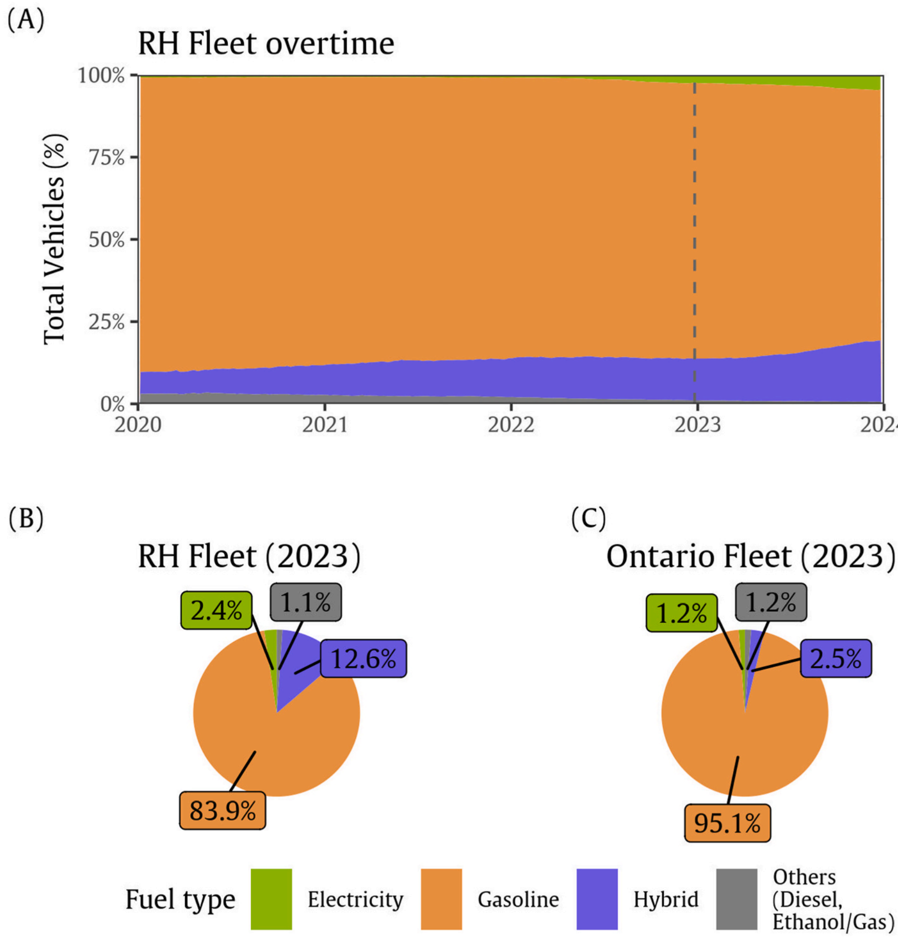

Fig. 10. Relative growth of RH fleet by fuel type (A); RH fleet by the last week of 2023 (B); Ontario fleet in 2023 (C).

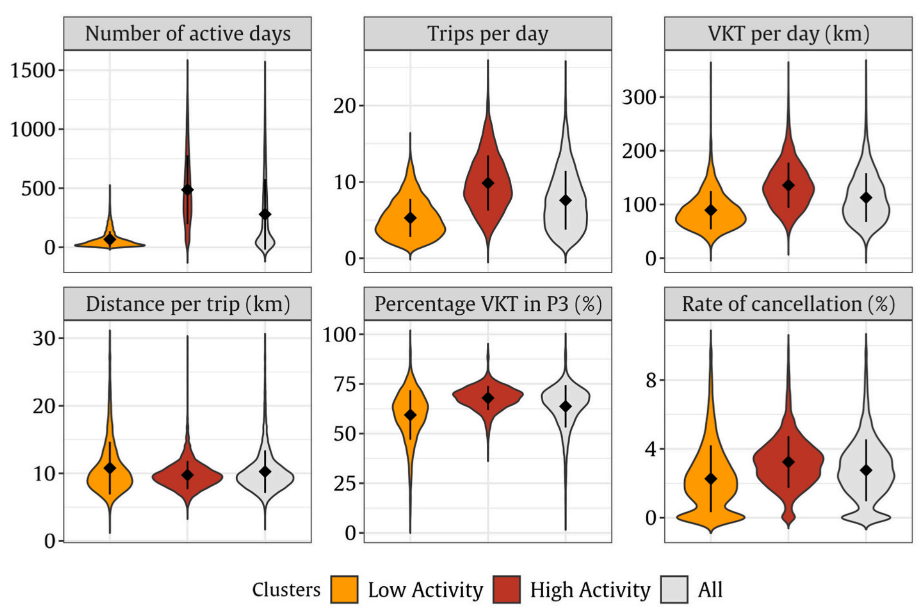

Fig. 11. Main operational characteristics of drivers and their two main clusters.

Due to their lower mileage, drivers classified in the Low-Activity group had a lower overall cost of ownership than the High-Activity group (see Table S1 for detailed values of TCO). However, they tend to commit for a much shorter time, making it challenging to invest in a cleaner vehicle.

Part-time and full-time drivers may benefit differently from EV incentives provided by TNCs. Some incentives, such as a $1 bonus per fully electric trip (introduced by Uber in February 2025) and participation in 'Uber Green' services, are equally accessible. Through 'Uber Green',

Table 2
Mean Total Cost of Ownership (in CAD) for active drivers by clusters and commitment periods.

Cluster	Commitment Period (months)	Electric		Gasoline		Hybrid		VKT (km)	Probability of leaving the business (%)
		New	Pre-Owned	New	Pre-Owned	New	Pre-Owned		
High Activity	12	13,965	20,355	17,119	21,574	15,148	17,897	42,792	45
	24	23,957	29,558	39,815	46,244	29,396	34,043	85,584	83
	36	36,352	40,900	73,509	81,880	48,879	55,557	128,376	96
	48	50,606	54,030	118,185	128,479	73,581	82,411	171,168	100
Low Activity	12	13,048	18,503	14,156	18,354	13,576	16,199	22,038	99
	24	22,134	27,637	29,723	36,417	25,074	29,845	44,076	100
	36	32,440	37,141	50,984	60,081	39,356	46,379	66,113	100
	48	43,653	47,350	78,142	89,727	56,653	66,095	88,151	100

[1]Estimated based on historical data for active drivers in each cluster.

HEV and EV drivers receive an extra $0.50 per trip, paid by riders (Uber, 2025). However, other incentives are only available to more active EV drivers—for example, a bonus after completing 50 trips within a week (Lyft, 2025) or after 1000 trips within three months (Uber, 2025).

Another limitation of electrification is the vehicle purchase price (Naseri et al., 2024). Our results indicate that purchase and financing prices were around 68.4 thousand for a new EV, and 47.8 and 39.6 thousand for HEV and ICEV. Considering that a great proportion of drivers have a low-income socioeconomic status (Qiao et al., 2023) or are looking for a job outside the RH sector (Lyft, 2023), it could pose a barrier given the higher initial investment. Current policies implemented in Canada provide rebates of up to 5000 CAD for new EVs with a base model price under 55,000 CAD (Canada, 2025), but they overlook important criteria such as mileage contribution and support for low-income groups. Evidence shows that incentives for pre-owned EVs can improve access to more affordable vehicles (Washington State, 2025), while alternative acquisition pathways, such as leasing and renting, may be more cost-effective than traditional financing (Ju et al., 2025).

For high-activity drivers (mean mileage of 42,792 km/year), pre-owned vehicles have a higher proportion of TCO, attributed to depreciation and maintenance costs, while gasoline and hybrid vehicles have proportionally higher expenses than EVs (Fig. 12). Using pre-owned ICEV as a baseline, the repair and maintenance cost factor was found to be 68 % for new ICEV, 51 % for EV (new and pre-owned), 71 % for new HEV, and 98 % for pre-owned HEV. These results are similar to those of Burnham et al. (2021), who found scaling factors of 89 % for HEV and 67 % for EV in the United States. When comparing a pre-owned HEV with a new EV, the lower depreciation cost found for the new HEV was sufficient to offset the incremental cost of EV depreciation.

Given that the TCO is highly influenced by operational costs, particularly for drivers operating at higher mileage, we investigated the LCO. Fig. 13 shows the LCO for commitment periods of 12, 24, 36, and 48 months for active drivers, categorized by their respective clusters. The results indicate that highly active drivers tend to have a much lower LCO over time compared to those with lower activity. In addition, because of the maintenance and depreciation costs, the LCO for ICEVs presented a slight increase over the years.

Since GHG emissions in RH systems are highly dependent on each driver's VKT, electrifying high-mileage drivers produces greater emissions savings. Fig. 14 shows the proportion of GHG emission savings achieved by electrifying the fleet across different mileage quintiles of active drivers. The Figure captures only mileage within RH operations and excludes distances driven for personal use. The first quintile represents the 20 % of vehicles with the lowest VKT, while the fifth quintile represents the 20 % of vehicles with the highest mileage. Electrifying the top 20 % of highest-mileage vehicles results in a 43.1 % reduction in emissions, while electrifying the bottom 20 % of lowest-mileage vehicles results in only a 5.1 % reduction in total emissions. This suggests that the highest-mileage group is rarely part of the Low-Activity cluster. Therefore, policies should target drivers from the High-Activity cluster who work more days per month and have higher daily VKT. Although life-cycle emissions were not included in this analysis, this omission does not affect our overall conclusions. In regions with low electricity grid emission intensity (CO_2/kWh), such as the province of Ontario (Pereira and Posen, 2020), life-cycle emission factors for EVs remain the lowest

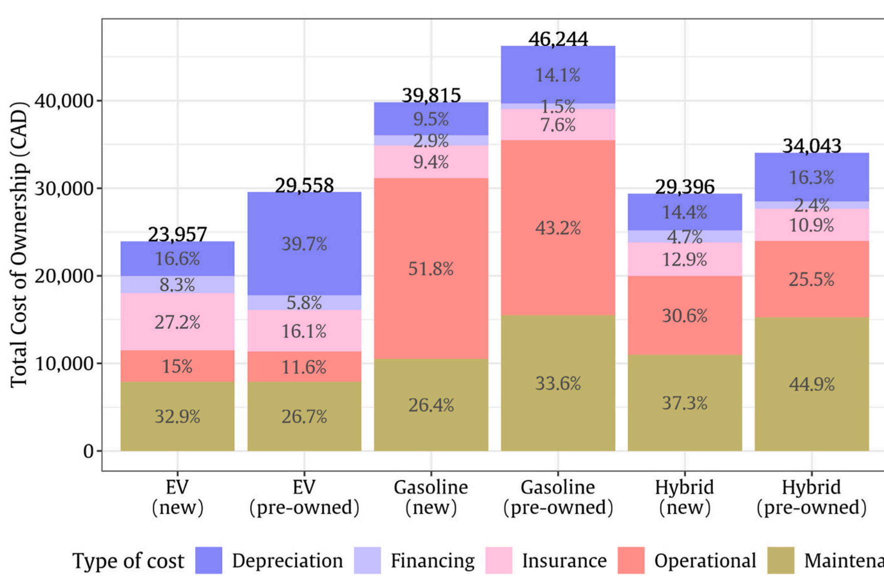

Fig. 12. Mean TCO breakdown costs after 24 months of commitment for drivers classified as High Activity.

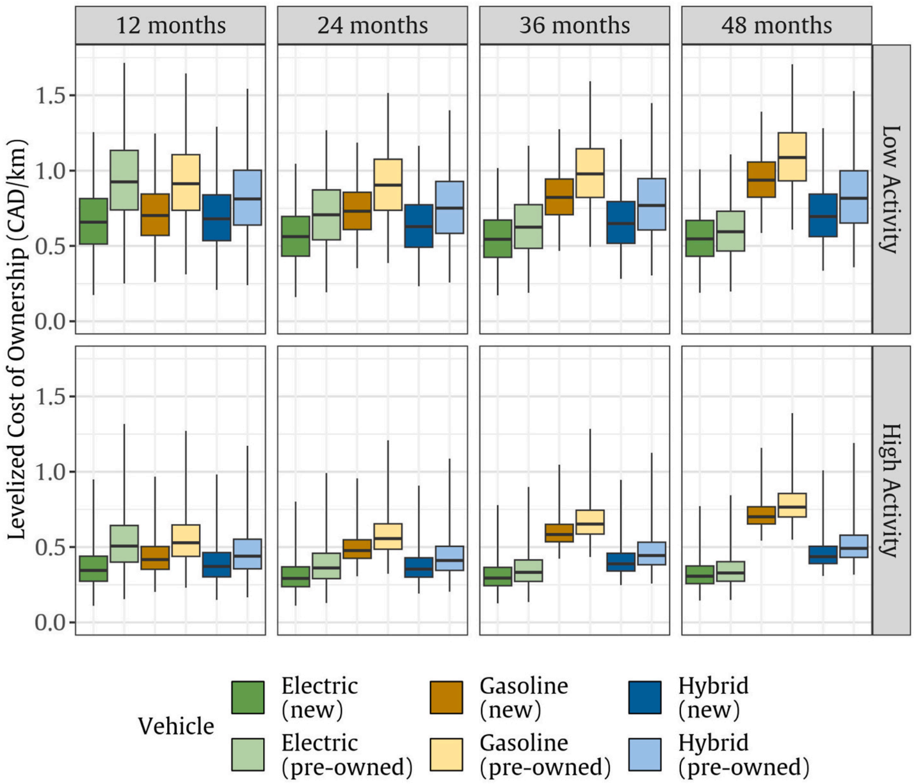

Fig. 13. Levelized Cost of Ownership by vehicle type according to different commitment periods (12, 24, 36, and 48 months) and driver clusters.

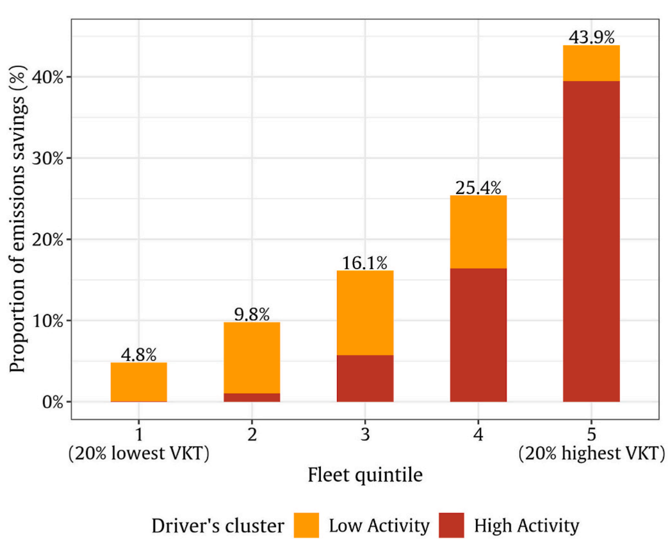

Fig. 14. GHG emission savings by fleet VKT quintile. Note: Analysis includes only mileage within ride-hailing operations and excludes distances driven for personal use.

when compared to ICEVs (Kannangara et al., 2021).

5. Conclusions

This study examined the evolution of RH in Toronto from 2020 to 2023, focusing on GHG emissions, the operational profile of drivers, and their relation to the TCO. We investigated how different driver operations influence the TCO of three vehicle fuel types (electric, hybrid, and gasoline) and two conditions (pre-owned and new). Our analysis indicates that RH in Toronto has grown in the number of trips, traveled distances, and GHG emissions. Although Toronto tends to have similar levels of deadheading as other cities, around 33–37 %, in the past two years (2022 to the end of 2023), it did not decrease deadheading events. Regarding the current state of electrification, we have shown that the TNC fleet has a slightly higher participation of EVs, 2.3 %, compared to 1.7 % in Ontario Province.

The study also identified the main characteristics of the drivers over time and how such aspects influence their VKT and efficiency. We noted that 42.9 % of drivers tend to do less than 200 km/week over a few days, and with a higher turnover rate. Although this group tends to contribute only 7.2 % to the total VKT, they are the least efficient in managing deadheading levels, with 43.9 % of the total mileage without passengers. In contrast, we found that 40.2 % of the drivers operate more than 400 km/week, more than five days a week, and have a higher chance of staying longer in the business. This group is more likely to cancel trip requests and operate for more than one TNC.

Our analysis of the TCO across different groups of RH drivers has shown higher competitiveness of EVs over hybrid and gasoline vehicles. Due to the higher depreciation costs of pre-owned cars, we found a 7–46 % smaller cost of ownership for new models across the three fuel types assessed. We have shown that the costs per mile tend to be lower when drivers operate more mileage and for a longer commitment period, which benefits those who want to pursue a longer career in the business. Finally, we have shown that an electrification policy focusing on the 20 % of drivers with the highest mileage tends to save 43.1 % of total emissions.

Given the lack of longitudinal data across RH studies (Sheldon and Dua, 2024), this work contributes to the literature by providing unprecedented trends in RH, as it relies on a universe of over 179 million trips, completed by more than 181 thousand drivers, alongside information on cruising and fleet data. From a policy perspective, this study supports low-carbon transition strategies by diagnosing current emissions and supply behavior, and by revealing where vehicle electrification is most viable based on actual driver characteristics. Policies should be implemented to decrease deadheading levels, as it hasn't shown a decrease in the last two years of analyzed data. In addition, given that higher deadheading is more common among drivers with part-time-like operations, TNCs should target these groups to provide more informational tools so they can better manage their operations.

From a vehicle transition perspective, although the TNC fleet has shown slightly higher participation of EVs than the Ontario Province, there is a long way to fully decarbonize the fleet. Policies focusing on RH drivers should be evaluated because they have higher mileage than regular drivers. Incentives from TNCs should also be considered for drivers operating EVs. In addition, despite the low TCO for electric cars, particularly for drivers with high mileage, the associated low commitment period in the business makes them less likely to make such a transition. Given the high probability of leaving the business in less than six months or a year, TNCs should provide incentives for long-term contractors, provide attractive EV rental deals, and governments should consider policies to ensure drivers a fair wage, which would incentivize a career within TNCs.

This study has a few caveats. First, we examined exhaust emissions over time, not including the life-cycle emissions of different vehicles and GHG emissions from energy consumption. In addition, we did not have data for previous vehicles that drivers might have had when operating TNC. Therefore, we couldn't observe any particular transition of vehicle types at the driver level over time. Regarding the limitations of the TCO results, we used average market values for maintenance, insurance, purchase, and financing, addressing the effects of high mileage when possible. However, given the high mileage of TNC drivers, such values might differ from those experienced by them. Also, TNCs might partner with maintenance and insurance companies to provide better deals for RH drivers, which might influence the final TCO. In addition, challenges associated with EV usage were not assessed, such as the drop in efficiency during wintertime, access to charging stations, and detours required to charge. Finally, we assumed that EV recharging was primarily done at home and disregarded the cost of charging at public stations and energy prices from external providers.

In conclusion, in terms of the methodological approaches for analyzing longitudinal behavior, artificial intelligence (AI) could offer valuable opportunities to strengthen future analyses. Techniques such as anomaly detection and natural language processing can enhance data cleaning and extract insights from unstructured sources, including driver feedback or platform usage logs (Belhadi et al., 2021). Long-Short Term Memory (LSTM) networks can capture temporal dynamics in driver activity, enabling more accurate predictions of operational efficiency (Bansal et al., 2021). Reinforcement learning can simulate the effects of various electrification policies and charging infrastructure scenarios, helping identify optimal interventions (Wan et al., 2019; Shi et al., 2020; Qin et al., 2022). Additionally, predictive models can inform the strategic siting of charging stations by forecasting spatio-temporal demand patterns (Jin et al., 2025). Integrating these AI-driven tools in future research would complement empirical, data-intensive analyses and improve policy design for decarbonizing RH systems.

CRediT authorship contribution statement

João Pedro Bazzo: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Marc Saleh:** Writing – original draft, Visualization, Supervision, Software, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Marianne Hatzopoulou:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of conflicting interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of competing interest

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Acknowledgments

We thank the City of Toronto's Big Data Innovation team (Matt Lee, Jesse Coleman, Raphael Dumas), and the University of Toronto Transportation Research Institute team (Shuoyan Xu, Ya (Lucia) Gao, Eric Miller).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2025.146252.

Data availability

The authors do not have permission to share data.

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