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Review

A quantitative assessment of daily transportation energy demand and electrification potential across the dwelling types in the Greater Toronto and Hamilton Area

Sumaiya Afrose Suma [a,*], Melvyn Li [a], Felita Ong [a], Kaili Wang [a], Eleftheria Kontou [b], Khandker Nurul Habib [a]

[a] Department of Civil & Mineral Engineering, University of Toronto, 35 St. George Street Toronto, ON, M5S 1A4, Canada
[b] Civil & Env. Engineering, University of Illinois, Urbana Champaign, 205 N Mathews Ave, Urbana, IL, 61801, USA

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ABSTRACT

The urban passenger transportation sector is a major energy consumer in Canada, accounting for nearly 48% of transport-related energy use and is heavily reliant on fossil fuel-based vehicles. Electrifying private vehicles offers a promising solution to reduce fossil fuel consumption and greenhouse gas (GHG) emissions, but its full potential remains underexplored. This study focuses on the Greater Toronto and Hamilton Area (GTHA). It examines how residential dwelling types influence daily household transportation energy demand, with a specific focus on electrification barriers in multi-unit residential buildings (MURBs). Using personal and household travel surveys, the study applies supervised machine learning models, such as Random Forest and Decision Tree models, to impute vehicle engine types and estimate daily transportation energy use. The results show significant variation in energy demand by dwelling type, with detached homes consuming the most, followed by MURBs and townhouses. Moreover, there is an increase in reliance on private vehicles and ridesharing post-pandemic. Scenario analysis reveals that a complete transition to electric vehicles (EVs) has the potential to reduce daily household private vehicle energy consumption by up to 77.3%. The reductions vary by dwelling type, with detached homes projected to achieve a 54.4% decrease, while MURBs are expected to see a 14.8% reduction. Peak hour charging demand in 100% EV scenarios would reach 6640 gigajoules (GJ) for houses and 1792 GJ for MURBs. These findings underscore the need for targeted policies to promote EV adoption, particularly for MURBs, and tailored incentives for households with detached homes.

1. Introduction

Energy consumption in the transportation sector is a major driver of national energy demand. In 2020, transportation was the second-largest sector for end-use energy consumption in Canada (~27%), following closely behind the industrial sector [1]. Within the transportation sector, road-based passenger travel accounts for approximately 48% of total energy use [2]. This sector also plays a substantial role in climate change. In 2022, transportation energy use accounted for approximately 156 Mt CO_2 equivalent—nearly 22% of the country's total emissions [3]. In response, Canada has implemented a range of sustainability strategies to reduce emissions across various sectors. For instance, Toronto, one of the country's most prominent urban centers, has implemented the Net Zero Strategy aimed at achieving net-zero GHG emissions by 2040 [4], with a particular focus on passenger vehicle electrification, which contributes nearly 30% of the city's emissions [5]. Understanding the nature of passenger travel energy demand is, therefore, essential for identifying actionable opportunities for electrification. However, to craft effective and targeted electrification policies, it is critical to examine the underlying sources of transportation energy demand in greater detail.

Transportation energy use can generally be analyzed at two levels: (a) network-level (aggregated) and (b) daily (disaggregated). Aggregated demand has been widely examined in the literature, as it aligns with national and regional interests in understanding fuel use across the transport sector. These studies rely on macro-level indicators such as

* Corresponding author. Department of Civil & Mineral Engineering, University of Toronto, 35 St. George St, Toronto, ON, M5S 1A4, Canada.
E-mail addresses: afrose.suma@mail.utoronto.ca (S.A. Suma), melvyn.li@mail.utoronto.ca (M. Li), felita.ong@mail.utoronto.ca (F. Ong), jackkaili.wang@mail.utoronto.ca (K. Wang), kontou@illinois.edu (E. Kontou), khandker.nurulhabib@utoronto.ca (K.N. Habib).

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population [6], urbanization [7], economic activity [8], total vehicle kilometers travelled [9], and fleet characteristics [10]. A variety of techniques have been applied, including regression [11], machine learning [6,8,12–14], and simulation-based approaches [9,10].

On the other hand, daily energy demand analysis offers a disaggregated perspective rooted in individual travel behavior, and the existing literature employs a variety of methodologies that can be applied to estimate, including regression [15], discrete choice [16,17], machine learning [18,19], and simulations [20–22]. Moreover, existing studies at international [15] and national levels—such as those conducted in the U.S. [18,21], the U.K [16,22]. and Croatia [20]—have shown that demographic factors [23], trip attributes [24], vehicle technologies [22], and infrastructure availability [25] significantly influence travel patterns and, consequently, energy demand. For example, households with dedicated off-street parking tend to own more vehicles and drive more frequently [26]. In contrast, limited parking options are associated with reduced driving and a greater reliance on public transit [27]. Similarly, suburban households often generate more vehicle trips and exhibit higher ownership levels than those in compact, mixed-use areas [28].

Within both urban and suburban divides, the residential dwelling type plays a critical role in shaping the choice of travel mode and the kind of vehicle technology used, especially regarding the transition to electric vehicles (EVs). Studies have shown that residents of single-family houses have significantly greater access to EV charging compared to those living in multi-unit residential buildings (MURBs) [29,30]. Moreover, the physical and infrastructural characteristics associated with different dwelling types, such as access to private parking or charging facilities, directly influence whether individuals are more likely to rely on private vehicles or public transit [27], and whether they can feasibly adopt EVs [31] over conventional gas-powered cars, as home charging is essential for both charging and regular use of EVs [32]. However, MURB residents face several barriers, including physical (e.g., parking, electrical systems), financial (e.g., installation costs, retrofitting), regulatory (e.g., guidance, permissions), and management (e.g., governance, ownership) challenges when facilitating home charging [33].

Additionally, previous studies have highlighted the need for strategically placed charging infrastructure near and within MURBs, as research in Los Angeles County revealed that the charger-to-vehicle ratio for plug-in hybrid vehicles remains below the recommended level in the literature [34]. Furthermore, expanding access to private overnight charging for MURB residents will become increasingly critical in the coming years—not only to reduce EV charging costs but also to ensure convenient and equitable access, especially as the population of MURB dwellers continues to grow [35]. The shift towards EV adoption is also economically beneficial, as a study by Horesh et al. [36] demonstrates that MURB-based EV infrastructure offers a cost-effective solution for reducing GHG emissions compared to conventional fuels, even when ownership lies with utilities or private companies. Despite this, a gap remains in the literature: no study has systematically explored how dwelling type influences both mode and fuel technology choices, and how this intersection ultimately affects daily transportation energy consumption and the potential for electrification.

In the Canadian context, research has addressed EV adoption [37,38] and infrastructure planning [39–41]. While much attention has been given to the adoption of EVs and infrastructure planning, a comprehensive understanding of how MURB residents' share in daily energy consumption can benefit the passenger car electrification process is lacking. Moreover, a notable gap exists in the estimation of total daily transportation energy demand, particularly across different dwelling types, primarily due to the absence of granular data on vehicle fuel and engine types at the household level, a critical factor given the sensitivity of energy consumption to vehicle technology. Addressing this gap is crucial, as it can inform more targeted infrastructure policies for different dwelling type residents. Furthermore, understanding the complex dynamics between dwelling type and travel behavior can enhance our approach to reducing transportation energy consumption and GHG emissions. By bridging this gap, we can better develop strategies for equitable EV adoption across all types of dwellings, ultimately contributing to more equitable urban transportation systems.

This study contributes to the literature in two ways. First, it develops a methodology to predict household vehicle engine type using available socioeconomic data. Second, it offers one of the first comprehensive evaluations of daily transportation energy demand differentiated by dwelling type. The primary aim of this study is therefore to estimate daily transportation energy consumption with a focus on different dwelling types and travel modes, aiming to identify strategic opportunities for electrification in the Greater Toronto and Hamilton Area (GTHA). Specifically, it addresses the following research questions: (a) What are the energy demands associated with different travel modes? (b) How does this demand vary across dwelling types? (c) What energy consumption reductions are possible under various electrification scenarios? and (d) Which dwelling types offer the greatest potential for electrification? The results can support the design of targeted and sustainable transportation and energy policies. They also enhance our understanding of how the dwelling type and travel characteristics interact to influence regional patterns of fuel consumption.

The remainder of this paper is structured as follows: data and descriptive statistics (section 2), methodology for predicting vehicle engine type and estimating energy demand (section 3), results and discussion (section 4), electrification scenario analysis (section 5), conclusion and policy recommendations (section 6).

2. Data

This study draws on data from the regional household travel survey known as the Transportation Tomorrow Survey (TTS), conducted every five years in the Greater Golden Horseshoe Area [42]. The TTS samples approximately 5% of households in the study region and is aligned with the national census cycle, allowing census data to be used in calculating expansion factors that scale the results to the full population. The large and representative sample provides a unique and robust basis for estimating household transportation energy demand, as it captures a comprehensive snapshot of daily travel behavior across the region.

To ensure manageability and reduce respondent burden, the TTS collects key personal, household, and trip-level attributes at a streamlined level of detail. While this design ensures survey feasibility at scale, it also results in the omission of certain granular variables, such as household vehicle fuel and engine types, which are critical for energy-related analyses. However, the dataset's structure allows for the integration of supplementary sources to fill these gaps through data fusion techniques.

To address the missing vehicle technology information, this study leverages a companion dataset—the Multi-day Travel Survey (MTS)—conducted in 2025 within the same geographic area. Importantly, the MTS targeted participants from the same sampling pool (a subset of the TTS participants who agreed to be contacted for further travel survey research) as the TTS, effectively functioning as a satellite survey. This close alignment enables reliable imputation of household vehicle types in the TTS dataset using appropriate data fusion methods grounded in matched respondent characteristics.

The MTS dataset classifies household vehicles into four fuel and engine types: (a) Internal Combustion Engine Vehicle (ICEV), (b) Plug-in Hybrid Electric Vehicle (PHEV), (c) Hybrid Vehicle (HV), and (d) Electric Vehicle (EV). Fig. 1 presents the distribution of these vehicle types across households owning one, two, or three vehicles. A clear trend emerges among single-vehicle households, ICEVs dominate (86.9%), while PHEVs (2.3%), HVs (6.5%), and EVs (4.2%) remain limited, as shown in Fig. 1[a]. However, as household vehicle ownership increases to two, the diversity in engine types becomes more pronounced. Although the majority (75.7%) of two-vehicle households own two

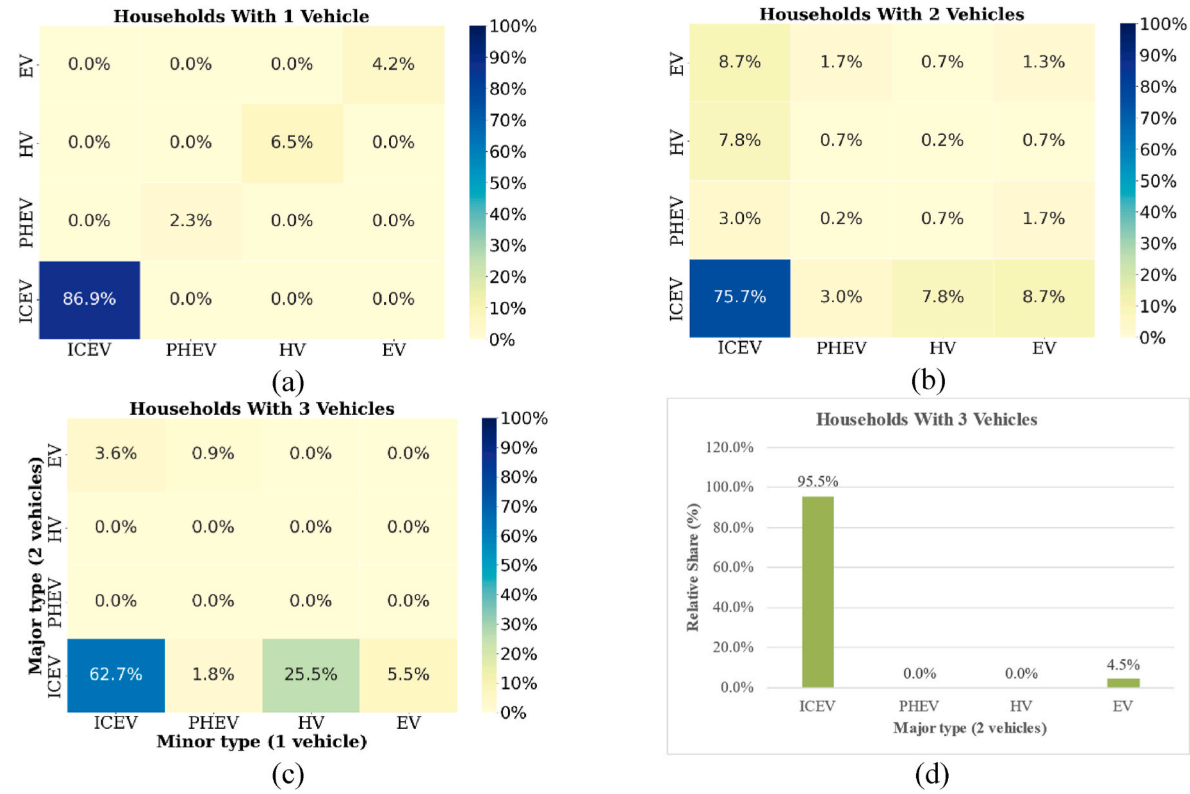


Fig. 1. Vehicle engine type with different levels of household vehicle ownership.

ICEVs, a growing share includes at least one PHEV (3.0%), HV (7.8%), or EV (8.7%), signaling a gradual uptake of alternative fuel technologies—often alongside one conventional ICEV, as shown in Fig. 1[b].

Fig. 1[c] illustrates the combination of vehicle types categorized as major-minor for three-vehicle households. The major type is defined as two vehicles with the same engine type, while the minor type refers to the third vehicle. The data shows that among households owning three vehicles, the proportion of ICEVs as the third vehicle—alongside two existing ICEVs—declines to 62.7%. At the same time, HVs account for a noticeably larger share at 25.5%. This trend signals a gradual diversification in the adoption of vehicle technology. Fig. 1[d] further illustrates the most common engine type combinations within three-vehicle households. The aggregated relative share of major engine types in these households shows that ICEVs dominate with 95.5%, while EVs account for 4.5%. Notably, there were no households with PHEVs or HVs as the primary engine type in these three-vehicle households. These combinations underscore a cautious yet discernible integration of cleaner vehicle technologies within conventionally ICEV-dominant household fleets.

Fig. 2[a] compares the distribution of engine types in the MTS dataset against the latest available Ontario vehicle registration data from Statistics Canada [43]. The comparison reveals a generally consistent representation of vehicle engine types between the two datasets. While ICEVs appear slightly underrepresented in the 2025 MTS, they still account for a commanding 83.8% market share. In contrast, alternative fuel vehicles remain in the minority, with HVs and EVs each comprising 6.3%, and PHEVs at 3.5%.

Fig. 2[b] illustrates how engine type shares shift with increasing household vehicle ownership. Although ICEVs continue to dominate across all ownership categories, the figure reveals a clear pattern: multi-vehicle households are more likely to diversify their fleets by incorporating HVs, PHEVs, or EVs. This trend suggests that households with more vehicles may be experimenting with alternative technologies while retaining conventional options, potentially due to varying usage needs

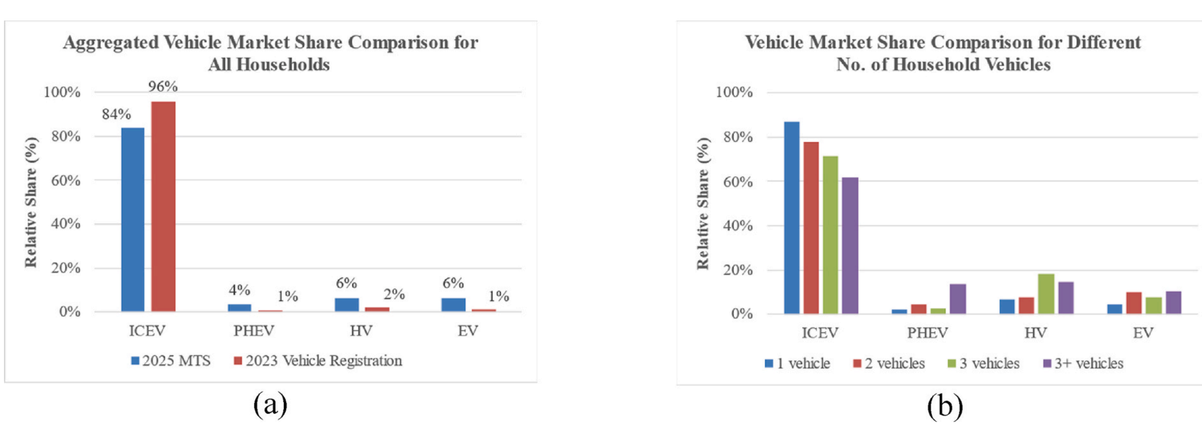


Fig. 2. Vehicle market share comparison.

or charging infrastructure constraints.

3. Methodology

The TTS dataset lacks vehicle engine type information, which is critical for estimating daily transportation energy consumption from private vehicle use. Therefore, the methodology analysis was divided into two phases. First, vehicle engine types were predicted based on available household and personal attributes. Second, representative daily energy consumption was estimated using the imputed engine types. This two-phase framework is illustrated in Fig. 3.

3.1. Prediction of vehicle engine and fuel type

Recent studies have increasingly applied machine learning techniques to predict fuel-related vehicle attributes using both vehicle specifications and household-level data. The use of demographic and household variables to forecast vehicle ownership is well established in the literature [44,45]. In addition, machine learning has been widely employed in predicting vehicle fuel types and usage patterns [46,47]. Building on this foundation, this study developed a set of supervised machine learning models using household-level attributes from the TTS dataset to predict vehicle engine types.

Seven machine learning algorithms were evaluated: Linear Regression (Model 1), K-Nearest Neighbors (Model 2), Decision Tree (Model 3), Support Vector Machine (Model 4), Random Forest (Model 5), AdaBoost (Model 6), and Gradient Boosting (Model 7). Both the 2016 and 2022 TTS datasets were used in model development to enable a comparative analysis of daily transportation energy demand before and after the COVID-19 pandemic.

All models were trained with hyperparameter tuning to optimize prediction accuracy. Thresholds for the predicted engine type shares were calibrated to align with Ontario's vehicle market share distribution [43]. Results from the 2016 TTS showed that four household attributes: (a) household size, (b) household income, (c) dwelling type, and (d) total number of vehicles yielded the best predictive performance in terms of Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). For the 2022 TTS, the addition of a fifth variable, "household structure," which captures the composition of household members, further enhanced model accuracy. A summary of the model performance comparison is presented in Fig. 4.

As illustrated in Fig. 4[a], the Decision Tree model yielded the best predictive performance for the 2016 TTS dataset. In contrast, for the 2022 TTS dataset, the Random Forest model outperformed all others, as shown in Fig. 4[b]. In both cases, these models achieved the lowest values of Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE), indicating superior accuracy. Further validation of the model outputs is presented in Fig. 4[c] and [d], which compare the predicted engine type distributions against vehicle registration data from Statistics Canada [43]. The close alignment between predicted and actual market shares supports the reliability of the selected models. As noted in earlier sections and confirmed by the registration data, Internal Combustion Engine Vehicles (ICEVs) continue to dominate the private vehicle market, comprising over 95% of the fleet.

Following the prediction, the estimated vehicle engine types were mapped back to the respective households in the TTS datasets to determine the available vehicle technologies for household auto trips. For households with multiple vehicle types, trip assignments were randomized among the available vehicles to reflect realistic usage behavior within mixed-technology fleets. While the random assignment of trips to vehicles in mixed-technology households is a simplified approach, this assumption could lead to slight overestimations of EV adoption and underestimations of ICEV usage, potentially affecting the accuracy of energy demand estimates for each vehicle type. The impact of this simplification is likely minimal in the context of aggregated energy demand at the household level, as both vehicle types are used across various trip distances.

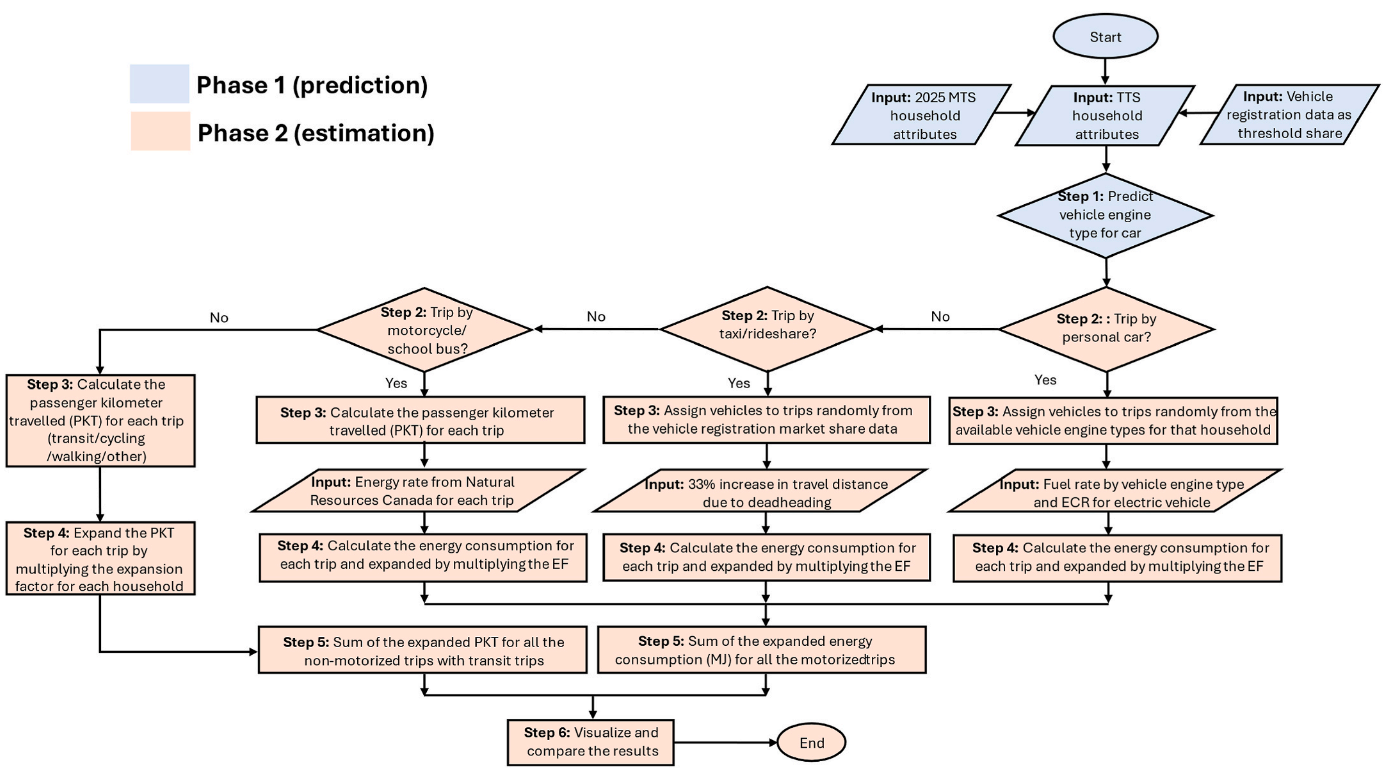


Fig. 3. Methodological process.

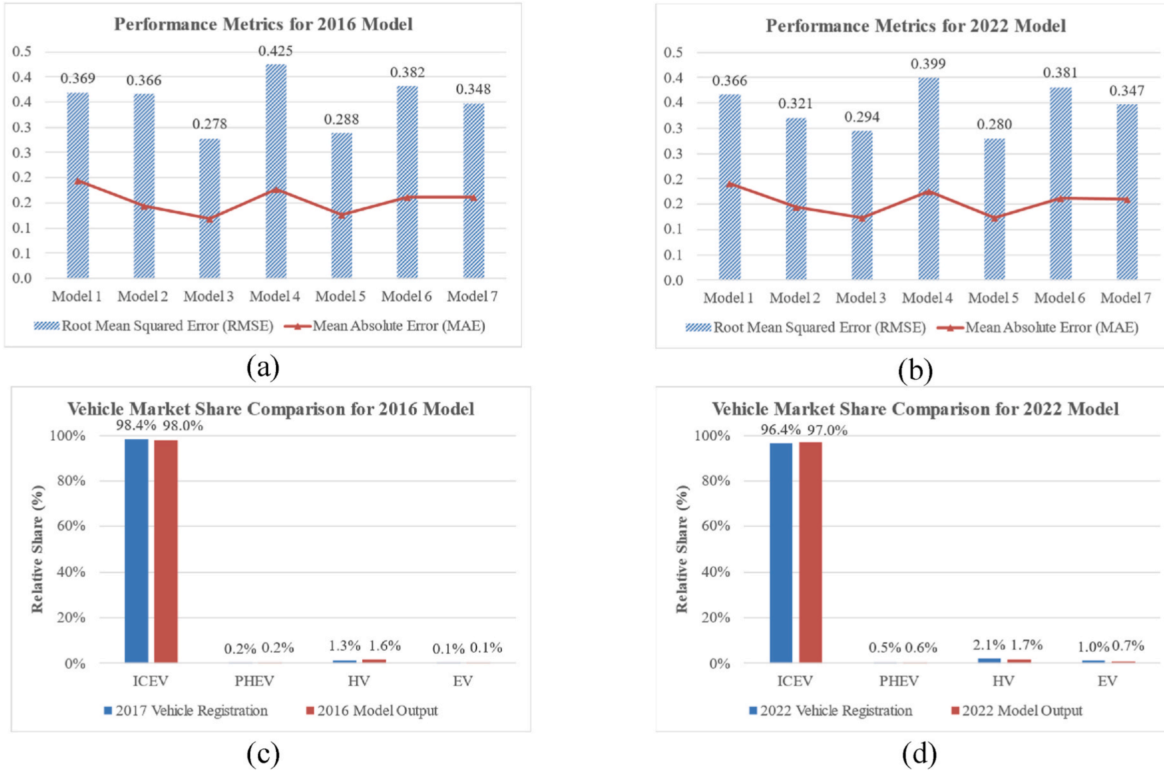


Fig. 4. Model performance for vehicle fuel and engine type prediction.

3.2. Estimation of energy consumption rate

To estimate daily transportation energy demand using level-of-service (LOS) variables such as speed, travel distance, and travel time, fuel consumption rates for different vehicle types are required. Natural Resources Canada [48] publishes an annual fuel consumption guide by vehicle model and fuel type, based on model year. Additionally, the Canadian Automobile Association [49] provides a fuel cost calculator for various vehicle types. However, applying these consumption rates requires accurate information on vehicle model years and age distributions specific to the GTHA. Since the TTS dataset does not include vehicle model year or make, an alternative approach was adopted using a weighted average fuel consumption rate. This was derived based on the market share of common vehicle makes and the approximate age profile of the vehicle fleet.

According to Natural Resources Canada [48], fuel consumption rates for typical mid-sized passenger vehicles such as the Toyota Corolla, Honda Civic, and Hyundai Elantra are relatively similar under city driving conditions. However, Ford—Canada's top-selling vehicle brand (Focus2Move, 2023 [50])—has comparatively higher fuel consumption for a similar vehicle class, such as the Ford Fusion. Based on the Canadian Automobile Association's cost calculator [49], average combined (55% city/45% highway) fuel consumption rates for the Ford Fusion, Toyota Corolla, Honda Civic, and Hyundai Elantra are 9.4, 8.15, 7.7, and 7.4 L/100 km, respectively. These rates are standardized to the 2017 model year, which was adopted in this study to represent the vehicle fleet within the 2022 TTS, given that the average vehicle age in Canada ranges from 6 to 9 years [51].

To derive a representative ICEV fuel rate for this analysis, a weighted average was calculated based on the relative Canadian market shares of the four major makes—Ford, Toyota, Hyundai, and Honda [52]. The resulting average fuel consumption rate used for ICEVs in this study is 8.33 L/100 km. The use of a single weighted average fuel consumption rate for all ICEVs simplifies the analysis. Consequently, variability in fuel consumption due to factors such as vehicle size, age, and type may not be fully captured, which could introduce some uncertainty in the energy estimates. However, since this study compares energy demand at the aggregated level for different dwelling types, the effect of this simplification is mitigated. Moreover, this value aligns closely with findings from Lei et al. [53], who estimated energy consumption rates using the MOVES-Matrix model. They found an average consumption ranging from 4 to 5 megajoules per vehicle per mile (MJ/vehicle/mile), with a central value of 4.5 MJ/vehicle/mile. This is approximately equivalent to 8.33 L/100 km of gasoline in moderate-speed conditions, as supported by conversion estimates from the U.S. Energy Information Administration [54].

For EVs, the energy consumption rate was represented in terms of distance (kWh/km), based on estimates from the Canadian Automobile Association [49] and range data from the Natural Resources Canada fuel consumption guide [48]. However, given that this study aims to explore the potential for electrification, it is crucial to estimate trip-level energy use, especially in urban environments where factors such as stop-and-go traffic, frequent acceleration, and deceleration can significantly affect EV energy consumption. Therefore, to estimate trip-specific energy use, an average speed–based model was employed, allowing electricity consumption to be calculated dynamically based on trip speed. Specifically, Equation (1) presents the adopted model for estimating energy consumption rate, *ECR* (kWh/km) as a function of average speed, v (km/h).

This Equation (1), originally developed by Yao et al. [55], was derived using a multiple linear regression approach. It models the relationship between average vehicle speed and corresponding energy consumption rates across various vehicle-specific power (VSP) bins. The formulation was based on empirical data collected for a light-duty electric vehicle undergoing an urban drive cycle ranging from 0 to 90 km/h speed and using a chassis dynamometer, making it well-suited for modeling real-world EV performance under urban conditions.

$$Energy\ Consumption\ Rate\ (\boldsymbol{ECR}) = \mathbf{0.218} + \frac{\mathbf{1.359}}{\boldsymbol{v}} - \mathbf{0.003}\boldsymbol{v} + \mathbf{0.0000281}\boldsymbol{v}^2 \quad (1)$$

The market shares of both plug-in hybrid and hybrid vehicles were relatively small in the dataset. As a result, rather than applying a weighted average fuel consumption rate as done for ICEVs, a fixed (flat) rate approach was adopted for these vehicle categories. According to the Canadian Automobile Association [49], a typical plug-in hybrid vehicle—such as the 2017 Toyota Prius—exhibits an average fuel consumption rate of 4.5 L/100 km. This estimate is further supported by Peng et al. [56], who conducted a real-world analysis of plug-in hybrid vehicle performance. Their findings, based on empirical comparison with a developed fuel consumption model, also confirmed an average rate of approximately 4.5 L/100 km within moderate-speed driving conditions. Consequently, this study adopts 4.5 L/100 km as the representative consumption rate for plug-in hybrid vehicles.

In contrast, conventional hybrid vehicles typically have higher fuel consumption than their plug-in counterparts [57]. Therefore, a fixed rate of 5.95 L/100 km was used to represent fuel consumption for standard mid-size hybrid vehicles, such as the 2017 Toyota Camry Hybrid [49].

For trips made by ridesharing and taxi services, vehicle types were randomly assigned based on market registration shares from Statistics Canada [43]. According to the Vehicle-for-Hire (VFH) bylaw, vehicles used in these services can be up to ten model years old. Therefore, an average vehicle age of five years was assumed for the 2022 TTS, resulting in 2017 being selected as the representative model year for assigning vehicle types [58].

The energy consumption of taxi and ridesharing services is significantly higher than that of private modes due to the presence of deadheading, which refers to the period when vehicles travel without passengers. This additional travel attribute contributes to increased energy use, as vehicles continue to operate without generating passenger-related demand. To account for the impact of deadheading, a 33% increase in travel distance was applied to ridesharing trips in the analysis [59]. This adjustment provides a more realistic estimate of energy demand compared to private vehicle use.

For other modes, fixed energy consumption rates were adopted based on Ontario's 2022 average value [60]: 1.73 MJ per passenger-kilometer travelled (PKT) for motorcycles (Tabe 32) and 0.46 MJ/PKT for school buses (Tabe 28). For public transit trips, PKT was used as the unit of analysis rather than energy, reflecting the fact that transit services typically operate on fixed schedules regardless of ridership levels. Similarly, active modes such as cycling and walking were assessed based on total travel distance.

4. Results and discussions

This section presents the estimated daily transportation energy consumption results derived from the TTS dataset, with a particular focus on dwelling types, as discussed in the preceding sections. The analysis specifically differentiates between the various dwelling types available in the TTS dataset—houses, apartments, and townhouses. In the context of the TTS dataset, apartment corresponds to MURB, where multi-family residences are located. Therefore, the term "MURB" will be used to refer to apartments throughout the analysis of the TTS dataset.

Fig. 5 illustrates the distribution of energy consumption associated with private vehicle driving trips across these types of dwellings. As shown in Fig. 5[a] MURB residents consume only 19.9% of total driving energy consumption, and almost 100% of them rely on ICEVs. In contrast, residents of houses and townhouses exhibit more varied energy use patterns across different vehicle types. For example, residents of homes and townhouses exhibit 98.4% and 97.3% of their daily energy consumption from ICEVs, respectively. In contrast, HVs account for the second-largest share of daily driving energy consumption, both for houses and townhouses, at 1.2% and 1.6% of the total, respectively. However, EVs hold the largest share in townhouses, albeit a small one, at just 1% of overall energy consumption.

However, as indicated in Fig. 5[b], MURB residents contribute only 20% of the total ICEV-related driving energy consumption, whereas residents of houses account for a disproportionate share, approximately 70%. In contrast, townhouse residents emerge as the largest contributors to EV energy consumption, representing 60% of total EV-related usage in driving trips. Moreover, houses account for the major share of the other two types of vehicles, with 94% and 83% for PHEVs and HVs, respectively. These findings underscore the influence of dwelling type on both vehicle technology adoption and associated daily driving energy demand.

Additionally, Fig. 6 represents similar trends for daily energy consumption for auto passenger modes. MURB residents still consume almost 100% of their daily transportation energy by ICEV, although the individual share of MURBs in total ICEV energy consumption is still low with a value of 18%.

Fig. 7 represents a comparative analysis of both aggregated and disaggregated changes in total daily transportation energy consumption and travel distances across all modes of transportation from 2016 to 2022, considering residents from all dwelling types. Clear patterns emerge, particularly considering the COVID-19 pandemic's effects on travel behavior. The private vehicle comparison reveals that, while daily energy consumption for auto driving decreased by 7%, it increased by 25% for auto passengers during the same period. This suggests that people travel more in their personal cars, but not alone—family members accompany them. Similarly, daily energy consumption by taxis and ridesharing services rose by 35%, indicating a greater reliance on

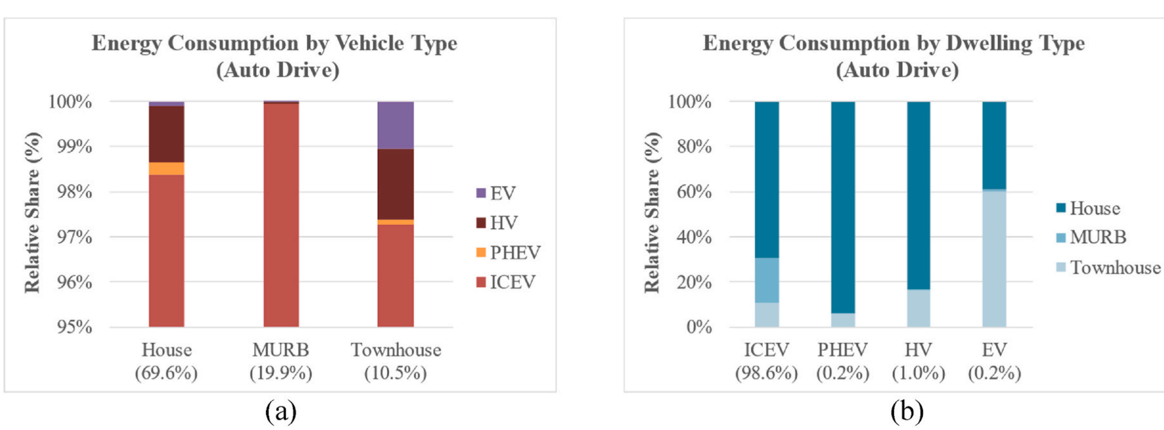


Fig. 5. Auto driving energy consumption (2022).

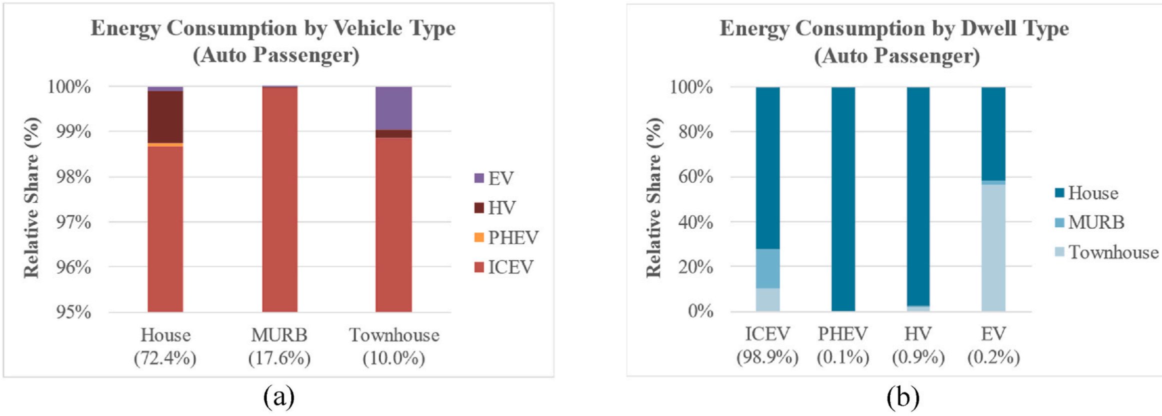


Fig. 6. Auto passenger energy consumption (2022).

Fig. 7. Total energy consumption and travel distance changes between 2016 and 2022.

passenger cars. This shift may be driven by a significant reduction in local and regional transit total PKT, which decreased by 36% and 48%, respectively. Post-pandemic, people have preferred passenger cars over public transit due to safety concerns and the need for social distancing [19]. In contrast, motorcycle daily energy consumption remained stable, with only a 2% increase. School bus daily energy consumption, however, rose by 34%. Finally, the total travel distance for active modes, such as cycling and walking, increased by 16% and 60%, respectively, with walking showing the highest increase among all modes.

Fig. 8 represents a more detailed and disaggregated pattern of total

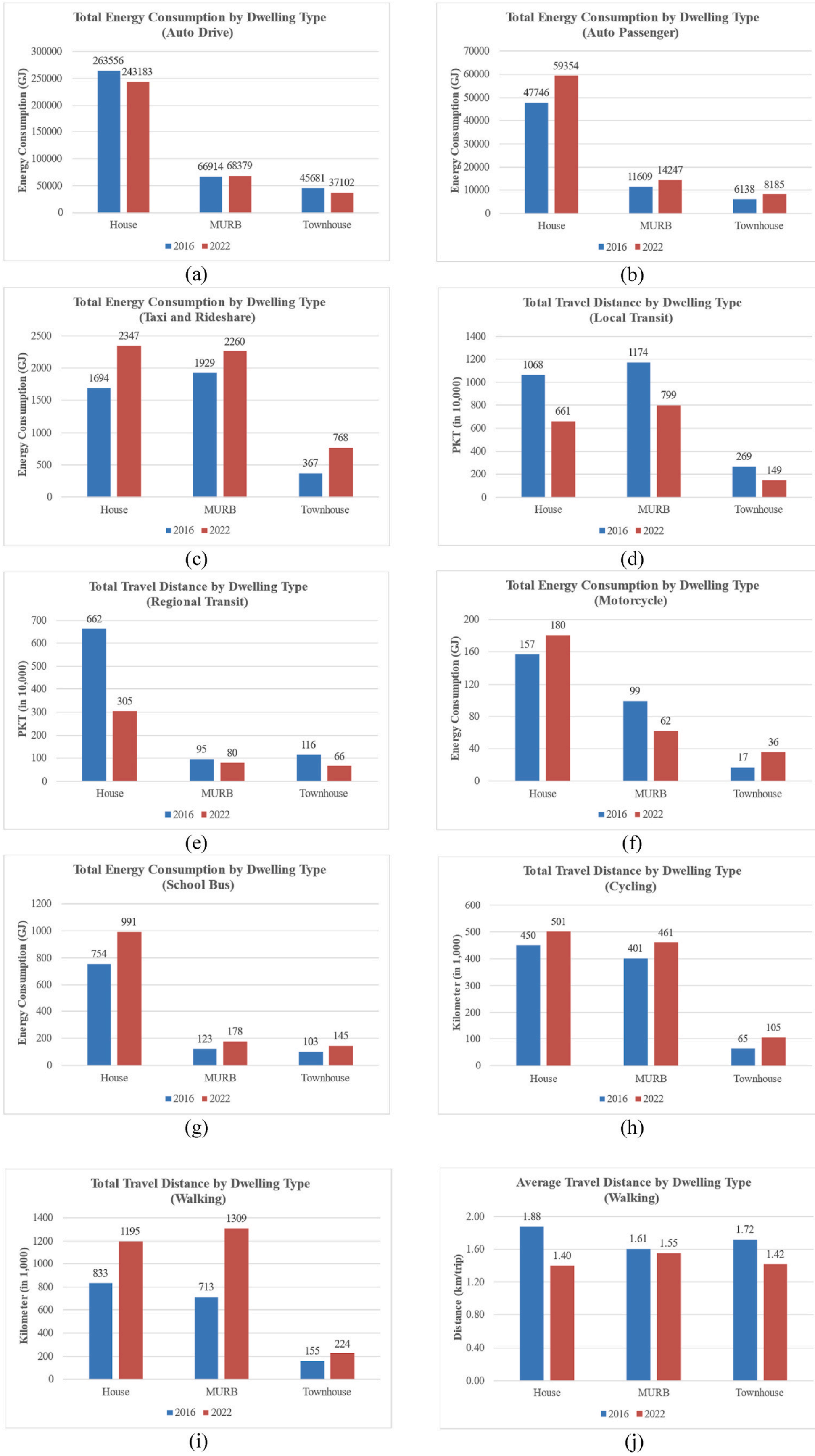


Fig. 8. Mode-wise energy consumption and travel distance comparison by dwelling type.

energy consumption by dwelling type for all modes. For auto driving (Fig. 8[a]), total energy consumption slightly declined for house and townhouse residents between 2016 and 2022. In contrast, MURB residents showed a small relative increase of about 2% (Fig. 7[b]), suggesting they expended more energy on private vehicle driving trips after the pandemic. However, total energy consumption for passenger trips by private vehicles increased from 2016 to 2022, irrespective of the dwelling type (Fig. 8[b]), with the least relative increase of 23% for MURB (Fig. 7[b]). This implies that residents of houses and townhouses have shifted towards utilizing more private vehicle passenger trips, with a reduction in driving trips from 2016 to 2022. This shift may be due to a transition from single occupancy to multi-occupancy trips, such as carpooling or family trips. On the other hand, for MURB residents, both driving and passenger trips by private vehicle increased, likely due to post-pandemic travel behaviour, leading to a greater reliance on private vehicles for daily commuting [61].

Meanwhile, Fig. 8[c] demonstrates that all dwelling types experienced an increase in total daily energy consumption for taxi and rideshare services. Notably, townhouses saw a significant rise, with a 109% increase in energy consumption (Fig. 7[b]), reflecting a growing reliance on these alternatives to crowded public transit [19]. However, MURB residents saw the smallest increase, with only a 17% rise in energy consumption for taxi and ridesharing services. This could be attributed to better access to other modes and more walkable urban environments, which likely reduce their reliance on taxis and ridesharing compared to residents of houses and townhouses. The relative changes in walking modes for MURB residents further support this, as they experienced the largest increase (84%) in walking trips post-pandemic (Fig. 7[b]).

Moreover, both local and regional transit (Fig. 8[d] and [e]) experienced a significant decrease in total PKT across all dwelling types. However, the relative reduction was the least for MURB residents, with a 32% reduction in local transit and a 16% reduction in regional transit (Fig. 7[b]). This suggests that while MURB residents reduced their transit use post-pandemic, they did not do so as significantly as residents of houses or townhouses. This may indicate barriers to shifting to private vehicles, even after the pandemic [27]. However, townhouses showed the highest reduction in local transit (45%), while houses experienced the largest reduction in regional transit (54%) as shown in Fig. 7[b]. This implies that townhouse residents were more dependent on local transit for commuting, leading to a significant decline in local transit use post-pandemic. In contrast, residents of houses, often situated in suburban areas, may have relied more on regional transit for longer commutes. Consequently, the pandemic's impact on commuting patterns contributed to a more substantial reduction in regional transit for house residents.

Motorcycle total daily energy consumption increased for house and townhouse but decreased for MURB (Fig. 8[f]). The relative change was 15% for houses 106% for townhouses, and −38% for MURB residents (Fig. 7[b]). This trend is likely to be due to higher and longer motorcycle trips made by the post-pandemic single-house and townhouse residents. However, school bus total energy consumption increased over the same period (Fig. 8[g]) for all dwelling types. Cycling patterns indicate that houses consistently have the largest share, while MURB residents have the second largest share (Fig. 8[h]). The comparison of changes showed an overall increase for all dwelling types (Fig. 7[b]), but the highest for townhouse residents (61%). This suggests a shift toward local travel and greater adoption of cycling as a safer, more sustainable option for all. Walking total distances increased notably for house residents (Fig. 8[i]) and the relative change was 84% (Fig. 7[b]). However, the walking trip length reduced to 1.40 km from 1.88 km for MURB (Fig. 8[j]). Similar trends can also be observed in other types of dwellings. This reflects a decrease in long walking trips, while shorter trips increased post-pandemic.

Fig. 9 compares energy consumption and travel distance time distributions over the day between 2016 and 2022, highlighting the post-pandemic shifts in travel behavior. Peak auto driving energy consumption decreased (Fig. 9[a]), but mid-day off-peak consumption rose, likely due to more flexible work schedules. Auto passenger energy consumption increased significantly during both morning and afternoon peaks and mid-day (Fig. 9[b]), reflecting higher shared private vehicle use. Similarly, taxi and rideshare energy consumption increased throughout the day (Fig. 9[c]). In contrast, local and regional transit experienced substantial declines during peak hours, due to overall commuter losses after the pandemic (Fig. 9[d] and [e]). Motorcycle energy consumption showed mixed increases and decreases over time, resulting in a more dispersed peak (Fig. 9[f]). School bus energy consumption increased overall in 2022 (Fig. 9[g]), while cycling remained stable during early hours with slight mid-day and afternoon increases (Fig. 9[h]). Walking trips also rose, outpacing cycling growth during these periods (Fig. 9[i]).

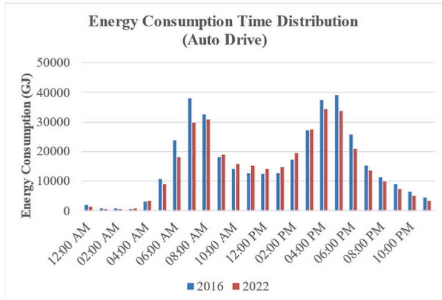
In summary, the data from Figs. 8 and 9 demonstrate how COVID-19 reshaped mobility patterns across different dwelling types and periods. Notably, MURB residents increased their use of private vehicles for both single and multi-occupancy trips. In contrast, residents of houses and townhouses shifted toward multi-occupancy trips, reducing their reliance on single-occupancy travel. However, transit usage declined the least for MURB residents, suggesting that they face fewer barriers to using public transit compared to residents of houses or townhouses. While cycling and walking usage increased across all dwelling types, MURB residents experienced the greatest rise in walking trips, albeit of shorter distances. This trend reflects evolving travel preferences, where residents are opting for safer and more sustainable modes of transportation post-pandemic.

5. Scenario analysis

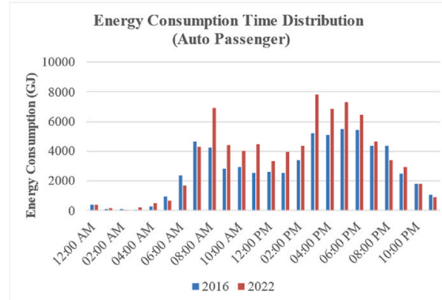
The Government of Canada has introduced policies and targets to decarbonize the transportation sector in support of its legislated goal of net-zero emissions by 2050 [62]. Increasing the adoption of zero-emission vehicles (ZEVs) is a key component of this goal. The federal government has published regulations to require ZEVs to make up a growing share of new light-duty vehicle (LDV) or passenger car sales, rising from 20% in 2026 to 100% by 2035 [63]. Considering this ambitious net-zero emissions target, the findings from daily private vehicle transportation energy consumption patterns provide crucial insights for further scenario analysis. The trends identified in this study, such as the highest share of ICEVs in daily private vehicle transportation energy consumption across all dwelling types, and the lowest relative share of MURB residents in the total ICEV share, form a basis for understanding the mobility trends of residents in different dwelling types.

The next phase of this research will involve conducting scenario analysis to explore how these mobility trends—particularly the disproportionate share of ICEVs—can be addressed in private vehicle electrification strategies for different dwelling types. By evaluating changes in daily private vehicle transportation energy consumption patterns across various stages of electrification, this analysis will offer insights into how the transition to EVs will influence the total energy consumption for each dwelling type. Ultimately, this analysis will help identify potential electrification opportunities and ensure that electrification strategies are customized to the distinct mobility patterns and infrastructure needs of each dwelling type.

To evaluate the potential impact of EV adoption targets on energy consumption, this study examines three EV penetration scenarios based on the federal EV sales target [63]. The three scenario years are: (a) 2026 (**SC-1**), (b) 2030 (**SC-2**), and (c) 2035 (**SC-3**). SC-1 represents the initial phase of EV adoption, with a modest 20% EV sales target in 2026. At this stage, the impact is relatively small due to the limited number of EVs, but this early adoption is crucial for facilitating future growth. By 2030, the target is to have 60% EV sales in the LDV fleet, while SC-3 represents a major shift, with 100% of private vehicles transitioning to EVs by 2035, marking a significant move away from fossil fuel-based transportation and yielding the greatest energy savings for private vehicle



(a)



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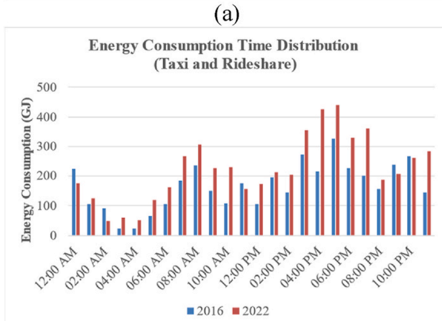

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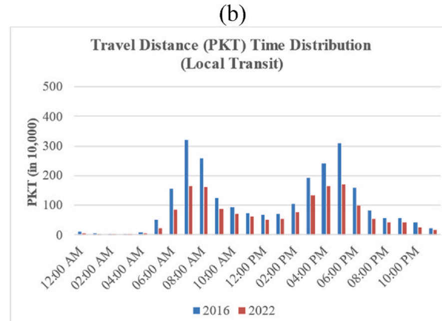

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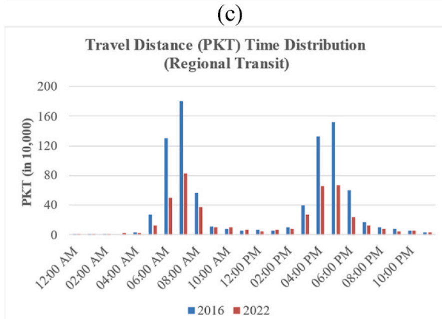
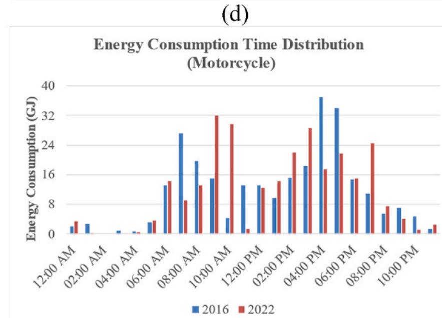
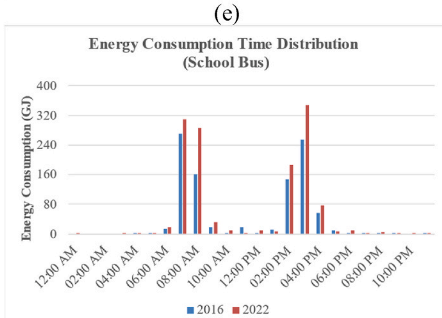


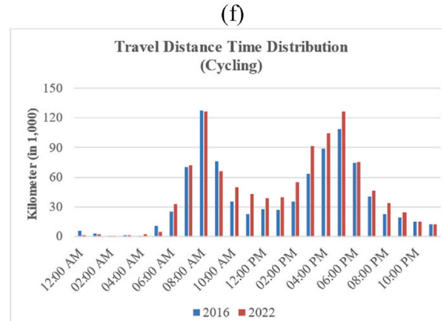
(e)



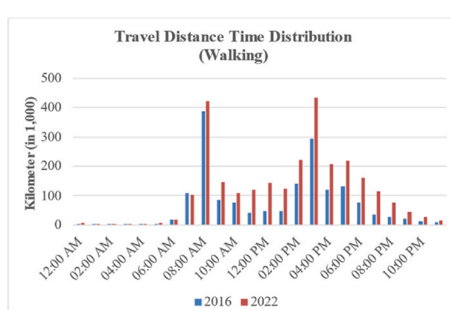
(f)



(g)



(h)



(i)

Fig. 9. Mode-wise start time distribution comparison for energy consumption and travel distance.

travel. A limitation in this scenario analysis is the range constraints of EVs, which could potentially influence the trip-level electrification potential. Furthermore, an implicit assumption in this analysis is the availability of adequate charging infrastructure to support the electrification of trips. However, the accessibility of such infrastructure may be restricted, particularly for residents of MURBs, thereby constraining their ability to adopt EVs effectively [30].

This study compares these scenarios to a baseline representing the 2022 daily private vehicle energy consumption patterns. EVs are randomly assigned to households, with corresponding trips adjusted to estimate the potential reduction in energy use as EV penetration increases. The total daily transportation energy consumption by private vehicles in the GTHA was observed to be 430 terajoules (TJ) in the base case, 365 TJ in SC-1, 230 TJ in SC-2, and 98 TJ in SC-3. Fig. 10 provides a comparison of the scenarios across six regions of the GTHA, factoring in the different dwelling types.

Fig. 10[a] shows how much energy consumption is expected to decrease in different regions if 20%, 60% and 100% of private vehicles are shifted to EVs by 2026, 2030, and 2035. Among all regions, Toronto is expected to see the biggest drop in energy use—about 19%. This is followed by Peel (16%), York (15%), Durham (11%), Halton (9%), and Hamilton (8%).

Toronto shows the greatest reduction in energy consumption, mainly due to its dense urban structure, where a larger number of people are likely to switch to EVs. This higher rate of EV adoption results in a greater impact on energy savings. The data emphasizes the need to prioritize the installation of charging stations, especially in densely populated areas like Toronto, to support convenient home and public charging. At the same time, as more residents transition to EVs, the electricity demand will significantly increase. Consequently, it is essential to proactively plan and upgrade the electrical grid infrastructure to ensure it can reliably handle this growing demand, with a maximum of 98 TJ/day needed for a full transition to EVs, based on the 2022 TTS private vehicle trip data.

Fig. 10[b] illustrates the pattern of energy consumption reduction per trip across the four scenarios, with houses showing the most

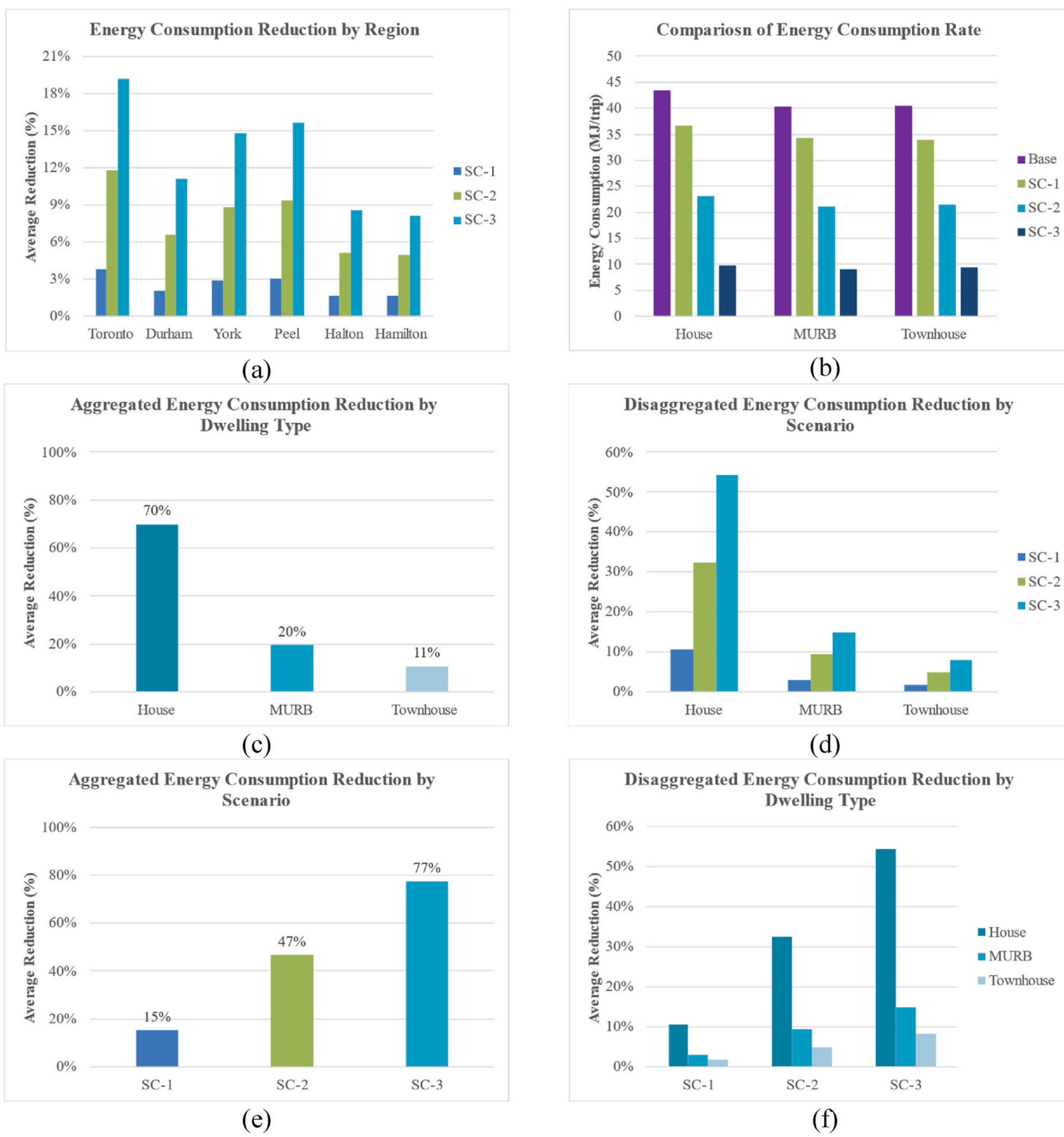


Fig. 10. Comparison between electrification scenarios.

significant decrease in energy use, dropping from 43 MJ/trip to just 10 MJ/trip, resulting in a 79% reduction in SC-3. For both MURB and townhouse, the reduction is from 40 MJ/trip to 9 MJ/trip from base to SC-3. This is crucial for understanding the relationship between EV range and charging requirements at the end of an average private vehicle trip in the GTHA. According to the Canadian Automobile Association [49], the average electricity consumption of an EV is 15.15 kWh per 100 km, with a mix of 55% city and 45% highway driving. Additionally, the range of EVs typically varies between 200 and 800 km [48]. Therefore, with 100% EV adoption and an average EV range of 500 km, a fully charged EV could complete approximately 27 average private vehicle trips per day in GTHA. However, since the average daily trip rate for the 2022 TTS is 2.13 trips per person [64], which is significantly lower, home charging becomes even more essential to ensure vehicles are fully charged for daily use, while charging stations along the route provide additional support.

Additionally, Fig. 10[c] shows that the relative private vehicle energy consumption reduction for houses is 70% on average for three scenarios, followed by MURB (20%) and townhouses (11%). Moreover, Fig. 10[d] represents the disaggregated private vehicle energy consumption reduction in these dwelling types for three scenarios. As expected, the most significant and rapid changes are observed in the daily private vehicle travel energy consumption for houses, with a reduction ranging from 11% in SC-1 to 54% in SC-3. Fig. 10[e] highlights the projected energy reductions for scenarios with the highest decrease in SC-3 (77%), followed by SC-2 (47%) and SC-1 (15%), in line with the EV sales target. Fig. 10[f] complements the previous findings by emphasizing the highest reduction in house daily private vehicle travel energy consumption, showing that detached homes typically have more private vehicles and longer travel distances, thus gaining the most from EV adoption. In contrast, MURB and townhouse residents generally own fewer private vehicles and travel shorter distances, resulting in smaller relative reductions in energy consumption.

Fig. 11 illustrates the time distribution of charging demand for various electrification scenarios across different dwelling types. In the base case, townhouses account for most of the EV charging demand in 2022. However, as EV penetration increases and the proportion of household private vehicle trips is high, the peak hour charging demand for houses rises significantly, from 37 gigajoules (GJ) in 2022 to 1268 GJ, 3916 GJ, and 6640 GJ in SC-1, SC-2, and SC-3, respectively. In contrast, the peak hour charging demand for MURBs increases more modestly, from 3 GJ in 2022 to 364 GJ, 1113 GJ, and 1792 GJ in SC-1, SC-2, and SC-3, respectively. Although the townhouse sector also experiences an increase in EV charging demand, it does so at a slower rate compared to houses and MURBs, given its smaller share of existing private vehicle energy demand.

6. Conclusions

This study offers a thorough and insightful analysis of daily transportation energy demand within the GTHA, with a particular focus on how residential dwelling types of influence energy consumption patterns. The results demonstrate that energy use is strongly correlated with dwelling type, with detached houses exhibiting the highest consumption levels. This group stands to benefit most substantially from the transition to EVs, given their generally higher vehicle ownership rates and longer average travel distances.

Furthermore, the study captures a significant transformation in travel behavior following the COVID-19 pandemic. There has been a marked increase in reliance on private vehicles and ridesharing services, while public transit usage has declined considerably. This shift not only affects energy consumption but also presents new challenges and opportunities for sustainable transportation planning in a post-pandemic context.

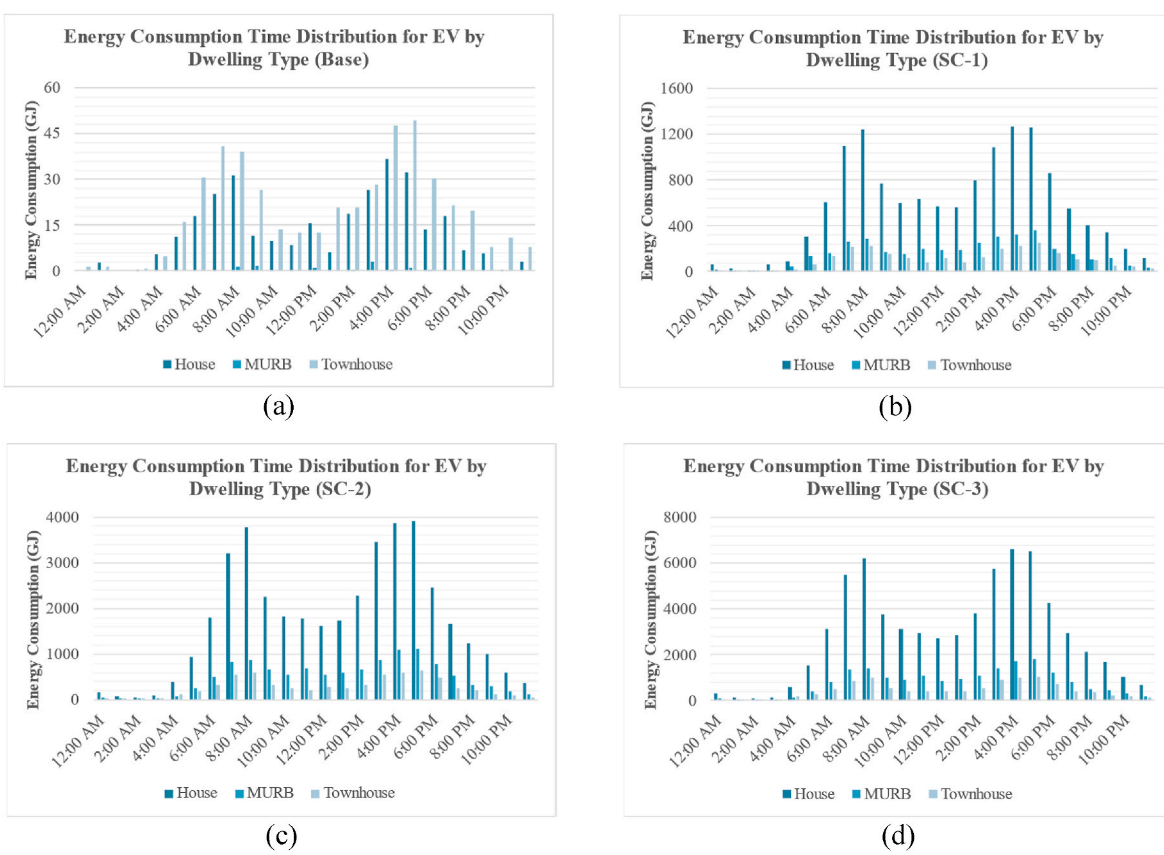


Fig. 11. Energy consumption time distribution for EV.

Crucially, the findings underscore the need for differentiated, dwelling-type-specific strategies to promote EV adoption and realize meaningful energy savings effectively. For residents of detached houses—who often own multiple vehicles and undertake longer commutes—policy measures such as direct financial incentives for EV purchases, subsidies or rebates for home charging infrastructure, and educational campaigns that emphasize both environmental benefits and long-term cost savings are likely to be most effective. These targeted approaches can accelerate EV uptake in this segment and drive significant reductions in transportation energy demand.

In contrast, MURB and townhouse residents generally face distinct barriers to EV adoption, including limited access to private parking and charging facilities, as well as a higher dependence on local transit and shorter trip lengths. To address these challenges, it is essential to prioritize the development of shared charging infrastructure within MURB complexes. Incentivizing property developers and building managers to integrate EV charging stations during construction or retrofitting will be critical to overcoming infrastructure gaps [25]. Additionally, supporting shared vehicle programs or community-based EV fleets could provide alternative pathways to electrification for residents without direct vehicle ownership.

By implementing such nuanced, context-aware policies, urban planners and decision-makers can maximize the benefits of EV adoption across diverse residential landscapes. This approach ensures that reductions in energy consumption are not only substantial but also equitable, supporting a transition to electric mobility that is inclusive of all population segments. Equitable access to EV-ready infrastructure and incentives, particularly in densely populated urban areas, will be vital to achieving broad-scale sustainability goals and preventing disparities in transportation opportunities.

Furthermore, the grid load is expected to be higher in residential areas with houses compared to MURBs under the increased electrification scenarios. Policymakers should consider this when managing electricity demand from home charging. For instance, residents of houses or townhouses may benefit from direct charging through alternative energy sources, such as solar power, while MURB residents could potentially benefit from midday tariff subsidies for grid-based charging [65].

Overall, this study provides vital evidence that the interplay between residential dwelling types, vehicle technology adoption, and travel behavior is complex but actionable. The tailored electrification strategies recommended here offer a roadmap for policymakers and planners to design energy-efficient and environmentally sustainable transportation systems that respond to the distinct needs and challenges of different residential environments. By doing so, the GTHA can move toward a cleaner, more resilient, and socially just transportation future—one that supports reduced greenhouse gas emissions, improved air quality, and enhanced quality of life for all residents.

7. Limitations and recommendations for future work

This study primarily focuses on quantifying the existing energy demand and exploring hypothetical scenarios for the transition to EVs for passenger cars. However, several limitations should be acknowledged to provide a clearer context for future research.

The study centers on the energy demand associated with EV adoption without addressing the broader environmental impacts, such as carbon emissions. While EVs offer reduced energy consumption, the environmental benefits are significantly influenced by the energy mix used to charge them. A shift to cleaner energy sources, such as photovoltaic and wind power, is crucial to reducing carbon emissions, even if overall energy consumption rises. This aspect of energy optimization, especially in terms of grid load and the adoption of sustainable power generation methods, is beyond the scope of this study but should be a central consideration in the future to maximize the environmental benefits of EV adoption. Future research could explore how the energy mix can be optimized alongside the transition to EVs to reduce carbon emissions further.

Additionally, this study assumes a uniform transition to EVs across all dwelling types, which does not account for the varying willingness to adopt EVs based on different dwelling types. Factors such as range anxiety and disparities in access to charging infrastructure may affect EV adoption in households with different residential characteristics. This limitation suggests that future research should focus on ensuring equitable access to charging infrastructure across different dwelling types to promote uniform EV adoption, irrespective of housing conditions. The study also exclusively considers passenger cars, without addressing other transportation modes. Future research could explore how the adoption of EVs in various sectors, such as public transit and e-bikes, might influence travel behaviors. Understanding these dynamics will be crucial for informing policies and infrastructure development to support a sustainable transition to electric transportation across all modes, not just passenger vehicles.

Moreover, the analysis uses a single weighted average fuel consumption rate for all ICEVs, which simplifies the model. This approach does not fully capture the variability in fuel consumption due to factors like vehicle size, age, and type. Future research could incorporate these variables to provide a more accurate representation of energy consumption at the trip level, improving the precision of energy demand estimates. Additionally, the random assignment of trips to vehicles in mixed-technology households is another practical approach but may not fully reflect actual use patterns. EVs are typically used for shorter trips, while ICEVs are often preferred for longer journeys. This assumption may result in slight overestimations of EV adoption and underestimations of ICEV usage. Future studies could refine this approach by considering the actual trip assignment patterns to improve the accuracy of energy demand estimates. Furthermore, the study assumes that travel patterns, including trip lengths and frequencies, will remain constant between 2022 and 2035. However, changes in urban form, the rise of remote work, and shifts in transit accessibility could significantly alter travel behaviors. These factors should be considered in future research to project future transportation energy demands more accurately.

In conclusion, this study emphasizes several key areas for future exploration, including optimizing the energy mix for carbon reduction, addressing disparities in charging infrastructure, and understanding the behavioral changes associated with EV adoption. Future research will also focus on integrating charging infrastructure deployment models with energy demand projections to offer a more comprehensive understanding of electrification potential. A major focus in the next phase will be equity in the transition to EVs, particularly in relation to the accessibility of home charging infrastructure for residents in MURBs, who face unique challenges in installing personal chargers and often rely on shared facilities. Investigating the convenience, cost, and feasibility of implementing communal charging infrastructure will provide valuable insights into the socio-economic and infrastructural contexts surrounding EV adoption. These areas should be prioritized in future research to better address the challenges and opportunities of electrification in the transportation sector.

CRediT authorship contribution statement

Sumaiya Afrose Suma: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Melvyn Li:** Methodology, Formal analysis, Data curation. **Felita Ong:** Writing – review & editing, Writing – original draft. **Kaili Wang:** Methodology, Formal analysis, Data curation. **Eleftheria Kontou:** Writing – review & editing, Conceptualization. **Khandker Nurul Habib:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

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Declaration of competing interest

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.

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Data availability

The authors do not have permission to share data.

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