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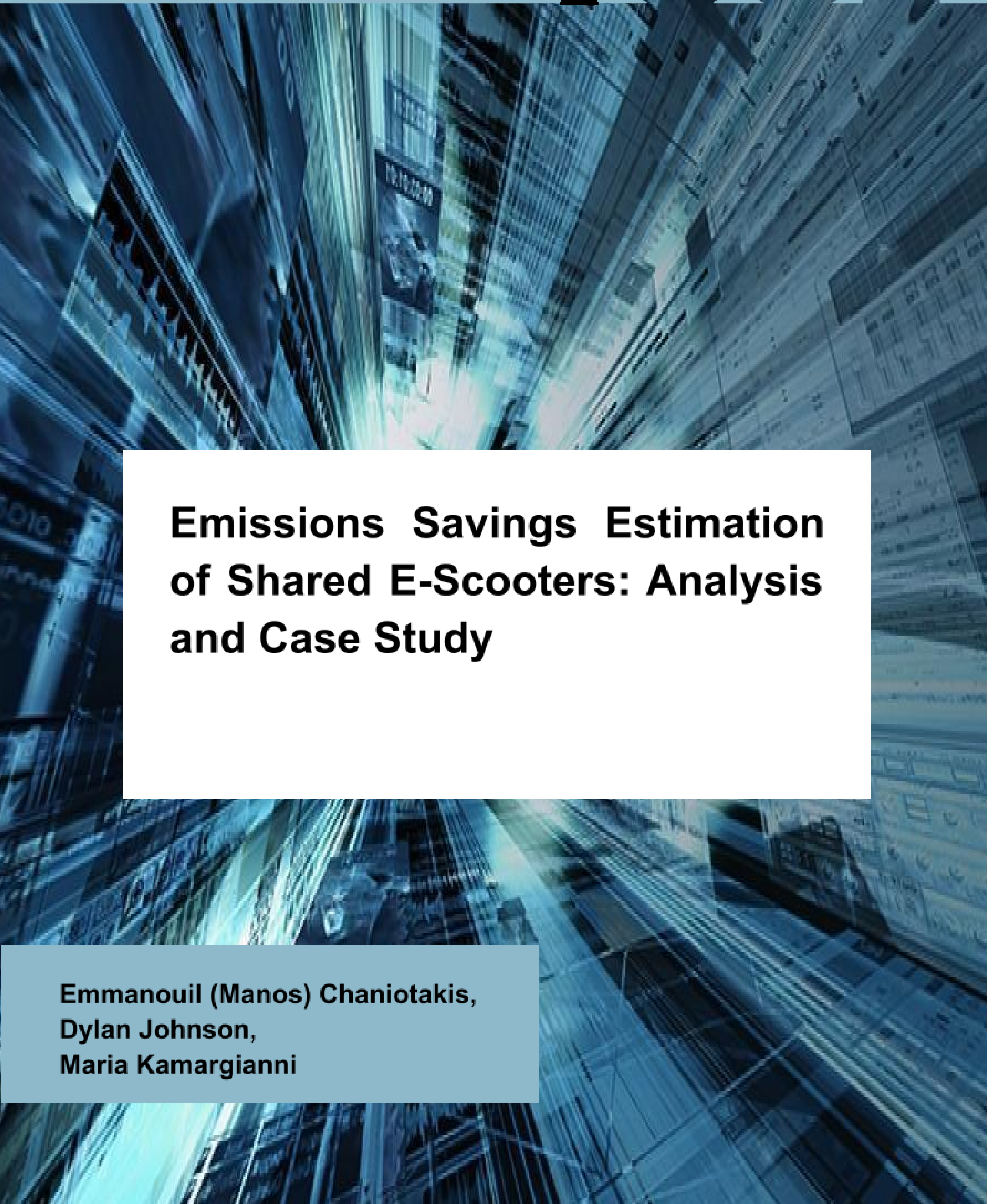

Emissions Savings Estimation of Shared E-Scooters: Analysis and Case Study

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Produced by Dr. Emmanouil (Manos) Chaniotakis, Dylan Johnson and Prof. Maria Kamargianni and represents the views of these academics and not UCL. This report is not peer reviewed and its production has been largely funded and supported by Voi Technology.

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Executive Summary

This report provides a comprehensive evaluation of the potential impact of the adoption of shared e-scooters, focusing on emissions reduction, congestion reduction and time-saving benefits. The analysis focuses on a sample of shared e-scooter trips conducted in Bristol, UK. The research and analysis presented were carried out by researchers from the Energy Institute at University College London (UCL).

Background and Objectives

This project aims to provide a transparent and independent estimation of the average savings in emissions from e-scooter use. Voi Technology provided UCL Consultants with raw data and independent reports, used to perform a Life Cycle Assessment (LCA). Furthermore, Voi conducted a large-scale in-app user survey to evaluate the reduction in emissions when users substituted alternative modes of transport for e-scooters, based on completed trips and survey responses. The report is accompanied by a non-systematic review of the pertinent literature.

The objective is to provide a clear and comprehensive framework for estimating the savings in emissions associated with e-scooters, which can be used to inform policymakers and urban planners in developing sustainable transportation strategies.

Main findings

Emissions Impact:

- Six scenarios are modelled for differing carbon intensities of shared e-scooters. Of these scenarios, we find those that assume a limited kilometre lifespan of up to 3,000 km lead to increased CO2 emissions
- In scenarios assuming average or long e-scooter kilometre lifespans (6,500 km and above) and medium-high operational impact (0.06–0.15 operations km/e-scooter km), the adoption of e-scooters saves emissions up to 45.8% CO2 equivalent (CO2eq) compared with substituted modes of transport.
- The impact on emissions is highly sensitive to operational efficiency, vehicle utilisation and lifespan and the replacement rates of motorised vehicle trips by e-scooters.

Congestion Benefits:

- For the case study examined, e-scooters saved trip time on all substituted modes, apart from bicycle trips. We estimate the median time savings per e-scooter trip to be 5.6 minutes, equivalent to a 47.2% reduction in median travel time.
- Considering the trips examined in the case study, 6,878 hours of journey time were saved. This is equivalent to a 45.3% decrease in the total travel time of the substituted trips.
- During peak congested periods (16:00–20:00), shared e-scooter trips saved 2,240 trip hours or a 46.4% reduction in travel time during peak hours. Furthermore, during those peak periods, shared e-scooter trips removed 15,811 km from motorised transport modes.
- The median distance saving per e-scooter trip compared with the motorised mode was 0.1 km.

Mode Shift:

- A large dataset of 190,932 shared e-scooter trips accompanied by stated replacement modes was analysed.
- According to the data, 37% of all the examined trips would have been taken by foot, 19% by car, 14% by bus, 10% by cycling, 2% by another public transport mode, and 2% by motorbike.

1 Introduction

Urban transport faces significant challenges, particularly in terms of emissions and congestion. For instance, in 2019, the UK Government committed to decarbonising all sectors of the UK economy to meet a Net Zero target by 2050. European governments have set out on similar journeys. Transport is the highest emitting sector, accounting for more than 31% of all territorial CO2 emissions in the UK (BEIS, 2021). In urban areas, trips by cars and taxis are the largest contributors to these emissions accounting for 68% of total transport emissions (Department for Transport, 2021). This is a concerning figure, considering the UK's goal to become carbon neutral by 2050. Reducing car dependency and decarbonising urban transport is a vital step in achieving this goal and improving the well-being and efficiency within cities. In addition, congestion has a significant economic burden, with the Mayor of London stating that congestion is costing London's economy £5.1bn a year.

Over the last few years, there has been a significant shift towards the provision of various transport modes that have transformed the availability of transport options. Where initially there was only private mobility and public transport, shared options, such as ride sharing, car sharing, bike sharing and many others are available to the public. Evidently, sharing of mobility resources is not something new. Public bike sharing schemes have existed since 1965, the first being launched in Amsterdam, NL, while one of the first notable examples of station-based car sharing can be found in Zurich, Switzerland in 1948. These early attempts of shared mobility concepts either failed (e.g. due to theft, vandalism or emergence of low-cost private modes) or survived on a small scale (e.g. car clubs). Lately, with the fast-increasing availability of information and communication technologies (ICT), many of the associated challenges have been addressed, while, through handheld devices, end-users can retrieve information and interact with mobility providers in a seamless way (Shaheen & Chan, 2016). Of particular interest is the emergence of micromobility, commonly defined as the category of transport modes which weigh less than 35 kilograms and have a maximum speed of 45 km/h (Santacreu et al., 2020), such as e-scooters. Shared micromobility usually refers to lightweight vehicles available on a pay-as-needed basis. Shared e-scooters were first launched in 2017 in Santa Monica, California. Since then, the transport industry has seen an astonishing expansion of their deployment. Within ~1.5 years (Summer 2017–Winter 2018), 38.5 million trips were completed using e-scooters in the USA. In 2019, e-scooters were deployed in 109 cities in the USA, and have expanded throughout Asia, Europe, and Australia (Abouelela et al., 2023). Recent estimates place micromobility's value at $330–500 billion by 2030 (Heineke et al., 2019). Shared e-scooters have received a lot of attention from scientific literature, some pointing towards increased curbside space utilisation, accessibility, energy savings, and congestion reduction (Allem & Majmundar, 2019; Smith & Schwieterman, 2018). Others point towards challenges such as fleet size control, organisation, permit cost, displacing users from active modes, and insufficient safety (Gössling, 2020; Janssen et al., 2020; McKenzie, 2019).

One of the most widely debated aspects of e-scooter deployment is the potential saving in Greenhouse Gas emissions (GHG). This debate started with the very first generation of e-scooters, which were retro-fitted, commercially available e-scooters that were designed to serve as a private mode of transport yet deployed as shared. As such, e-scooters' lifespan was generally assumed to be rather limited, given their specifications and vulnerability to vandalism and theft. Additionally, e-scooter operations required transport for charging and rebalancing, whilst substituting a large share of active travel modes. For example, Hollingsworth et al. (2019) examined a Xiaomi M365 e-scooter as a representative model of the scooters used by the operators Bird and Lyft. They evaluate a lifespan of 0.5–2 years, leaning towards lower lifespans, given the shared operational model, and estimate a rebalancing and charging distance driven of 0.6–2.5 miles per scooter. Reck et al. (2022) analysed revealed preference data collected using a mobile phone app, and derived a distance-based mixed logit model which was used to estimate model-based substitution rates. Utilising the derived mixed logit model, researchers predicted that in a majority of cases (51% of the time), shared e-scooters substitute trips that would have been performed on foot, resulting in a much higher emission rate. However, results from all available studies in the pertinent literature are strongly based on assumptions, which in many cases neglect recent development in terms of operations and e-scooter lifespan, or are based on data/models with limited applicability.

In this context, this report aims to explore the pertinent literature and develop a comprehensive analysis of the impact of shared e-scooters as a mode of urban transportation. We first conduct a Lifecycle Assessment (LCA) for the latest generation of Voi e-scooters relying (when available) on independently produced reports and relevant research studies, logged (raw) data and parameters supplied by Voi for climate change impact category investigation, focusing on CO2. The resulting emission factors are then used for the investigation of the impact on trip CO2 emissions for the UK city of Bristol, using a raw dataset of the 190,932 trips available, for which substituted modes were stated by users through an in-app end-of-trip survey, as discussed in Wang et al. (2023).

The remainder of the document is structured as follows: Section 2 provides an overview of the relevant academic literature on e-scooter technology; Section 3 presents the methodology, data used and the results from the analysis performed, and finally; Section 4 presents conclusions, limitations and future work.

2 Literature Review

The environmental performance of a mobility service is affected by factors that cover its use, production, and end-of-life. For the latter, the literature is rather generic and covers primarily material end-of-life, however, for the former two factors, there have been several studies that cover aspects of micromobility usage and production. The studies primarily target some of the main identified points that affect their sustainability, such as the overall use, mode substitution and lifecycle emissions.

Regarding the use of shared micromobility, the literature has analysed various factors that can influence it. Overall, these services are typically used by young, university-educated males in full-time employment and few to no children (Reck & Axhausen, 2021), while several studies point towards differences in preferences towards shared e-bikes or e-scooters in terms of user characteristics (Curl & Fitt, 2020; Y. Wang et al., 2021; Zhu et al., 2020). The ownership of e-scooters or e-bikes can also influence the use of shared micro-mobility services. Shared micro-mobility trips are usually shorter than other modes of transport, and the usage patterns by time of day can vary. However, there is significant variation in the literature findings surrounding whether shared e-scooter trips have two commuting peaks (Caspi et al., 2020; McKenzie, 2019) or just a single afternoon usage peak (Bai & Jiao, 2020; Mathew et al., 2019). The availability of parking and charging infrastructure, as well as separated bike lanes and cycle tracks, can also affect the usage of shared micro-mobility (Hawa et al., 2021; Zuniga-Garcia et al., 2021). Finally, weather conditions can impact usage, with rain, snow, and extreme heat decreasing usage while sunny and mild weather increases it (El-Assi et al., 2017; Gebhart & Noland, 2014). However, studies target a limited geographic scope, with most research conducted in the United States and Europe, limiting the generalisability of the results to other regions of the world. Another limitation relates to the data used, which, in most cases, is short-term data that results from trials not capturing a stable situation, or surveys with a small sample size. As such, results are heavily influenced by the characteristics of early adopters of the technology. Additionally, given that the emergence of e-scooters in many cities coincided with the COVID-19 pandemic, temporary factors, like COVID-19, also influence the data. A more comprehensive understanding is therefore needed for factors that drive mode-choice in different regions and how they may evolve over time. A selection of the pertinent literature on user and trip-related factors affecting micromobility use is included in Table 1.

Table 1: User and trip characteristics influencing usage of e-scooters: a selection of relevant studies

Variable	Impact	Authors
User demographics	Users of shared micro-mobility services are typically young, university-educated males in full-time employment and few to no children. Larger shares of middle-aged groups use shared e-bikes while shared e-scooters are particularly popular among younger people. Income distributions vary by region.	Reck et al. (2022), Shaheen et al. (2020) Y. Wang et al. (2021), Christoforou et al. (2021)
Vehicle ownership	Those who own e-scooters/e-bikes are more likely to use shared e-scooters/e-bikes.	Reck et al. (2022), Shaheen et al. (2020)
Trip characteristics	Trips with shared micro-mobility vehicles are shorter than with other modes of transport. Shared e-scooters are used for short distances in central business districts or near universities, while shared e-bikes are used for longer distances and often uphill.	Fishman and Cherry (2016), Bai & Jiao (2020), Caspi et al. (2020), Hawa et al. (2021), Reck et al. (2022)
Time of day	The evidence on use of shared e-scooters by time of day is inconclusive. Some studies find two commuting peaks (Caspi et al., 2020; McKenzie, 2019), whereas others find single afternoon usage peaks (Bai and Jiao, 2020; Mathew et al., 2019; Younes et al., 2020)."	Caspi et al. (2020) (Caspi et al., 2020; McKenzie (2019), Bai & Jiao (2020), Mathew et al. (2019), Younes & Baiocchi (2022)
Weather conditions	Weather affects the use of shared micro-mobility. Rain, snow, and extreme heat decrease usage while sunny and mild weather increase usage.	El-Assi et al. (2017), Gebhart & Noland (2014)
Availability of parking, charging infrastructure and bike lanes	Availability of parking and charging infrastructure affects the use of shared e-scooters/e-bikes. Separated bike lanes and cycle tracks also increase usage.	Cohen & Shaheen (2018), Hawa et al. (2021), Zuniga-Garcia et al. (2021)

The literature on mode substitution provides insight into how different modes of transportation are used and how they impact overall carbon emissions. Many studies on mode substitution have employed regression or logit models to understand usage patterns and the factors that influence them. For example, Reck et al. (2022) used a logit model to investigate the impact of precipitation and low temperatures on the usage of all shared micro-mobility services, while Bai and Jiao (2020) used a regression analysis to identify the characteristics of e-scooter use, finding that they are frequently used for short distances in central business districts or near universities. Additionally, Reck et al. (2022) used a mixed logit model to estimate the carbon emissions of shared e-scooters, incorporating emissions factors from ITF. They found that shared e-scooters can have a net negative impact on emissions due to their higher carbon intensity rate and lack of replacement of private car journeys. A selection of studies related to mode substitution is presented in Table 2. In most cases, these studies do not account for intermodal trips, which can significantly impact the overall carbon emissions of a given mode of transportation. Furthermore, they often fail to consider how different vehicle trips may be substituted at different times of day, particularly during peak versus non-peak travel times. This can have significant implications for overall carbon emissions, as different modes of transportation may have different carbon intensities, depending on the time of day they are used. Finally, many studies rely on outdated or global averages for carbon-intensity figures for shared e-scooters, which can lead to inaccurate estimates of their GHG emissions impact. Taken together, these limitations highlight the need for more comprehensive and up-to-date analyses of mode substitution and its impact on carbon emissions.

Table 2: E-scooters' mode substitution: a selection of relevant studies

Author	Location	Method	Findings
Bai and Jiao (2020)	USA	Regression	Shared e-scooters, for example, are used for short distances, most frequently in central business districts or near universities.
Reck et al. (2022)	Switzerland	Mixed Logit model, Emission Factors from TIS	Overall conclusion is that shared e-scooters were a net negative on emissions. This is due to the following reasons: i) They have a higher carbon intensity rate (this derives from their life cycle of the batteries and how they send e-scooters back to docking locations) and ii) There is a lack of replacement of private car journeys.

Estimating the life-cycle emissions of shared e-scooters requires comprehensive analysis of the various stages of an e-scooter's life, from manufacturing to end-of-life treatment. The first step is to estimate the emissions generated during the manufacturing process, which includes the production and distribution of e-scooter components. Emissions from manufacturing have been estimated using life-cycle assessment (LCA) methodologies, utilising data from available databases and models, such as the Ecoinvent database or the GREET model. The second step is to estimate the emissions associated with the e-scooter's use, which includes the energy consumed during charging, and the emissions generated from e-scooter collection and redistribution. These emissions can be estimated using data on e-scooter usage patterns, energy mix, and charging infrastructure. The final step is to estimate the emissions associated with the e-scooter's disposal or end-of-life treatment, which can vary depending on the region's recycling and waste management practices. Carbon intensity can also vary between countries, depending on factors such as the energy mix used in e-scooter charging and the manufacturing processes of components. For instance, Moreau et al. (2020) estimated the life-cycle emissions of e-scooters in Belgium and found that the average carbon intensity was 131g CO2eq/km, whereas Chester Energy & Policy (2018) estimated the life-cycle emissions of e-scooters in the US and found that the average carbon intensity was 200–400g CO2eq/km. A more comprehensive review of the findings in the literature is stated in Table 3. Despite the growing body of literature on the life cycle emissions of shared e-scooters, there are some limitations that need to be acknowledged. Firstly, the assumptions made are rather diverse, leading to significantly different results (exacerbated by the lack of real-world data). Some notable examples of ambiguity include the lifespan of e-scooters, related operational emissions (charging and rebalancing), end-of-life measures (particularly recycling), recycled content for material and components, and manufacturing emissions. In addition, there is a lack of standardised methodology for estimating life cycle emissions, with some studies relying on simulation models while others use real-world data. This can lead to variations in the findings, particularly when considering different geographic regions with varying energy sources and transportation infrastructure.

Table 3: E-scooters' lifecycle emissions: A selection of relevant studies

Author	Location	Method	Carbon Intensity (CO_2eq/km)
Chester Energy & Policy (2018)	USA	GREET Model for e-scooter production in China, typical US distance travelled, Washington DC energy mix for recharging.	200–400g
Hollingsworth et al. (2019)	USA	Bottom-up aggregation of the processes of e-scooter manufacturing and operations. Monte Carlo simulations are then used to find the sensitivity of different inputs to the scenarios.	88–125g
International Transport Forum (Cazzola & Crist, 2020)	Global	Underlying assumptions taken from a mix of sources (academic articles, workshops with operators and manufacturing estimators).	38–102g
Kazmaier et al. (2020)	Germany	E-scooter production in China modelled using data from Ecoinvent 3.5, usage patterns based on interviews, average German energy mix for recharging, end-of-life treatment included.	165g
Moreau et al. (2020)	Belgium	E-scooter production in China modelled using data from Ecoinvent 3.4, using Simapro 8.5 usage patterns based on local survey, average Belgium energy mix for recharging.	131g
Severengiz et al. (2020)	Germany	E-scooter production in China modelled using data from Ecoinvent 3.4, using Simapro 8.5 usage patterns based on local survey, average Belgium energy mix for recharging.	77g
Reis et al. (2023)	Portugal	Interview based with scenario analysis taking into account use rates, limited lifespan and distance driven (up to 180 days and 5km, respectively) and end-of-life conclusions.	804–1,679g

3 Methods

To quantify the impact of the latest generation of e-scooters, this report has combined different datasets, methodologies and processes. These are outlined in the following diagram (Figure 1) and further elaborated in the following sections.

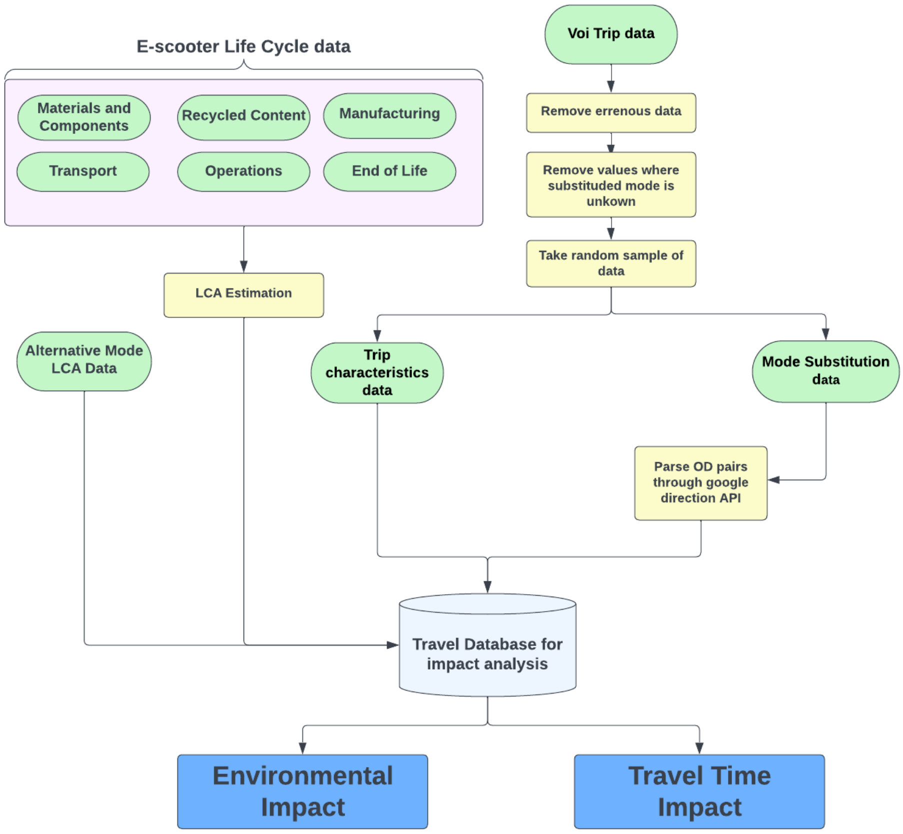

Figure 1: Methodological framework of analysis

3.1 Lifecycle Assessment

A lifecycle assessment (LCA) is defined as the examination of the emissions produced for the overall lifetime of a product. As presented in the literature review, several previous studies have examined the lifecycle carbon emissions of e-scooters. They collectively conclude that there is a strong influence of operations on vehicle lifespan. To assess the climate change impact category for e-scooters, we produced an LCA, following the provisions of the corresponding ISO (14040) closely.

The **goal** is to provide a comprehensive and transparent set of plausible values for CO2eq emission factors from shared e-scooters' operations. Our **scope** is defined upon the evaluation of the V5 e-scooter model which the operator analysed in this study, Voi Technology, widely deploys. Our system boundaries are defined upon pertinent LCA categories (Figure 2), while we follow a recycled content approach based on specifications provided by the e-scooter manufacturer and end-of-life providers. The functional unit of our analysis is passenger kilometre travelled.

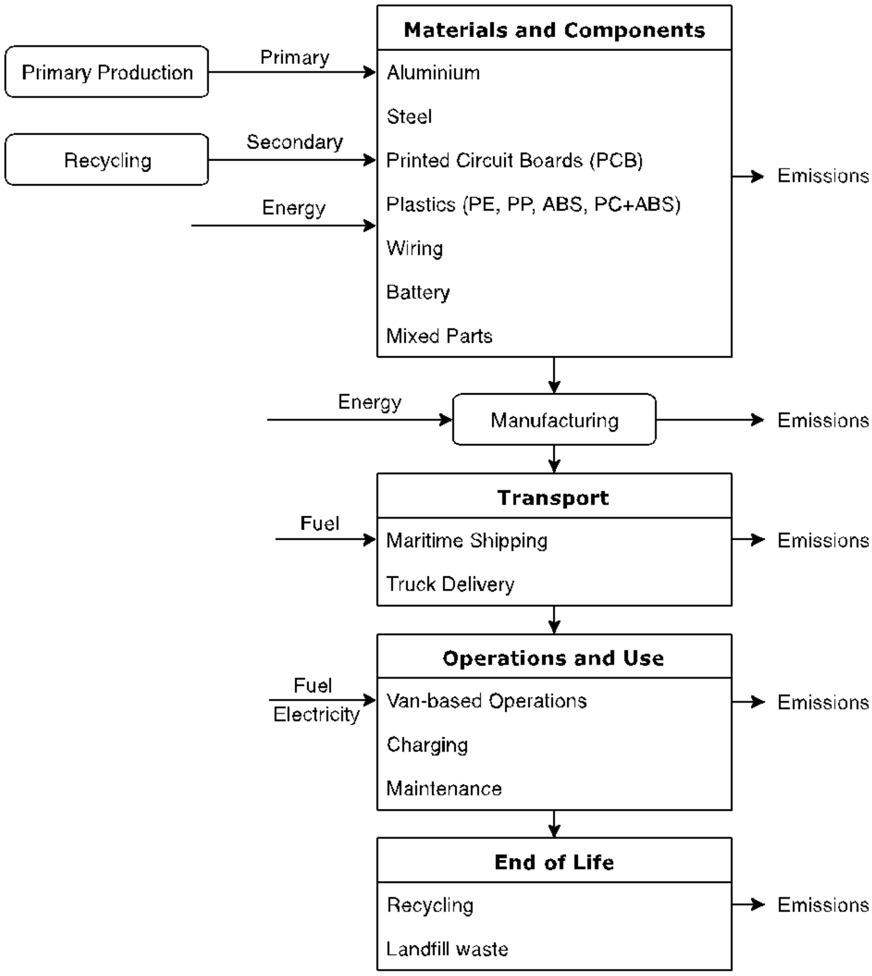

Figure 2: System boundary for shared e-scooter operations

Considering the system boundaries, our lifecycle analysis is defined upon Equation 1.

$$I = \frac{M_s + T_s + \left(O_v \cdot F_v + E_s \cdot F_g + N_s\right) \cdot D_s + L_s}{D_s} \quad (1)$$

Where:

I is the estimated e-scooter emissions factor ($kgCO\_2eq/passengerkm$),
M is the manufacturing burden ($kgCO\_2eq/escooter$),
T is the transportation burden (from source to destination) ($kgCO\_2eq/escooter$) as a function of kilometres travelled by a) maritime shipping (e.g. China to UK) and b) truck-km (UK port to mainland),
O_v is the average kilometres driven per e-scooter kilometres (km/km) for operations related to running the e-scooters fleet (such as battery swapping, rebalancing, redistribution etc),
F_v is the average emissions factor for the vehicles that perform operations ($kgCO\_2eq/km$),
E_s is the energy consumption per km (kWh/km),
F_g is the electric energy emission factor ($kgCO\_2eq/kWh$),
N_s is the maintenance related emissions per e-scooter kilometres ($kgCO\_2eq/km$),
D_s is the total kilometres driven for e-scooters lifespan ($km/escooter$),
L_s is the end-of-life related emissions ($kgCO\_2eq/escooter$).

3.1.1 Material and Components, Transport and End-of-Life Lifecycle Inventory

The inventory we are using is devised by a set of independent reports, secondary data analysis and information provided by the e-scooter operator (Voi), presented in Table 4. The inventory composition is presented in the following table (Table 5). It should be noted that this does not include operations and maintenance (presented in Section 3.1.2).

Table 4: Inventory data sources

Type	Source
Material and components	Waste Electrical and Electronic Equipment recycling (WEEE) Report (No.: CANEC2117824201), produced by SGS-CSTC Standards Technical Services Co., Ltd. Guangzhou Branch
Recycled content	KickScooter MAX SNSC2.3.3 Voi V5 Specification report, produced by manufacturer
Manufacturing	Assumed upon pertinent literature (Hollingsworth et al., 2019)
Transport	Calculated upon common trip characteristics of maritime transport (China to the UK) and inland truck travel (within UK)
Operations and use	- Own data analysis - KickScooter MAX SNSC2.3.3 Voi V5 Specification report, produced by manufacturer - Information provided by Voi
End-of-life	- Paprec, SNAM and Stena Reports

Table 5: Material and manufacturing inventory

Flows	Amount	Flow Property	Description / Data Sources for Inventory
		Production Flows	
Aluminium	11.2936	Mass (kg)	WEEE, Frame, wheels, brakes, covers, misc
Steel	1.0846	Mass (kg)	WEEE, Screws, stand
Printed_Circuit_Board	0.1072	Mass (kg)	WEEE, Circuit boards for battery, power on, unlock, comm. Etc.
Plastic_Part_PE	0.0211	Mass (kg)	WEEE, Misc
Plastic_Part_PP	0.0214	Mass (kg)	WEEE, Misc
Plastic_Part_ABS	1.5683	Mass (kg)	WEEE, Misc
Plastic_PC+ABS	0.1027	Mass (kg)	WEEE, Misc
Plastic_TPU	2.5448	Mass (kg)	WEEE, Misc
Internal_wire	0.5142	Mass (kg)	WEEE, Wiring
Mixed_Parts	8.8618	Mass (kg)	WEEE, Mixed (e.g. plastic + steel) components

Battery	1.004 * 1.2[1]	Energy (kWh)	Manufacturer Battery (as a whole)
Manufacturing	1	Process	Proxy, As a whole incl. energy and heat.
Maritime Shipping	32	Mass (kg)	Packaged; Large Containership travelling 21694 km from China to UK
Inland Shipping	32	Mass (kg)	Packaged; Truck travelling 400 km in UK
		End of Life Flows	
Battery_recycling	50%	Mass (kg)	Paprec, SNAM and Stena Reports
Aluminium	95%	Mass (kg)	Paprec, SNAM and Stena Reports
Electronics	73%	Mass (kg)	Paprec, SNAM and Stena Reports
Plastics	100%	Mass (kg)	Paprec, SNAM and Stena Reports
Total Landfill waste	10.3%	Perc	Paprec, SNAM and Stena Reports

Values for CO2eq conversion factors for all material and operations have been updated, select conversion factors presented in Table 6.

Table 6: CO2eq conversion factors and sources

Flows	CO2 / Unit	Recycled Content: Emissions Reduction	Unit	Description / Data Sources for Inventory
Aluminium	14.65	80%:0.063	kgCO2e/kg	GREET 2022 (M. Wang et al., 2018)
Steel	1.44	0%	kgCO2/kg	GREET 2022 (M. Wang et al., 2018)
Printed_Circuit_Board	157.63	0%	kgCO2e/kg	Hollingsworth et al. (2019)
Plastic_Part_PE	2.30	0%	kgCO2e/kg	Verified Carbon Standard – Verra
Plastic_Part_PP	1.52	100%:0.5	kgCO2e/kg	Verified Carbon Standard – Verra
Plastic_Part_ABS	3.25	65%:0.5	kgCO2e/kg	Verified Carbon Standard – Verra
Plastic_PC+ABS	3.25	65%:0.5	kgCO2e/kg	Verified Carbon Standard – Verra
Plastic_TPU	2.49	0:-	kgCO2e/kg	Verified Carbon Standard – Verra
Internal_wire	3.03	0:-	kgCO2e/kg	Scaled from Hollingsworth et al. (2019)
Mixed_Parts	14.65	0:-	kgCO2e/kg	Assumed
Battery	157.44	0:-	kgCO2e/kwh	Kallitsis et al. (2020)
Manufacturing	8.80	-	kgCO2e/ Process	Proxy, As a whole incl. energy and heat. Hollingsworth et al. (2019)

[1] Swappable battery operations require approx 1.2 batteries/scooter on average to operate.

Maritime Shipping	0.18	-	kgCO2e/kg shipped from China to UK	ECTA: Packaged; Large Containership travelling 21694 km from China to UK
Inland Shipping	0.02	-	kgCO2e/kg shipped within UK	Transport and Environment: Packaged; Truck travelling 400 km in UK
	End of Life Flows			
Battery_recycling	157.44	50%: -0.518	kgCO2e/kg	Chen et al., (2022)
Aluminium	14.64	95%: -0.936	kgCO2e/kg	GREET 2022 (M. Wang et al., 2018)
Electronics	-	73%: N/A	kgCO2e/kg	Paprec, SNAM and Stena Reports
Plastics	-	100%: N/A	kgCO2e/kg	Paprec, SNAM and Stena Reports
Total Landfill waste	6.4	10.3%: 0	kgCO2e/kg	Scaled from Hollingsworth et al. (2019)

3.1.2 Operations and Maintenance

One major issue identified as contributing to increased emissions is the operations supporting the shared e-scooter service management.

High-intensity operations were common with early e-scooter models, which commonly included transporting e-scooters to a charging facility (in most cases with diesel vans). Additionally, the e-scooters had a rather short lifespan, which was commonly attributed to the fact that these were consumer-grade models not designed for sharing, as well as vandalism and theft (see discussion in Section 1). These problems have been widely addressed by e-scooter companies in general, including by Voi, with actions such as introducing swappable batteries, increased use of e-vans and cargo bikes, better e-scooter utilisation and more robust and repairable scooters with increased lifespans.

For the investigation of operations, we aim to quantify the vehicle kilometres travelled for operations (usually by vans, increasingly by electric van and e-cargo bikes) for each e-scooter kilometre. To this end, we analysed a dataset of operational shifts provided by Voi. This dataset has been the outcome of Voi collecting data from their operations management system, which tracks operational tasks completed, such as battery swapping, in-field quality control, e-scooter collection for repairs, rebalancing of the e-scooter fleet as well as km travelled during each shift. The dataset included 120,449 entries, with each entry representing a shift in one of 87 cities of operation. The dataset included operations for one year (2022). Some entries were infeasible and therefore excluded. In addition, it included cities which were in the initial phases of deployment (operational for less than 3 months) or had their operations paused/suspended. To correct for the above-mentioned data-related issues, we removed cities which did not have established operations through the examined period (7 cities). In addition, we removed entries which resulted in an estimated speed of more than 30km/h (stated km driven over shift duration). This choice was motivated by the fact that 30km/h would be higher than the average car speed for most of the cities examined, especially when taking into account that in most cases, operations include frequent stops to perform the assigned tasks (e.g. battery swapping). After cleaning the provided dataset, we aggregated the total distance travelled for operations in each examined city and merged it with the (provided) distance travelled by e-scooters for the corresponding city. The distribution of operations distance travelled per e-scooter distance travelled is presented in Figure 3. This demonstrated that the average operations distance travelled per e-scooter km is **0.0598 km/km**.

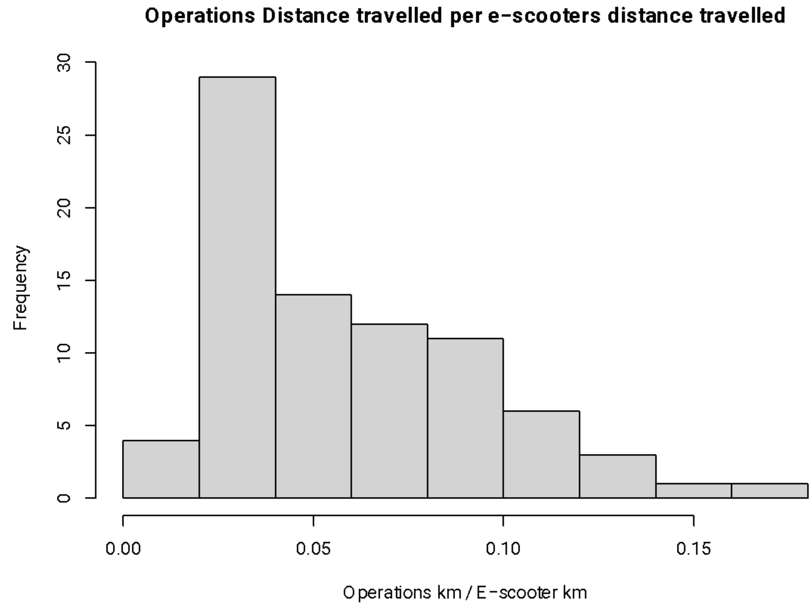

Figure 3: Operations distance travelled per e-scooter distance travelled

Regarding maintenance, finding independently produced data for its environmental impact has been significantly challenging. This is primarily due to the fact that each e-scooter company follows different maintenance protocols which differ from fleet maintenance procedures for other vehicle modes. As such, we used the estimated maintenance environmental impact data presented by Voi in their environmental report (Voi Technology, 2022). The resulting inventory composition for operations and use, as well as the corresponding conversion factors, are presented in Table 7 and Table 8, respectively.

Table 7: Operations and maintenance inventory

Flows	Amount	Flow Property	Description / Data Sources for Inventory
		Production Flows	
Charging e-scooters energy	0.0106	kWh/km	Voi
Operations	0.0598	km(operations)/ km(e-scooters)	Own analysis (Voi-provided data)
Maintenance	1	Overall Maintenance	-

Table 8: Operations and maintenance CO2eq conversion factors and sources

Flows	CO2 / Unit	Unit	Description / Data Sources for Inventory
Charging energy	0.19121	kgCO2e/kwh	DEFRA Conversion factors[2] (assuming UK average electricity mix)
Operations	0.21259	kgCO2/km	DEFRA Conversion factors[3] (assuming average petrol van, not accounting for lifecycle emissions of van, accounting for fuel lifecycle emissions).
Maintenance	0.000048	kgCO2e/km	Voi

3.1.3 Lifespan and Operations Scenarios

Sections 3.1.1 and 3.1.2 provide the context for quantifying the environmental impact of shared e-scooters (CO2eq) for various units of analysis, either per e-scooter or per e-scooter km. To estimate a conversion factor for e-scooters, a homogenised (per e-scooter distance travelled) conversion needs to take place for their lifespan. This must have the ability to scale the production and transport impact. Given the recent deployment of the latest generations of e-scooters, data on their lifespan and total distance travelled is not available. In a recent report by Brightside (Hanson et al., 2022), it is suggested that e-scooter lifespan may be much higher than previously thought, with an average of 6,529km travelled per e-scooter. In some cases, the average distance travelled over an e-scooter's lifetime is up to 12,000 km or higher. To better represent the potential trade-offs associated with e-scooter operations and lifespan, we have developed various lifespan and operational scenarios that explore emissions factors. With regard to lifespan, scenarios consider the potential loss or breakdown of e-scooters as a reduction of the average distance travelled. The scenarios examined are presented in Table 9.

Table 9: Scenarios examined

Scenario Title	Scenario Code	Lifespan Distance (km)	Operations Impact (km/km)	Resulting Conversion Factor (gCO2eq/km)
Long km lifespan + average operations impact	I	10,000	0.0598	37.69
Long km lifespan + high operations impact	II	10,000	0.15	56.86
Average km lifespan + average operations impact	III	6,529	0.0598	49.86
Average km lifespan + high operations impact	IV	6,529	0.15	69.04
Limited km lifespan + average operations impact	V	3,000	0.0598	91.12
Limited km lifespan + high operations impact	VI	3,000	0.15	110.30

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[2] Voi Technology energy-related emissions could be considerably lower, given the utilisation of renewable energy tariffs. However, the DEFRA conversion factors have been used as a point of reference.

[3] The increasing use of electric vans reduces operational emissions further. The corresponding DEFRA conversion factor for an electric van is 0 gCO2eq/km, which accounts for tailpipe emissions only, neglecting manufacturing and fuel emissions.

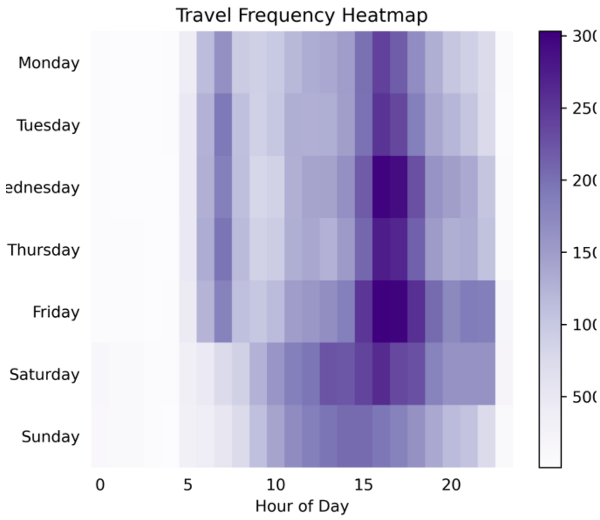
3.2 Environmental Impact Case study

Aiming to evaluate a real-world case study, we used primary anonymised trip data from the e-scooter operator for trips performed in one city (Bristol) from August 2021 to October 2021. This dataset included trip characteristics (trip length, duration, timing, origin/destination coordinates and distance) for 190,932 e-scooter trips by 17,746 users. It was also accompanied by an in-app survey for mode substitution. At the end of a trip, users were asked to specify what mode of transportation they would have used if shared e-scooters were not available (mode substitution question). The dataset also included vehicle characteristics (vehicle type and battery state), as well as user information (anonymised user ID, stated gender and age). The dataset was cleaned to remove erroneous data and cases where the substituted trip mode was unknown. To meet budget requirements, the alternative mode analysis was conducted using a random sample of the data from 73,507 trips. Each trip was parsed through the Google Directions API to query the distance travelled and duration for each of the transport modes used. The Google Directions API provides a selection of alternative routes for the same starting point and destination, characterised by mode-specific categories, such as car-based travel or public transport-based travel. Within each category, the selection of the alternative route is based on the shortest travel time. Although this is believed to broadly represent the alternatives available to travellers, it is also affected by the time of the query (departure time). Effort was taken to query the API using the departure times of e-scooter trips. However, this does not necessarily reflect the conditions experienced by travellers, as it represents the forecasted average travel time (and traffic conditions), taking into account current traffic conditions at the time of the query. Using this merged dataset of trip characteristics for the e-scooter trips and their alternatives, we performed a time-of-use, distance, and mode substitution exploratory analysis. We then used the dataset to explore the environmental impact of e-scooters, utilising the results from the LCA and the scenarios defined.

4 Results

4.1.1 Overall Descriptive Analysis

A time-of-day analysis was performed to understand temporal patterns. The data reveals that Voi's shared e-scooters are more frequently used during late afternoon hours, which aligns with the typical weekday PM rush hour. These results are shown in a heatmap demonstrating the frequency of travel (Figure 4). These findings are notable as they suggest that e-scooters may be a valuable mode of transportation that could potentially replace traditional modes of commuting. While further research is necessary to validate these findings statistically (e.g. in more cities, throughout different seasons), they are consistent with some of the previous research that has been conducted on the topic. In addition, the distance distribution for e-scooters was examined. As presented in Figure 4, the average distance is around 2.1 km with a long tail observed reaching a maximum of 15 km.



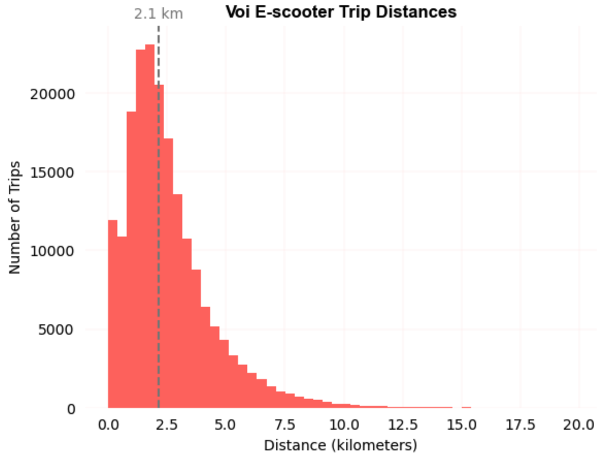


Figure 4: Time of day analysis (4a - left) and distance travelled (4b - right), before random sampling (n = 190,932).

An anonymised per-user analysis was also performed to understand sample characteristics. This included the few variables which were present within the trips dataset (age, gender and anonymised user ID). As presented in Figure 5, the number of trips performed by each user is quite diverse. The average number of trips performed by each user was 10.6 and the median was 4. It is also notable that a small proportion of users were found to take many trips (177 users performed 24,485 trips, equating to over 100 trips each), which is in line with power-law distributions.

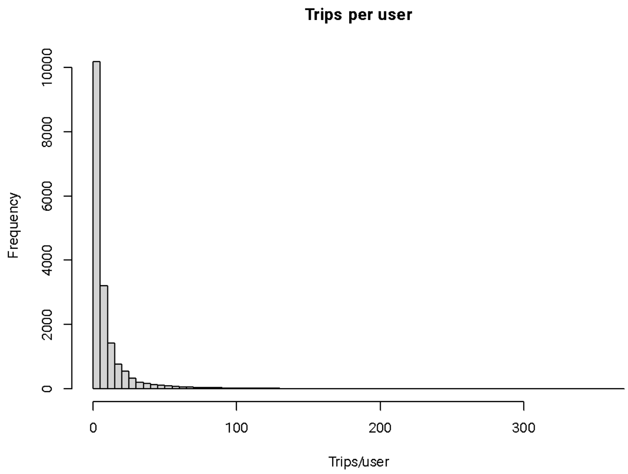


Figure 5: Trips per users (n = 17746), before random sampling.

Regarding gender, it has been evidenced that the majority of registered users performing trips identify as males, and the majority of trips are also performed by male users.

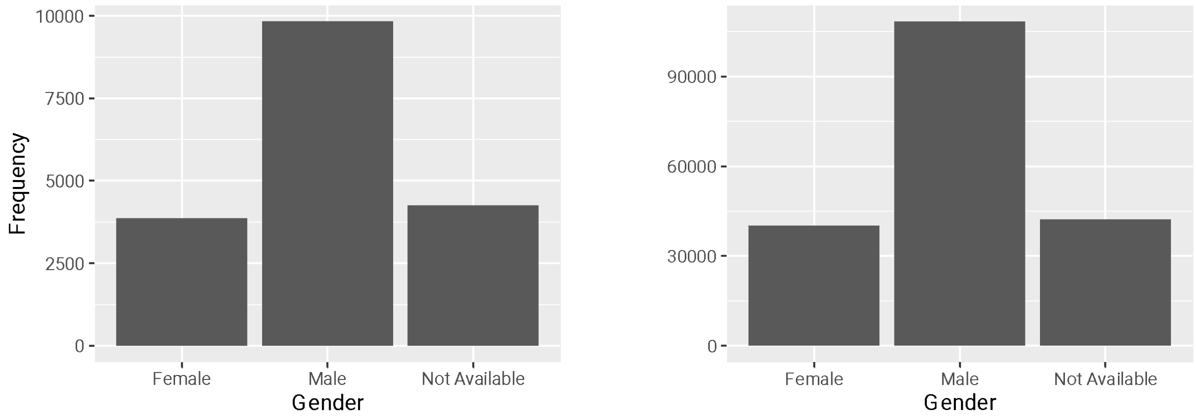


Figure 6: Gender (n = 17,746) (left); Trips per gender (n = 190932) (right), before random sampling, for those completing the mode replacement survey for trips.

Regarding mode replacement, the data set shared by Voi included trips and post-ride survey responses on mode substitution. After each ride, the user was asked "If e-scooters were not available, which mode would you have taken?" In order of magnitude, 25,782 trips were reported to have replaced walking (37%), 25,782 replaced bus (14%), 23,333 replaced an unknown mode (12%), 19,538 replaced cycling (10%), 16,414 replaced car/van as a driver (9%), 11,599 replaced taxi/app-based minicab services (e.g. Uber) (6%), for 9,232 trips the user stated "I would not have made this journey" (5%), 7,196 replaced car/van as a passenger (4%), 3,840 replaced motorbike or moped (2%) and 3,684 replaced other public transport (e.g train, 2%). Aggregated, 19% of trips replace a private or shared car or van.

The percentile distribution is presented below (Figure 7a). A 2021 study from DfT found that 42% of e-scooter trips replaced walking, 21% replaced private motor vehicles or taxis, 18% replaced public transport, 10% replaced cycling and 9% were new journeys. The post-ride data collected by Voi shows slightly lower mode replacement of motorised vehicles and a lower replacement rate of walking. A more recent survey conducted by Voi in summer 2022 shows 32% replacement of walking and 33% replacement of cars (taxi, ride-hailing and private motor vehicle) in Bristol. These results are generally in line with the available literature and include a large percentage (~12%) of trips that would have replaced an unknown mode.

The average distance travelled with each replaced mode is presented in Figure 7b. It is worth noting that a significant number of trips were removed from the analysis due to unknown mode shifts. A significant number of the removed trips are likely non-walking trips based on the distance they replaced. As a result, our findings may underestimate the actual emission reduction impact that would have occurred.

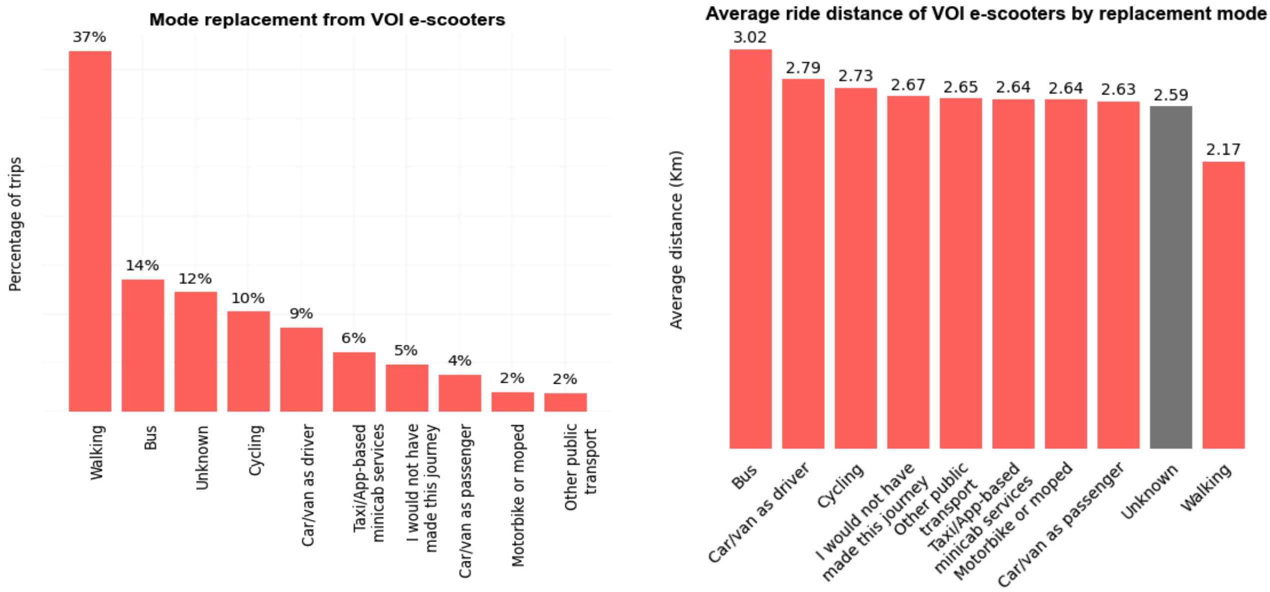


Figure 7: Mode replacement (7a - left) and stated distance for replacement mode (7b - right) before sampling (n = 190,932).

4.2 Mode Replacement Analysis

Based on the random sample resulting from data cleaning and generation of replacement alternative data (using the Google Directions API), we analysed the distance travelled with different modes. Figure 8 presents the median (left) and total impacts on trip distance (right) in kilometres when switching to e-scooters from different transportation modes. Negative values indicate distance savings (i.e. the trip was shorter because it was taken with an e-scooter), while positive values indicate additional distance. Results show that e-scooter trip distances increase when replacing cycling trips, bus and walking trips by 0.39, 0.24 and 0.12 km, respectively, but shorten when replacing private motorised modes, non-bus public transport and taxi services. This counterintuitive finding for bus trip distance is likely due to inaccuracies in calculating distances with the Google API (described in detail in the limitations section), and it is expected that e-scooter trips would take more direct routes than bus routes. These findings highlight the scope for e-scooter routes to be optimised, while at the same time suggesting the benefits of e-scooters when compared with other motorised modes. These routing benefits, compared with motorised modes, are highlighted by e-scooter trips removing 48,762 km from motorised transport modes, with 15,811 km being removed during key peak congested periods (16:00–20:00). This report recommends further investigation into this finding, as a geospatial analysis at these key periods would be of interest for understanding if shared e-scooters could relieve key traffic bottlenecks at peak traffic times.

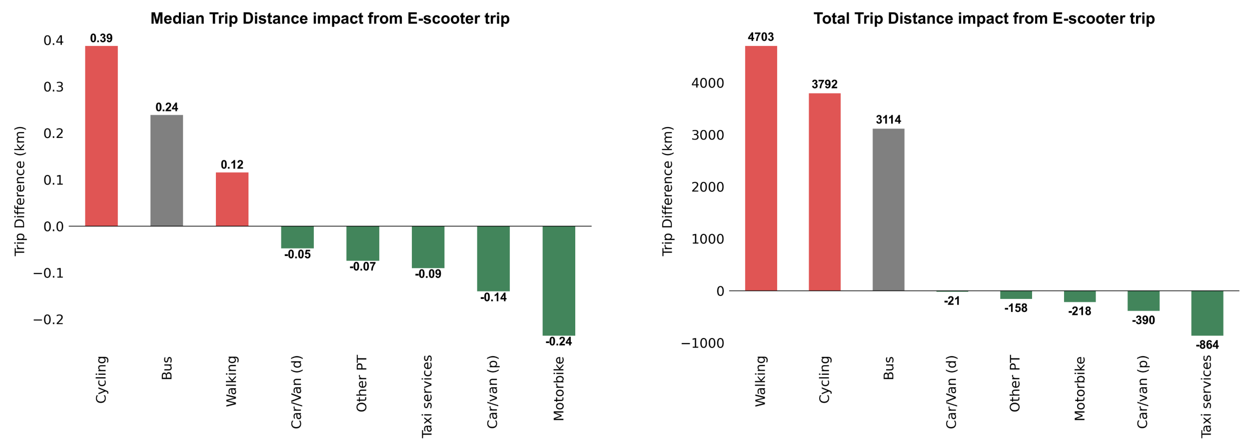


Figure 8: Median trip distance (8a - left) and total trip distance (8b - right) when comparing e-scooter (baseline) with stated replacement mode (n = 73,507).

A similar analysis was conducted for travel times. Overall, the results from the processed sample of 73,507 e-scooters trips indicate that e-scooters saved 6,877 hours of journey time, or equivalently a 45.3% decrease in total travel time compared with the substituted modes. Furthermore, in this Bristol case study, e-scooters saved a median of 5.6 minutes of travel time per trip. Figure 9 (left) illustrates the relative time-saving per mode, highlighting the time efficiency benefit of e-scooters in urban areas over other modes with the exception of cycling.

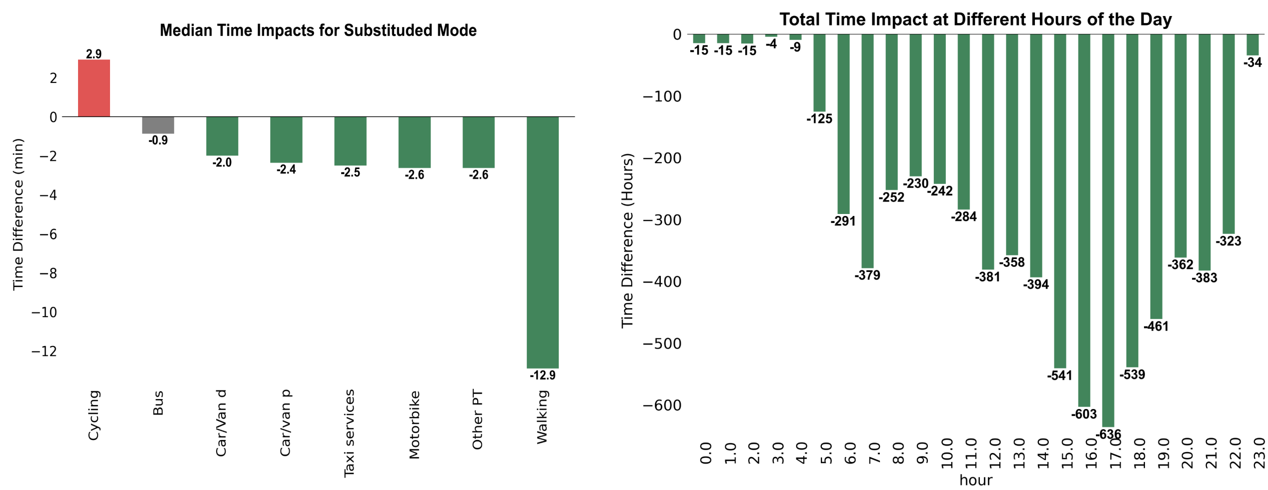


Figure 9: Median time savings (9a - left) and total (9b - right) when comparing e-scooter (baseline) with stated replacement mode (n = 73,507).

Figure 9 (right) highlights the time-saving impacts of e-scooter trips on an hourly basis. This graph reveals that during the afternoon peak hours of 16:00–20:00, shared e-scooter trips saved 1,092 trip hours during these peak congested periods.

4.3 Environmental Impact Analysis

The final part of this analysis estimates the environmental impact that shared e-scooter services might have. For its investigation, we apply the environmental impact scenarios developed as part of the LCA for the estimation of emissions within the examined case study (Bristol). To compare with alternative modes we use the conversion factors as published by the International Transport Forum (Cazzola & Crist, 2020), which are presented in Table 10. For distances travelled using e-scooters we use the data from the sample shared by the operator. For distances travelled using other modes, the distance collected by the directions API was utilised. Distances per trip were then multiplied with conversion factors to calculate emissions for each e-scooter trip.

Table 10: Transport mode emission conversion factors

Transport Mode	gCO2eq/passenger km	Source
Walking	0	ITF (2020)
Bike	17	ITF (2020)
Public Transport*	72	ITF (2020)
Motorbike**	73	ITF (2020)
Bus***	91	ITF (2020)
Car (private)**	161	ITF (2020)
Car (taxi)**	290	ITF (2020)

* Refers to sea transport as a public transport mode.
** Assumes an ICE average.
***Assumes an ICE average, does not account conversion factor changes due to ridership changes.

The aggregated impact on emissions of the trips replaced by shared e-scooters was evaluated for each of the emissions scenarios (Table 9). The overall impact on emissions of each scenario, either saved or induced emissions, is presented in Figure 10, with the percentage difference in emissions indicated on top of/below each of the corresponding bars. The emissions impacts are calculated by finding the difference between the emissions from e-scooter trips and the emissions from its new or replaced trip. As it becomes quite apparent, for average or longer lifespan scenarios, defined upon total ridden distance over lifespan (6,529 km and 10,000 km, respectively) and average operation-related distances travelled (e.g. 0.06 operational km/e-scooter km), there is an important reduction of CO2eq emissions. This quickly diminishes when operational distances shift towards the higher end (e.g. 0.15 operational km / e-scooter km). Limited lifespan (in this case 3000 km) results in a significant increase of CO2eq emissions.

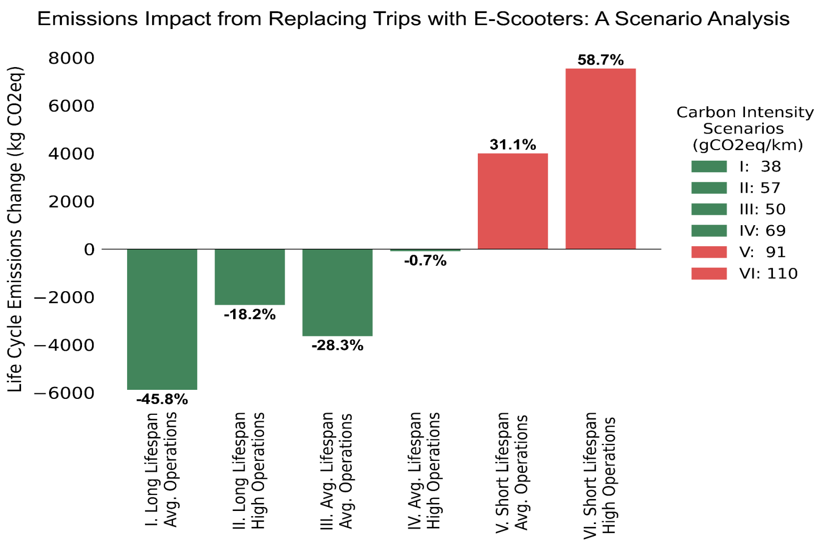
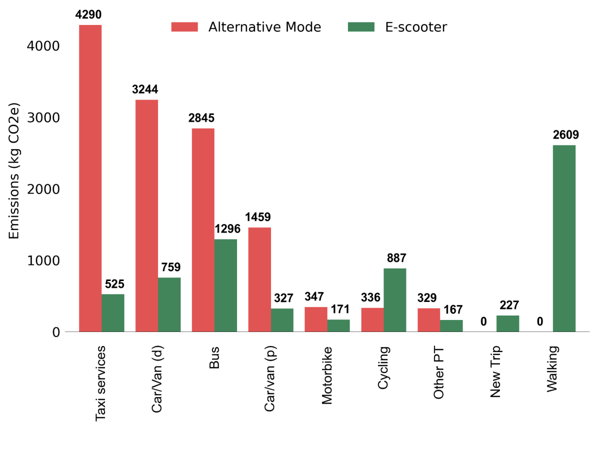
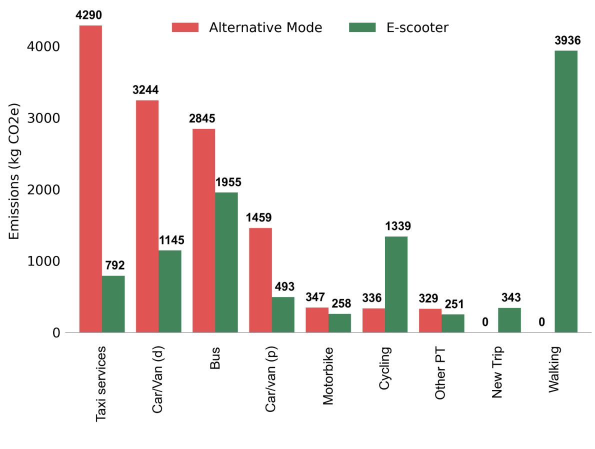


Figure 10: Overall impact based on scenarios' comparison.

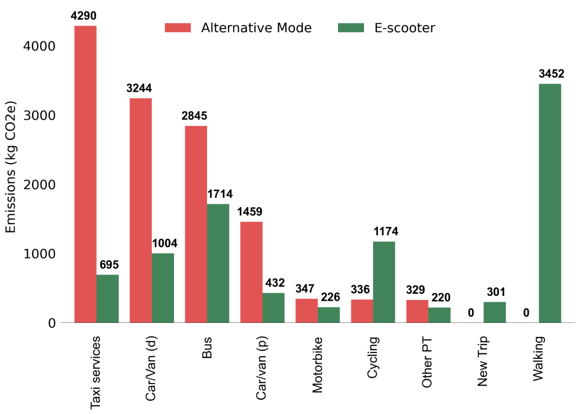
Figure 11 and Figure 12 present the emission impacts of substituting the alternative trip mode with an e-scooter trip. The low emission scenarios (combinations of long lifespan and low operations impacts) indicate how emissions savings are largely driven by substituting taxi services and private car trips, which is greater than those induced emissions caused by replacing walking trips. Bus replacement impact, given lower carbon intensities, might suffer from the issues identified above in terms of distance travelled. Assuming an average carbon intensity based on average lifespan and operations distance, replaced walking trips have the greatest absolute value in terms of emissions. However, the emissions savings from motorised modes outweigh the induced emissions impact.



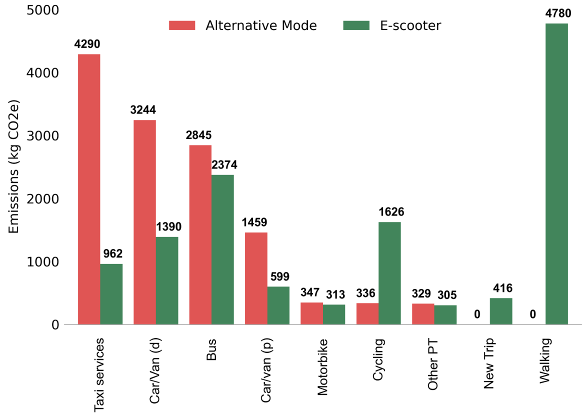
a) Lifespan: 10,000 km | Operations: 0.0598 km/km.



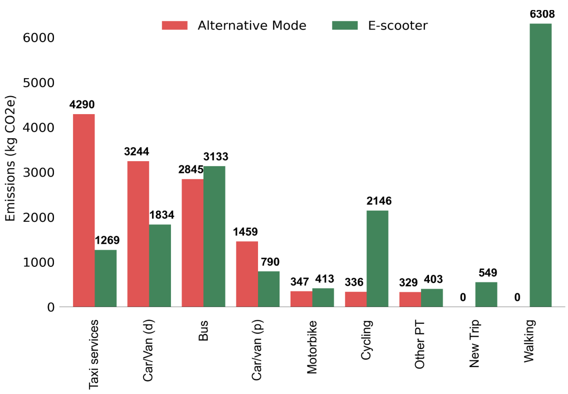
b) Lifespan: 10,000 km | Operations: 0.15 km/km.

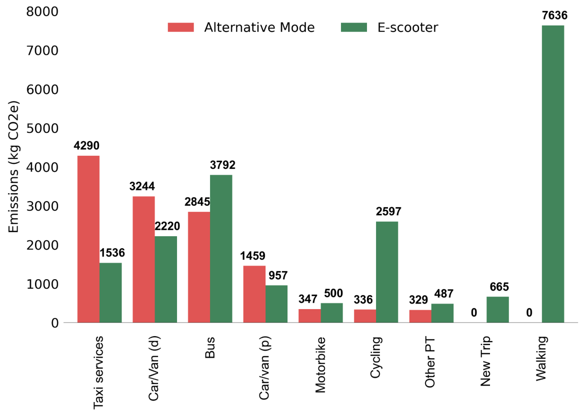


c) Lifespan: 6,529 km | Operations: 0.0598 km/km.



d) Lifespan: 6,529 km | Operations: 0.15 km/km.

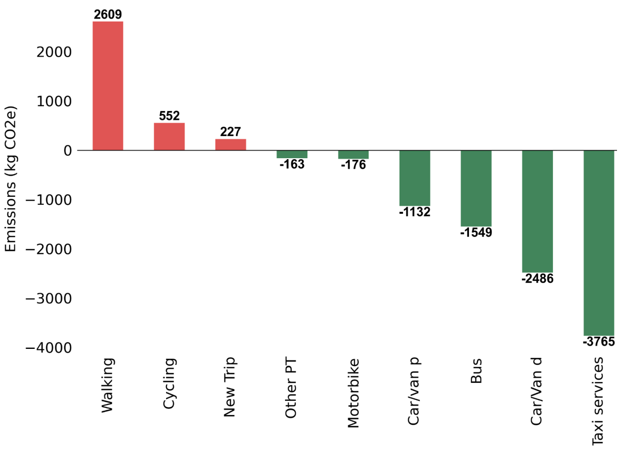




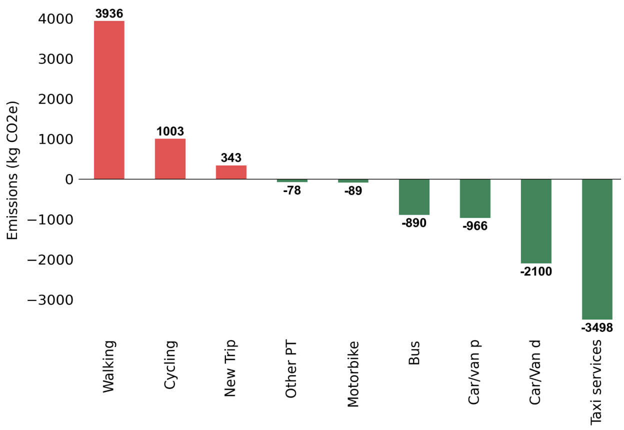
e) Lifespan: 3,000 km | Operations: 0.0598 km/km.

f) Lifespan: 3,000 km | Operations: 0.15 km/km.

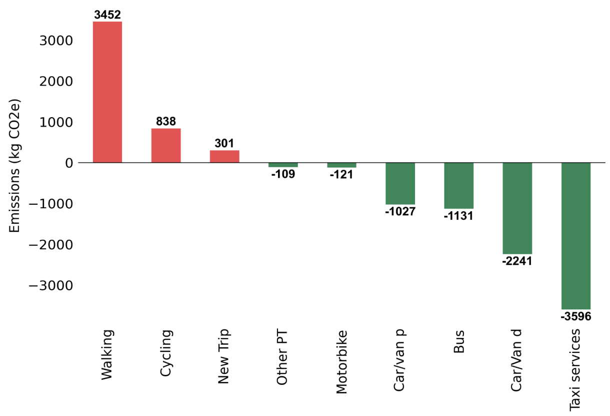
Figure 11: Comparison of emissions per mode for scenarios examined.

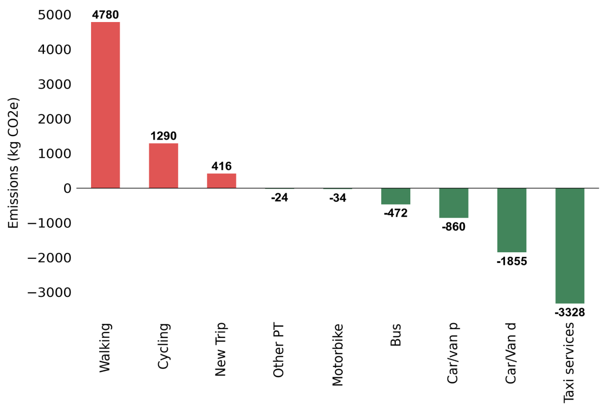


a) Lifespan: 10,000km | Operations: 0.0598 km/km.



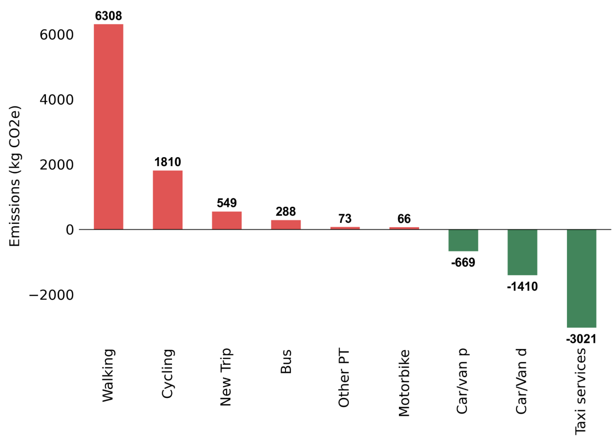
b) Lifespan: 10,000km | Operations: 0.15 km/km.

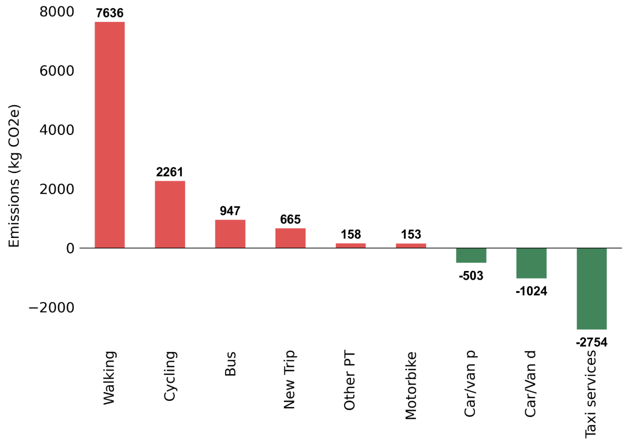




c) Lifespan: 6,529 km | Operations: 0.0598 km/km.

d) Lifespan: 6,529 km | Operations: 0.15 km/km.





e) Lifespan: 3,000 km | Operations: 0.0598 km/km.

f) Lifespan: 3,000 km | Operations: 0.15 km/km.

Figure 12: Emission difference per mode, when comparing with e-scooter emissions, for scenarios examined.

5 Conclusions

This report presents the evaluation and findings of the impact of the adoption of shared e-scooters in terms of mode shift, emissions and congestion. According to the survey results, shared e-scooters have largely replaced trips that would have been taken by other modes of transportation. Specifically, 37% of the trips examined would have been taken by foot, 19% by car, 14% by bus, 10% by cycling, 2% by another public transport mode, and 2% by motorbike.

From the processed sample of 73,507 trips examined, e-scooter trips removed 48,762 km from motorised transport modes, with 15,811 km or 2,240 trip hours removed during the peak e-scooter hours of 16:00–20:00. The median time savings per e-scooter trip is 5.6 minutes, equivalent to a 47.2% reduction in median travel time, showing the potential of e-scooters for helping cities address congestion. Furthermore, the report modelled the emissions impact of shared e-scooters for different carbon intensity scenarios. The findings showed that e-scooters had a positive impact on reducing emissions in scenarios with average-to-long kilometre lifespans and average-to-high operations impact. However, it also made clear that emphasis should be placed on the type of e-scooters being deployed by operators, including their recycled content and material management, fleet utilisation and kilometre lifespan, and the operations necessary to support this deployment. Essentially, the findings suggest that shared e-scooters have the potential to provide significant benefits in terms of mode shift, congestion, time savings and emissions reduction **if implemented effectively**. By replacing trips previously taken by other modes of transportation, shared e-scooters can reduce emissions and congestion during peak periods. However, it is important to consider the carbon intensity of the e-scooters and ensure that their operations, usage and manufacturing processes do not lead to increased emissions, such as those found for the high carbon intensity scenario examined.

Despite the insightful findings presented in this report, there are potential limitations that should be considered. Firstly, the report did not consider intermodality. E-scooters could increase accessibility of public transport, acting as a first/last-mile solution for longer trips, replacing private cars or taxis (Antoniou, 2021). Therefore, the potential positive impacts of shared e-scooters may have been underestimated, as the main substituted mode, particularly for longer trips, is not examined. Secondly, the report only studied one city case during a particular time period, which limits the generalisability of the findings to other contexts. Expanding the study scope over a longer time period, and including multiple cities, would provide a more comprehensive understanding of the impact of shared e-scooters on transportation modes, congestion, and emissions. The report findings are also limited by the fact that for a significant percentage of trips examined, the substitution mode was not available, resulting in a reduced—yet large—dataset. In addition, different material composition, operations and end-of-life measures (i.e. worse than those evidenced in this report, for example from different operators, manufacturers and end-of-life providers) could lead to significantly different lifecycle emission factors. As such, the findings of this report are only applicable to e-scooters and e-scooter operators with similar characteristics. Finally, the emission factors for alternative modes assumed ICE (internal combustion engine) averages provided by the ITF. Future research could consider a range of different emission factors more specific to the location for a more accurate comparison. At the same time, it is important to consider lifecycle emissions for all examined modes, to be able to understand the overall impact of mobility to climate change.

1.1 Recommendations

Based on the findings presented in this report, there are several recommendations for local governments and policymakers to consider regarding shared e-scooters. Firstly, local governments should continue to invest in and support shared e-scooter programmes that are well-regulated, and show proof of good fleet management and maintenance, and high utilisation leading to high kilometre lifespan, responsible end-of-life practices and efficient operations. They should also introduce and monitor compliance metrics regarding operations, use, manufacturing and end-of-life practices. Additionally, local governments should work to incentivise the use of e-scooters during peak periods to reduce congestion and emissions. This could include implementing concepts, such as congestion charging schemes, low emissions zones, or providing discounts for micromobility use during peak times.

Furthermore, policymakers should ensure that the carbon intensity of e-scooters is taken into account when planning and regulating these programmes. They should also ensure the promotion of low-carbon modes of transport, such as cycling or walking, working together with operators to protect these modes and nudge users to replace more carbon-intensive modes. Finally, local governments should work to promote equitable access to e-scooters, ensuring that the benefits of this mode of transport are shared by all members of the community, regardless of income, gender or location. Overall, by implementing these recommendations, local governments and policymakers can maximise the benefits of shared e-scooters while minimising the potential negative impacts.

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