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Evaluating the readiness for electric vehicle adoption among the urban population using geospatial techniques

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ABSTRACT

Electric mobility is critical to reducing emissions from transport and dependency on Internal Combustion Engine vehicles. This study attempts to model the suitability of the built environment for electric vehicle (EV) adoption in urban areas based on sociodemographics and access to driveways for installing charging infrastructure. A novel approach using geospatial techniques is adopted to detect driveways from multispectral remote sensing information. A region in Dublin, Ireland, has been chosen as the study area. The region is further categorised based on the feasibility of EV adoption using hierarchical cluster analysis. Initial results highlight the disparity in access to low-emission modes to those not dependent on cars. Results from zero-inflated count models at the neighbourhood level reiterate the impact of driveways and sociodemographic factors on EV adoption. The proposed methodology can help evaluate infrastructure availability for widespread EV transition and inform strategic planning. The driveway detection framework may be adapted to other regions while accounting for geographic characteristics.

1. Introduction

The transport sector accounts for 20% of Ireland's greenhouse gas (GHG) emissions, of which 96% can be attributed to road transport (Government of Ireland, 2021). These vehicular emissions lead to poor urban air quality and significantly contribute to climate change. A primary policy approach to reducing emissions from road transport has centred on decreasing the use of Internal Combustion Engine Vehicles (ICEVs) and promoting the electrification of transportation. While such policies are critical for reducing GHGs, significant additional benefits can accrue in urban areas due to air quality enhancement (Buberger et al., 2022; Kouridis and Vlachokostas, 2022; Metais et al., 2022).

Although initiatives have been taken to increase private passenger EV uptake, they have not reached their full potential due to high cost, low driving range, and unavailability of charging infrastructure (Bastida-Molina et al., 2022; Caulfield et al., 2022). Despite people's preference to charge their EVs at home, limited research has explored the infrastructure available for installing home chargers (Francfort et al., 2015). In urban regions, residences are Multi-Unit Developments (MUDs) with limited access to charging infrastructure, which could further hinder EV adoption. Therefore, a more nuanced understanding of the built environment is required to predict EV adoption in dense urban areas without targeted interventions.

This research proposes a methodology to evaluate the suitability of the built environment for private EV adoption in urban areas, considering their sociodemographics, travel characteristics and home charging infrastructure. The main contribution of this work lies in identifying the infrastructure for potential home charger installation to facilitate the widespread transition into EVs. Infrastructure is measured regarding access to private driveways where chargers can be installed. This study adopts a novel approach to identify driveways from multispectral remote sensing images using geospatial techniques, a unique problem that contemporary studies have not yet addressed to the best of our knowledge.

However, a rich body of work exists for detecting vehicles using machine learning-based object detection techniques (Q. Li et al., 2019;

Abbreviations: ICEV, Internal Combustion Engine Vehicle; EV, Electric Vehicle; GIS, Geographic Information System; GHG, Green House Gas; MUD, Multi-Unit Developments; SAP, Small Area Population; NDVI, Normalised Difference Vegetation Index; LiDAR, Light Detection And Ranging.

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Liu and Mattyus, 2015; Zambanini et al., 2020; Zhou et al., 2018). These methods can help detect parked vehicles within property boundaries, indicating an existing driveway. Nevertheless, identifying empty driveways is crucial since it shows the total number of available driveways and is an area unexplored by previous studies. The study also relates EV adoption to sociodemographic characteristics, which can inform targeted marketing. Results from this work can help identify locations with adequate infrastructure and those requiring additional support in terms of public charging points.

The remainder of the paper is organised as follows. Section 2 examines previous studies on EV transition. Section 3 outlines the study area and methodology. Section 4 presents the analysis, results, and discussion. The final section addresses the study's conclusions and limitations.

2. Literature review

This section discusses the factors influencing EV transition, charging infrastructure, transport policies and innovative modelling techniques adopted in the field.

2.1. Sociodemographic characteristics influencing EV adoption

EV adoption is highly influenced by people's sociodemographic characteristics and environmental awareness. Several sociodemographic and travel characteristics influence an individual's transition to EV. Having high educational qualifications, being a homeowner, and living in a detached or semi-detached house (with a driveway or garage) positively influences EV adoption (Hidrue et al., 2011; Williams and Kurani, 2006). However, living in rented accommodation and belonging to the younger age group (19 to 34 years) affects EV uptake negatively. Owning more than two vehicles and using a car more frequently are often considered characteristics of EV adopters (Campbell et al., 2012). Table 1 summarises some of the critical sociodemographic and travel characteristics and their influence on EV adoption.

2.2. EV charging infrastructure

EV charging can be categorised based on ownership (public, private), type (slow, semi-fast, fast) and location (home, public, workplace). Although home charging is slow, low cost and convenient, the owner requires access to an off-street parking space or a driveway to avail of it. Studies show that EV uptake, until now, has been dominated by those with off-street parking (Collett et al., 2022). However, off-street parking is not accessible to many people, especially in urban areas, as a high share of urban residents live in MUDs (Gilbert et al., 2020; International Energy Agency, 2018a).

Public charging infrastructure impacts EV uptake more than financial incentives (Hall and Lutsey, 2017). However, there are barriers to improving charging infrastructure, including uncertainty in utilisation, costs, and difficulty in assessing the revenue models (Falchetta and Noussan, 2021). Workplace charging provides an opportunity for those without access to home charging and can encourage EV uptake, considering the influence of peer communication (LaMonaca and Ryan, 2022). Nevertheless, >90% of EV owners in countries including Norway and Sweden, which have the highest share of EV sales, prefer to charge at home, thus reiterating the importance of access to home charging (International Energy Agency, 2018b).

Table 1
Sociodemographic *and travel characteristics* influencing EV adoption.

No	Parameter	Influence on EV adoption
1	People in the age group 25–59	Younger or middle-aged populations are more likely to adopt EVs (Campbell et al., 2012; Hidrue et al., 2011; Nayum et al., 2016).
2	Owner-occupier	Homeowners are more likely to invest in charging infrastructure (Campbell et al., 2012; Williams and Kurani, 2006).
3	Large households (at least four rooms)	More rooms indicate financial stability and large household size (Mukherjee and Ryan, 2020).
4	Highly educated (with an honours bachelor's degree and above)	Being highly educated is linked to environmental awareness and willingness to try new technologies (Hidrue et al., 2011; Nayum et al., 2016; O'Garra et al., 2005; Sierzchula et al., 2014).
5	Drive a car to work	Driving for daily commutes indicates dependence on their car (Campbell et al., 2012).
6	Households with at least two cars	Multi-car households have a conventional vehicle as a backup for long journeys, thus addressing range anxiety (Gärling and Thøgersen, 2001; Graham-Rowe et al., 2012; Kurani et al., 1995; Williams and Kurani, 2006).

2.3. Policies to facilitate EV uptake

To realise the full potential of EVs, there is a need for supportive transport policies. Ireland has introduced several policies, including a vehicle purchase and home charger installation grant, tax relief and toll incentives to support EV adoption (Pillai et al., 2022). Financial incentives can accelerate EV adoption, leading up to 1.91 times emission reduction compared to a do-nothing scenario (Wu and Kontou, 2022).

Though purchase subsidies have increased the EV penetration rate worldwide, these are not sustainable due to their financial burden on governments (Lu et al., 2022). Reduction in EV prices, operational incentives and sustainable transport policies are required to maintain EV penetration. Some policies adopted in European cities include offering public charging for EV owners without a driveway upon request and imposing elevated parking fees for conventional vehicles (Bernard et al., 2021; Held and Gerrits, 2019). The EU Commission proposes pre-cabling new buildings to ensure adequate access to charging (European Commission, 2021). Shared electric mobility, including shared e-cars, e-bikes and e-scooters, is another promising service that can potentially deliver the positive impacts of both shared mobility and electric mobility (Liao and Correia, 2022).

2.4. Innovative modelling techniques to facilitate EV transition

The most commonly used modelling techniques to predict EV adoption are agent-based models (Maybury et al., 2022). Recent studies have adopted innovative methodologies, such as the *Geospatial Evaluator for EV Charging in Car Parks Overnight,* which identifies potential car park locations through geospatial analysis for overnight charging (Collett et al., 2022). An integrated optimisation platform was formulated to estimate charging requirements at home and non-home locations while considering infrastructure and dynamic electricity costs (X. Li and Jenn, 2022). Determining the placement of charging stations relies on the nighttime demand from residential areas and the daytime demand from workplaces (Frade et al., 2011). Previous research has employed maximal covering models and mixed integer programming approaches to calculate the required number and capacity of charging points, considering user behaviours and budget limitations (Cavadas et al., 2015). More recent studies have explored geospatial methods and the potential for converting existing shared parking areas and streetlights into slow charging points for residents without off-street parking facilities (Charly et al., 2023; Janjić et al., 2021; Kaya et al., 2020).

While the decision to adopt an EV is made at the household level, it is influenced by socio-technical factors at the spatial level, such as familiarity with this technology within the neighbourhoods (Selena et al., 2022). Sheng et al. (2021) found that EV charging infrastructure in the neighbouring areas significantly impacts EV adoption. Spatial autocorrelations or "*neighbour effects*" are crucial in how vehicle owners respond to relatively new transport technologies. Hence, it is essential to incorporate the spatial component and sociodemographic characteristics while assessing the suitability of the built environment for EV adoption.

2.5. Inferences from the literature and objectives of the study

Electrifying transport plays a vital role in cutting GHG emissions from road transport, enhancing air quality, and addressing climate change. Charging infrastructure is essential for the widespread adoption of EVs, with home charging being the most favoured method. However, not everyone has access to a dedicated space for home charging, which could hinder EV uptake unless supplemented with charging points near residential areas lacking private driveways. Incentives are required at the operational level in addition to grants and subsidies. Identifying the residential areas where potential EV adopters are located can help policymakers and vehicle manufacturers create targeted strategies to boost EV adoption.

This research seeks to understand the suitability of the built environment for private EV adoption among urban dwellers based on their sociodemographic characteristics and access to driveways. A specific region within Dublin, the capital city of Ireland, has been chosen as the study area. Residents in the study area are classified according to the availability of infrastructure for adopting EVs. The current rate of EV uptake and accessibility to alternate low-emission modes of transport within the region is also examined. EV uptake is modelled at the neighbourhood and individual household levels to understand the influence of driveways and various sociodemographic factors.

3. Data and methods

This section describes the study area and the data used. Then, the overall framework is discussed, followed by a detailed methodology and description of the parameters.

3.1. Study area

The study focuses on a specific region in Dublin, the capital of the Republic of Ireland, as shown in Fig. 1. This study location was chosen due to its dense residential nature in Ireland's capital city. The availability of a high-resolution multispectral aerial remote sensing image and other geospatial data also helped in the study site selection. This region comprises 193 small area populations (SAPs), which are minor administrative divisions in the Republic of Ireland for which Census data is accessible. Each SAP contains between 80 and 120 dwellings. The chosen study area encompasses a total of 18,107 households and a population of 44,228. This area accounts for approximately 8.5% of the total households in Dublin City County.

3.2. Data collection

The datasets used in the study include census data for 2016 obtained from the Central Statistics Office, driveways detected using geospatial techniques, location of bus stops, location of shared bike stations, and EV data obtained from the Sustainable Energy Authority of Ireland. Sociodemographic information and travel characteristics of residents were aggregated from the census data. The 2016 Census data was used in this study as it was the most up-to-date data available. Two datasets corresponding to EV uptake are used: the EV grant data and the home charger installation data. The EV grant data and the sociodemographic data are available at the SAP level, whereas the home charger installation data and detected driveways are identified at the household level.

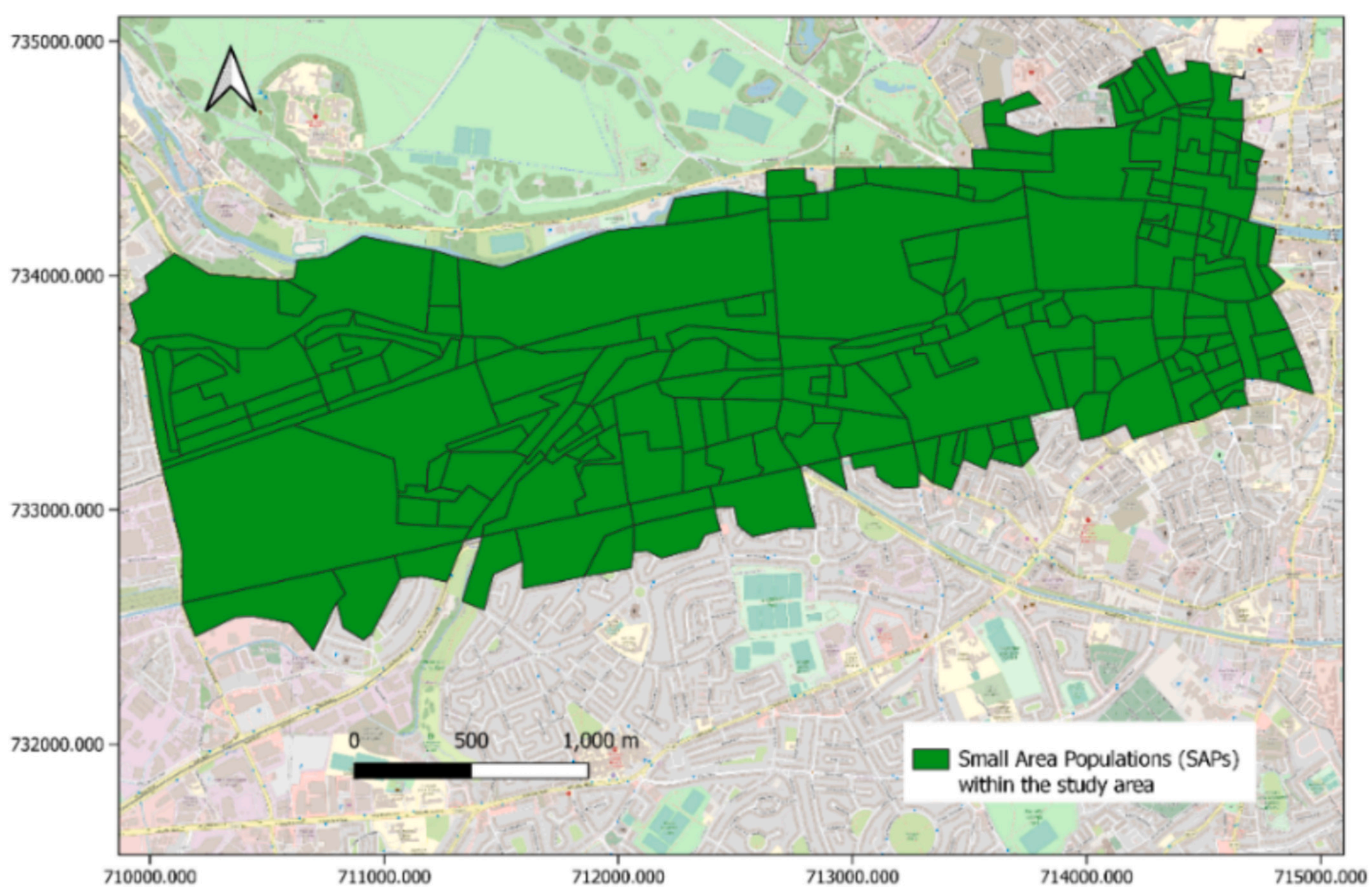

Fig. 1. Illustration of the study area in Dublin and boundaries of SAPs within the region.

3.3. Study framework

The study aims to assess the infrastructure suitability for private EV adoption in urban regions. The framework followed to achieve the same is illustrated in Fig. 2.

First, the factors influencing an individual's decision to transition to EV are identified based on literature and computed for each SAP. A driveway is necessary to install EV home chargers in Ireland (myenergi., 2024; Sustainable Energy Authority of Ireland, 2024). However, the information regarding driveways' presence is unavailable from Census information. Hence, driveways are identified from aerial images using geospatial techniques. The SAPs are grouped into clusters based on sociodemographic factors using hierarchical clustering analysis, and driveways are collated for these clusters. Cluster analysis was conducted as the first step to identify homogeneous groups in the study area and to better understand the relationship between sociodemographic factors and infrastructure availability. The clusters aid the analysis and help provide insights into different groups in the analysis.

Further, each cluster's actual EV adoption trend and accessibility to low-emission modes are examined using data from home charger installations, EV purchase grants, and the number of shared bike stations and bus stops. EV adoption is then modelled at the SAP level using zero-inflated count models and at the household level using a binary logistic regression approach. Finally, strategies for improving sustainable transport practices are suggested for each cluster. The following section discusses the sociodemographic and travel characteristics considered for clustering.

3.4. Sociodemographic and travel characteristics influencing EV adoption

All the sociodemographic and travel characteristics influencing EV adoption discussed in Error! Reference source not found. Are considered in this study. These parameters include *People in the age group 25–59, Owner-occupier, Large households (at least four rooms), Highly educated (with an honours bachelor's degree and above), Drive a car to work* and *Households with at least two cars.* The data corresponding to these sociodemographic parameters was extracted from Census data for every SAP. Further, driveway detection was conducted through image processing, as discussed in the following section.

3.5. Urban driveway detection using geospatial techniques

Visual interpretation of high-resolution multispectral images yielded a simple schema to detect driveways. An overview of the driveway detection framework is shown in Fig. 3.

Driveways were defined as accessible by road (driveways are expected to be in the front yard of properties), un-vegetated (mostly built/concrete surface), reasonably flat and of a minimum dimension to fit a vehicle. The parking spaces in the study area in Dublin are majorly located in the front yard of the property. Therefore, the front yard detection was included as a rule in the decision tree framework for detecting driveways. A buffer of 15 m from the road centre line intersecting the property boundary and simple thresholding of the Normalised Difference Vegetation Index (NDVI) data were sufficient to identify the property's front yard and un-vegetated pixels. NDVI enhances vegetation signals, and studies have successfully used NDVI-based thresholds to discriminate vegetation from other areas (Aryal and Sitaula, 2022; Montandon and Small, 2008; Spadoni et al., 2020).

The inputs in the model used were NDVI, a LiDAR (Reigl VUX-1LR and 15 points per metre points density) based height dataset and PRIME-2 (GIS dataset developed by the Ordnance Survey of Ireland consisting of property boundaries and road centre line) for constraining the model within the property boundaries (Ordnance Survey Ireland, 2018). The NDVI was calculated from an Altum Micasense 20 cm resolution multispectral aerial image, and the LiDAR data was resampled to 20 cm to match the aerial data.

The driveway detection model identifies flat and unvegetated pixels in the property's front yard. These were polygonised using QGIS and filtered based on a minimum area requirement (3*3 m^2). An additional filter was also applied to the area: perimeter ratio (> 0.50) was

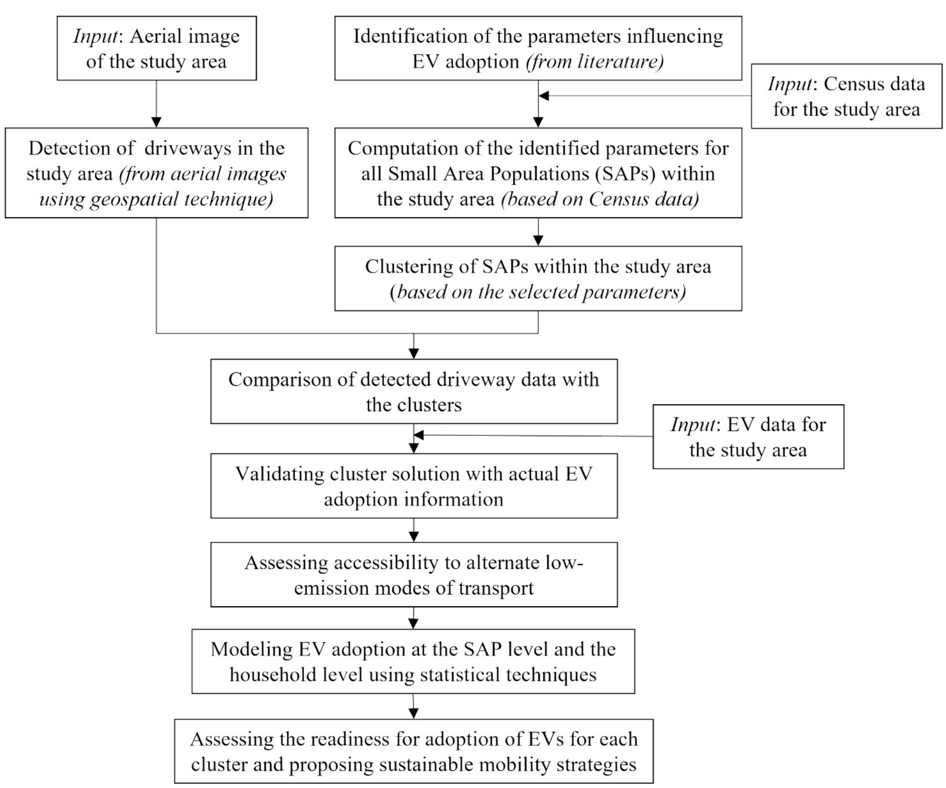

Fig. 2. Methodology to assess the suitability of the built environment for private EV adoption.

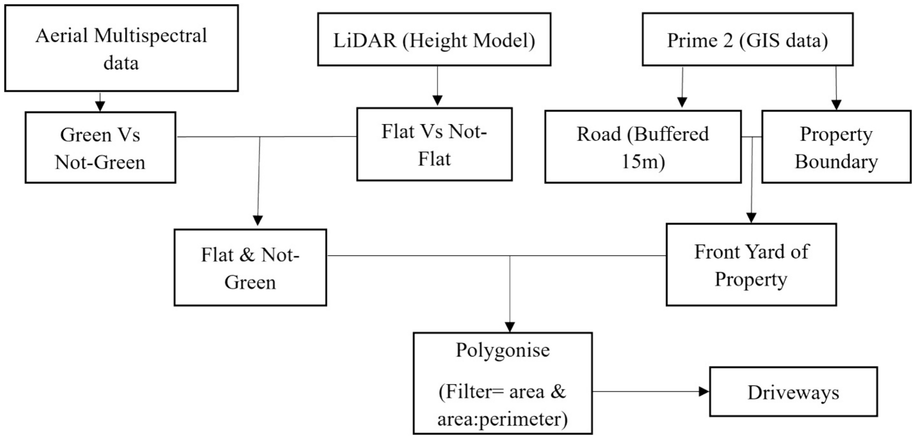

Fig. 3. Simplified framework to detect driveways within property boundaries.

calculated for each polygonised potential driveway to limit the detected driveways to only simple geometries. Pixels <2 m in height were considered flat areas to identify driveways with parked vehicles. This knowledge was then applied through a decision tree framework to detect potential driveways. Residential driveways have previously been identified using GIS datasets, remote sensing, and Google Street View maps (Brealy et al., 2022; Flynn et al., 2021; Flynn and Giannetti, 2021). These studies had limited capabilities to distinguish between paved driveways and front gardens, inability to detect driveways with parked cars and limited access to clear street view images. Our study's workflow leverages these studies' strengths and proposes a simple geospatial method to overcome some of their limitations. The property boundaries

Fig. 4. True colour aerial image of selected regions with property boundaries (in blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

and potential driveways for a few sample regions within the study area are shown in Fig. 4 and Fig. 5.

This model was applied across the selected study area in Dublin, the results of which are shown in Fig. 6. The driveway detection algorithm performed well, with approximately 90% accuracy for positive cases across multiple test sites within the study area.

4. Analysis and results

First, the SAPs were clustered based on sociodemographic factors. Further, statistical models were used to predict EV adoption at the SAP and individual property levels.

4.1. Clustering SAPs based on sociodemographic characteristics

Cluster analysis was performed initially to identify homogeneous groups within the study area and to enhance understanding of the relationship between sociodemographic factors and infrastructure availability to facilitate EV transition. Clustering analysis is suggested to be the most suitable approach to generate groups based on similarities among the data points (Hair Jr et al., 2009). Ward's hierarchical clustering technique was used to cluster the SAPs based on sociodemographic parameters. The data corresponding to these parameters was extracted from Census data and normalised into percentage values.

Clustering is done at the SAP level under the assumption that a household's decision to adopt EV, especially since it is a relatively new technology, is influenced by sociodemographic characteristics at the neighbourhood level. Analysis was done for varying numbers of clusters ranging from two to six. Finally, a four-cluster solution was considered based on the dendrogram and the variations observed between the different cluster solutions (Campbell et al., 2012; Choudhari and Maji, 2019). The descriptive statistics of each sociodemographic factor in each cluster are tabulated in Table 2.

The first cluster also referred to as *Potential early adopters*, has a high share of owner-occupiers (64.25%) who live in large houses (72.98%). They are also highly dependent on cars, with a significant percentage of residents owning at least two cars (15.44%) and driving to work (36.56%). The second cluster, also referred to as *Potential early adopters needing infrastructure*, has a high share of residents with high educational qualifications (45.1%). They mostly live in rented smaller accommodations but are expected to be aware of the environmental impacts of ICEVs owing to their level of education. The third cluster, also referred to as *Potential late adopters,* is not entirely dependent on cars (a lower percentage share of people driving to work and owning two cars). However, they still constitute the younger population (38.9%) of highly educated people (38.87%). Hence, they might adopt EVs later when provided with adequate infrastructure. The fourth cluster, *Unlikely adopters*, does not have the sociodemographic characteristics that match a potential EV adopter. Additionally, this group is not car-dependent, as it was observed that most of these households do not own a car.

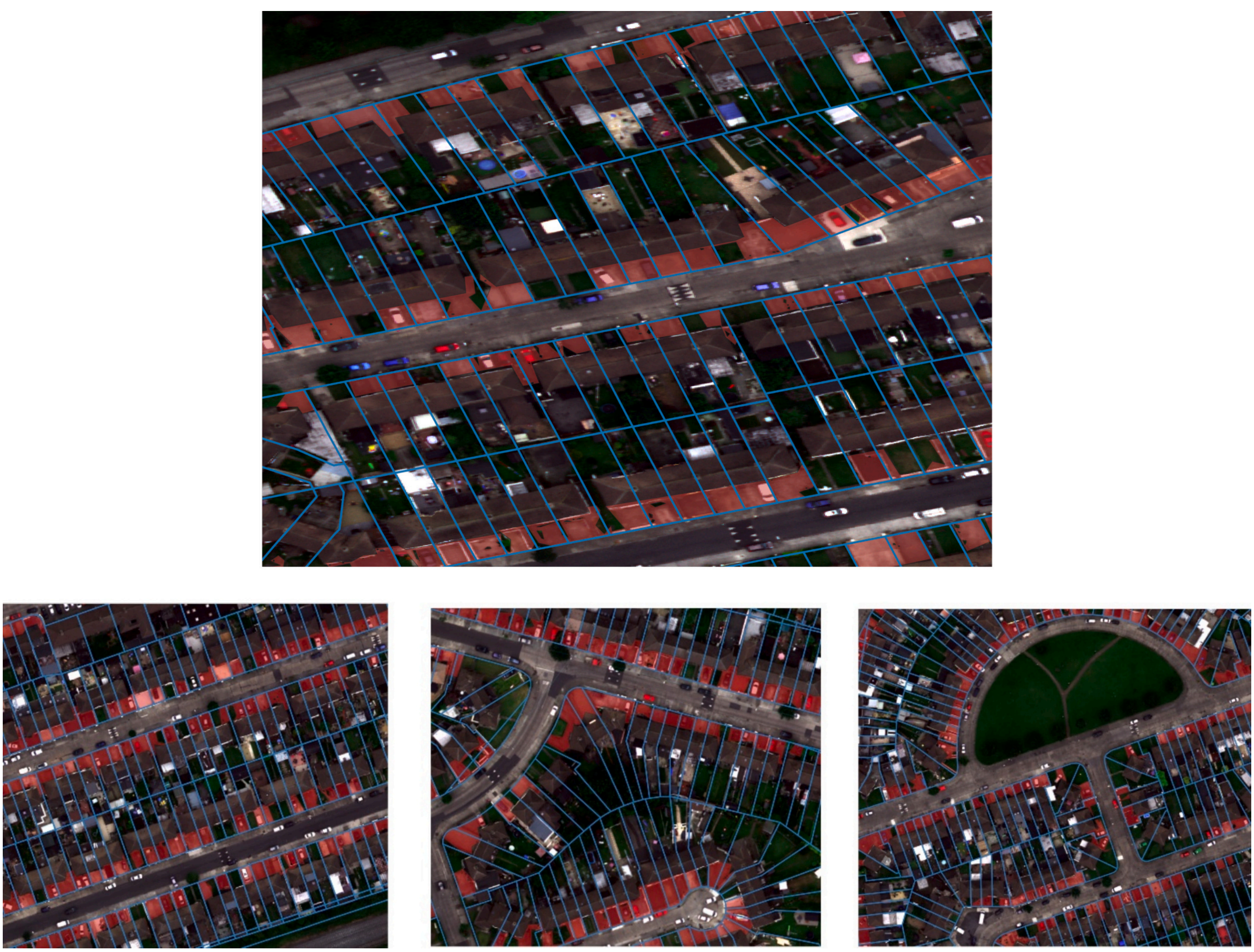

Fig. 5. Potential driveways (in red) detected in the test area. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

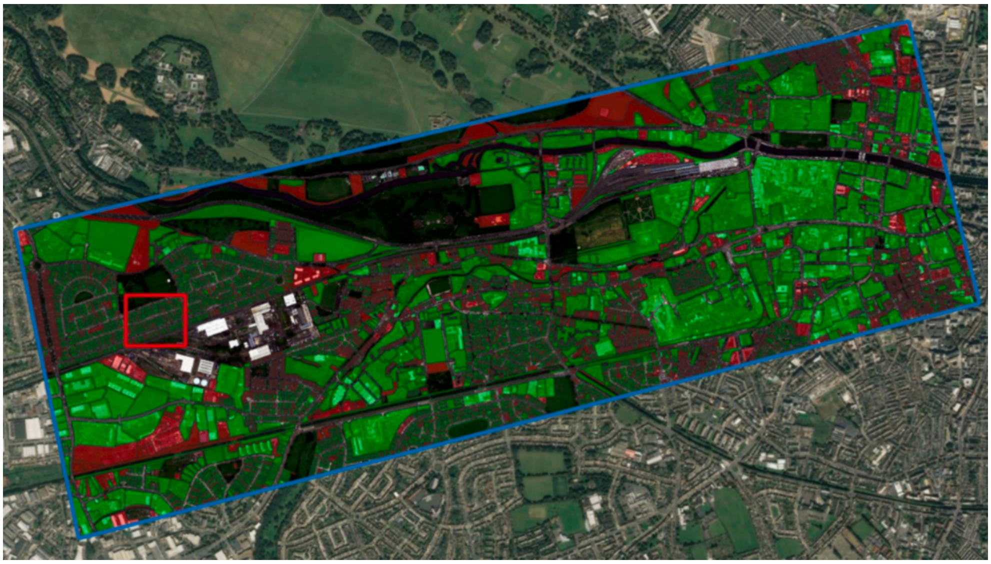

Fig. 6. Map showing driveway detection in the study area in Dublin (regions in green indicate properties with detected driveways, and regions in red indicate properties without driveways). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
Clusters based on sociodemographic characteristics (Results from cluster analysis).

No	Cluster	No of SAPs	Statistic	Population in the age group 25–59 (%)	Owner-occupiers (%)	Large houses (%)	High level of education (%)	Drive to work (%)	Households with at least two cars (%)
1	*Potential early adopters*	58	Mean	25.26	64.25	72.98	19.87	36.56	15.44
			Std. dev.	3.60	9.43	9.46	14.91	8.62	5.00
			Minimum	18	39	49	1	15	6
			Maximum	34	87	94	58	53	30
			Mean	35.3	35.51	34.05	45.1	28.43	11.01
			Std. dev.	5.23	11.18	15.42	12.70	8.54	5.73
			Minimum	22	14	4	21	14	1
2	*Potential early adopters needing infrastructure*	49	Maximum	46	68	67	70	50	28
			Mean	38.9	11.95	20.84	38.87	14.18	5.83
			Std. dev.	7.80	6.76	8.82	17.16	7.00	5.61
			Minimum	23	0	4	8	2	0
3	*Potential late adopters*	63	Maximum	57	27	40	77	39	28
			Mean	19.99	8.35	35.78	6.38	25.3	4.78
			Std. dev.	4.19	12.47	7.88	5.11	9.78	2.88
			Minimum	11	0	13	0	9	1
4	*Unlikely adopters*	23	Maximum	26	40	49	17	46	11

4.2. Comparison of clusters with driveways, EV adoption and access to low-emission modes

Further, the driveways detected in the region based on geospatial techniques were segregated for each SAP and then aggregated for each cluster, as illustrated in Fig. 7.

It can be observed that the *Potential early adopters* also had the highest share of driveways. Since driveways indicate the infrastructure required to install a home charging point, this suggests that the *Potential early adopters* have adequate infrastructure for a smooth transition to EVs.

The cluster solution was also compared with the actual EV adoption, using the count of home charger installations and the count of EV grants for each cluster, as shown in Fig. 8. The *Potential early adopters* have the highest *count of home charger installations* and *EV grants*, suggesting that the cluster solution based on sociodemographic characteristics aligns with the actual EV adoption trend. It was observed that the count of EV grant applications was also higher among *Potential early adopters needing infrastructure* and *Potential late adopters,* indicating a positive attitude towards EV adoption among these clusters despite not having infrastructure.

To assess the accessibility of low-emission transport options for different clusters, the locations of bus stops and shared bike stations were analysed (Fig. 9). The availability of these facilities was calculated per 100 people for each cluster, as detailed in Table 3.

Potential early adopters rely heavily on cars and have the highest number of bus stops per 100 people. In contrast, the *Unlikely adopters*, who depend more on public transport, have the lowest, indicating limited accessibility to low-emission options for this group. Bike station availability per 100 people is highest for *Potential late adopters*, followed by *Potential early adopters needing infrastructure*.

4.3. Modelling EV uptake at the SAP level

EV grant and home charger installation data were used to model EV uptake at the SAP level. The frequency distribution showed a significant number of SAPs with no home charger installations or EV grant applications (Table 4).

Table 5 displays descriptive statistics for the variables, with the count of home charger installations and EV grants as dependent variables. Independent variables were assessed for multicollinearity before model inclusion.

The dependent variables showed overdispersion, with variance exceeding the mean and a significant number of zeros. A zero-inflated

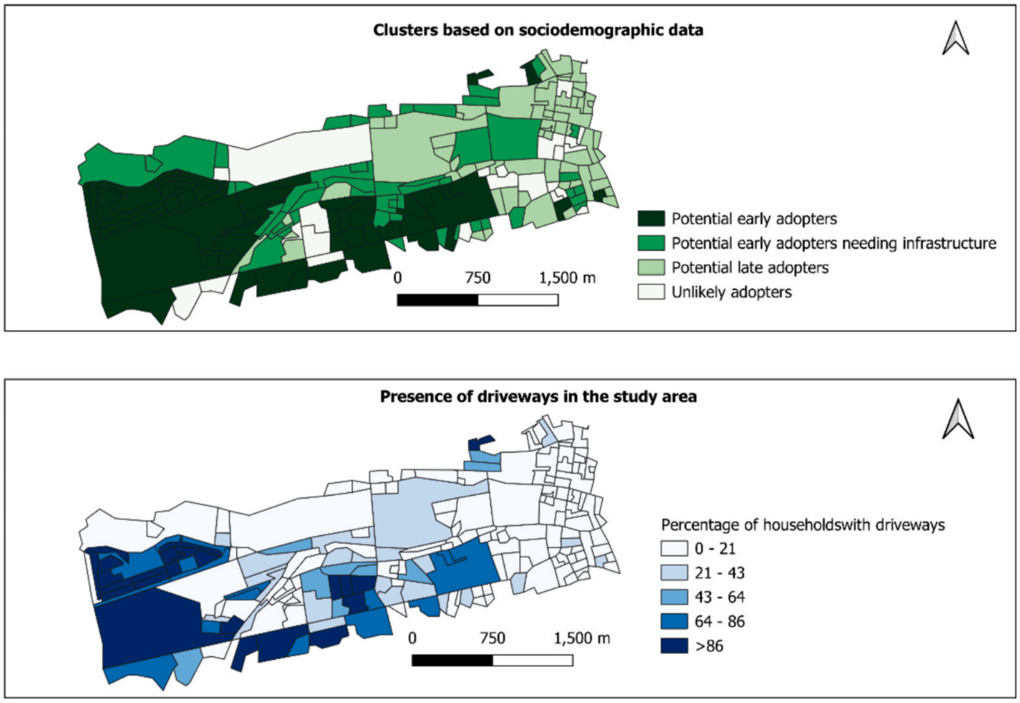

Fig. 7. Comparison of clusters based on sociodemographic characteristics and driveways.

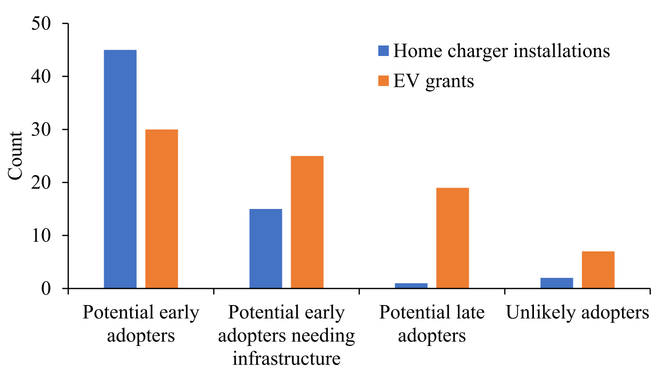

Fig. 8. Comparison of sociodemographic clusters with actual EV adoption.

negative binomial model was deemed suitable for modelling EV adoption at the SAP level due to these characteristics (Charly and Mathew, 2019a; Mukherjee and Ryan, 2020). Two zero-inflated negative binomial models were developed: one using *home charger installations* and the other using *EV grants* as dependent variables. Results are presented in Table 6 and Table 7. Home charger installations increased with higher education levels and driveway availability, likely due to the need for private parking (Table 6). This suggests that higher education may lead to greater environmental awareness and openness to new technologies. Regular car commuters are more likely to apply for EV grants, whereas households with multiple cars are less likely (Table 7).

Standard count models, including negative binomial and Poisson, were developed for comparison with the zero-inflated negative binomial models, as presented in Table 8. Log-likelihood and Akaike Information Criterion (AIC) values were used to assess model quality. A lower AIC indicates a better model fit for the data, while higher log-likelihood values suggest a better goodness of fit (Charly and Mathew, 2019b; Washington et al., 2011). Zero-inflated negative binomial models provided a better fit in both cases.

The discussed results focus on EV adoption at the SAP level, where neighbourhood factors play a role. However, EV adoption ultimately hinges on household-level decisions. Therefore, a binary logistic regression model is developed to understand EV adoption at the household level.

4.4. Binary logistic regression to model EV uptake at the household level

A binary logistic regression model was employed to predict EV adoption at the property level, with details of the included variables in Table 9. The dependent variable is home charger installation, a binary categorical variable. Independent variables, also categorical, include driveway presence, identified through geospatial analysis, and cluster membership, determined using Ward's hierarchical clustering technique.

Out of 9415 properties in the study area, only 0.5% had home chargers, indicating data limitations. However, 52.9% had driveways, 63.3% were in the *Early EV adopter* cluster, and 19.2% were in the *Potential early adopters needing infrastructure* cluster. Parameter estimates for the binary logistic regression model are presented in Table 10.

Results suggest that having a private driveway increases the likelihood of home charger installation. While the cluster categorical variable was insignificant, properties in clusters 1 and 2 were more likely to install home chargers, whereas clusters 3 and 4 showed less likelihood for EV adoption.

4.5. Discussion, policy implications, and limitations

Access to a dedicated driveway significantly influences the availability of EV infrastructure, with the study also revealing insights into the accessibility of alternative low-emission transport modes. Modelling results at both the SAP and household levels reinforced the relationship between the current state of EV adoption and access to a driveway. These findings also align with other recent studies in the field (Collett et al., 2022). Charging should be made available to those without driveways to achieve increased EV uptake.

This work reiterates the existence of population clusters with distinctive travel and sociodemographic characteristics influencing EV adoption. This is evident in the higher application rates for EV grants,

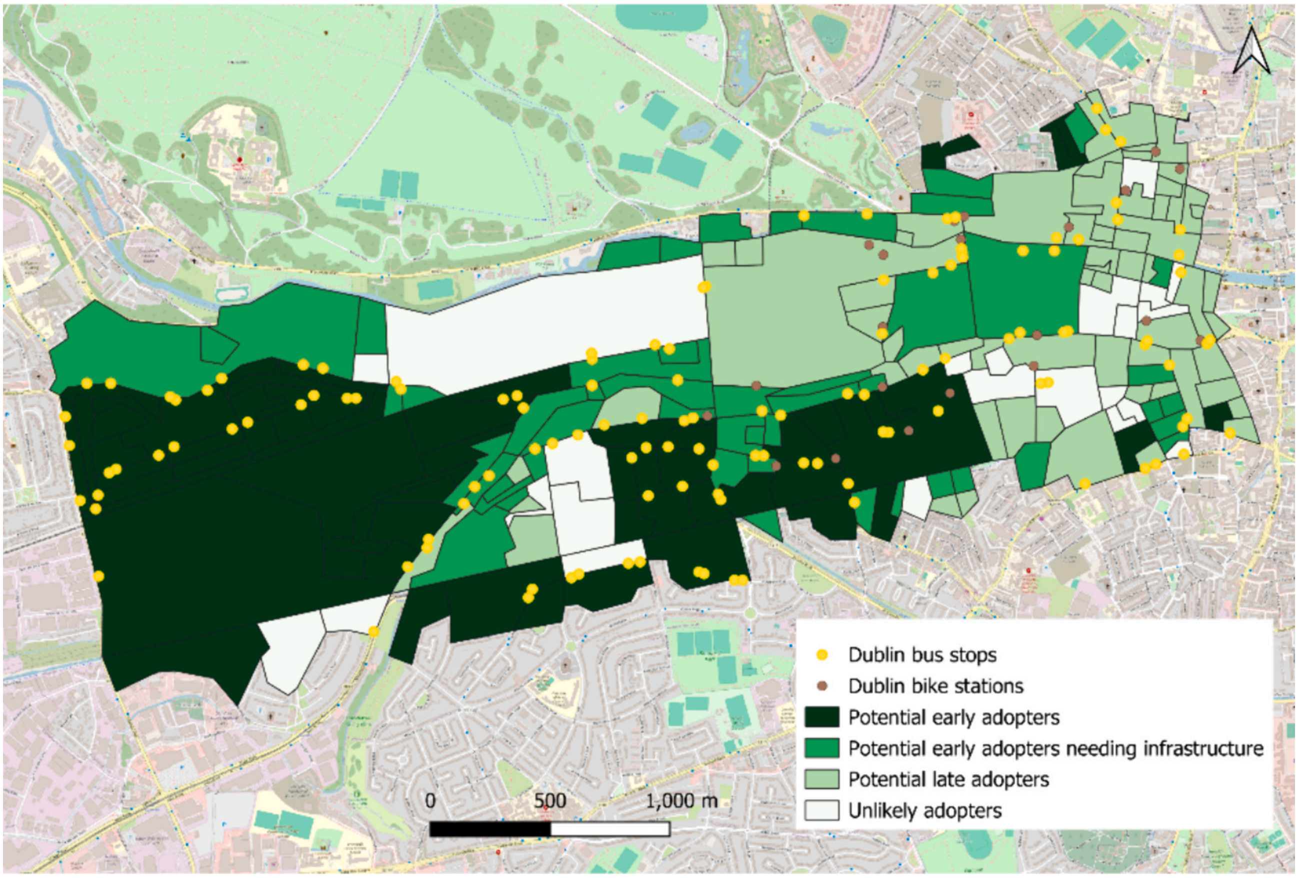

Fig. 9. Location of bus stops and shared bike stations.

Table 3
Number of bus stops and bike stations per 100 people in each cluster.

No	Cluster		No. of bus stops per 100 people	No. of bike stations per 100 people
1	*Potential early adopters*	Sum	21.02	0.54
		Mean	0.36	0.01
		Std. Dev.	0.47	0.05
2	*Potential early adopters needing infrastructure*	Sum	15.71	3.00
		Mean	0.32	0.06
		Std. Dev.	0.66	0.20
3	*Potential late adopters*	Sum	15.43	6.18
		Mean	0.24	0.10
		Std. Dev.	0.43	0.30
4	*Unlikely adopters*	Sum	6.26	0.32
		Mean	0.27	0.01
		Std. Dev.	0.50	0.07

Table 4
Frequencies of home charger installation and EV grants in SAPs.

Count of home charger installations			Count of EV grants		
Valid	Frequency	Percent	Valid	Frequency	Percent
0	154	79.8	0	139	72.0
1	24	12.4	1	38	19.7
2	9	4.7	2	10	5.2
3	4	2.1	3	4	2.1
4	1	0.5	4	1	0.5
5	1	0.5	7	1	0.5

Table 5
Descriptive statistics of variables considered in the model at the SAP level.

Variable	Unit	Minimum	Maximum	Mean	Std. dev.
Count of home charger installations	count	0	5	0.33	0.78
Count of EV grants	count	0	7	0.42	0.87
Population in the age group 25–59	%	11	57	31.63	9.03
Owner-occupiers	%	0	87	33.22	24.60
Large houses	%	4	94	41.64	24.00
High level of education	%	0	77	30.87	19.63
Drive to work	%	2	53	25.85	12.17
Households with at least two cars	%	0	30	9.91	6.70
Number of driveways	count	0	138	25.8	32.87

even among those without driveways but possessing favourable sociodemographic characteristics. This also indicates the influence of neighbourhood-level sociodemographic factors on EV adoption.

Another fascinating insight from the study is the accessibility to alternate low-emission modes of transport. Bus stops and shared bike stations were not easily accessible to those more likely to depend on them. These findings align with other studies examining the equity of urban transit, indicating that neighbourhoods with lower-income households tend to have more circuitous transit journeys (Dixit et al., 2021).

Hence, an in-depth understanding of the sociodemographic characteristics, travel patterns, and infrastructure availability is necessary to plan sustainable transportation alternatives for all. Such an

Table 6
Zero-inflation model coefficients for the *count of home charger installations*.

	Estimate	Std. Error	z Value	Significance
(Intercept)	27.126	11.427	2.374	0.018
Population in the age group 25–59	−1.037	0.425	−2.438	0.015**
Owner-occupiers	0.049	0.100	0.493	0.622
Large houses	−0.411	0.199	−2.067	0.039**
High level of education	0.400	0.174	2.298	0.022**
Drive to work	0.149	0.108	1.380	0.168*
Households with at least two cars	−0.145	0.165	−0.877	0.380
Number of driveways	0.135	0.064	2.123	0.034**

Dependent Variable: Count of home charger installations.

Table 7
Zero-inflation model coefficients for the count of EV grant.

	Estimate	Std. Error	z Value	Significance
(Intercept)	−15.939	8.441	−1.888	0.059
Population in the age group 25–59	0.168	0.161	1.046	0.296
Owner-occupiers	0.004	0.054	0.081	0.935
Large houses	0.085	0.060	1.416	0.157
High level of education	0.159	0.097	1.631	0.103
Drive to work	0.208	0.096	2.168	0.030**
Households with at least two cars	−0.681	0.235	−2.891	0.004**
Number of driveways	0.036	0.030	1.207	0.228

Dependent Variable: Count of EV Grants.

Table 8
Comparison of quality of estimated count models.

Dependent Variable	Model	Log-likelihood	AIC
Count of home charger installations	Zero-inflated negative binomial	−105.51	245.02
	Negative binomial	−117.79	251.58
	Poisson	−121.88	259.75
Count of EV Grants	Zero-inflated negative binomial	−145.71	325.41
	Negative binomial	−155.14	326.29
	Poisson	−161.40	339.58

Table 9
Descriptive statistics of variables considered in the binary logistic regression model.

Variable	Type	Levels	Description	Frequency	Percent
Home charger	Cat.	0	No	9368	99.5
		1	Yes	47	0.5
Driveway	Cat.	0	No	4435	47.1
		1	Yes	4980	52.9
Cluster	Cat.	1	*Potential early adopters*	5957	63.3
		2	*Potential early adopters needing infrastructure*	1808	19.2
		3	*Potential late adopters*	1040	11.0
		4	*Unlikely adopters*	610	6.5

Cat.: categorical.

understanding could lead to a targeted provision of facilities based on the population's needs while adhering to the State's goals.

For instance, the '*Potential early adopters'* identified in the study are highly dependent on cars and probably contribute to a high share of emissions yearly as per their current travel pattern. However, since they already have the infrastructure for EV transition, the focus should be on improving environmental awareness among them and providing alternative solutions. Considerable emission reduction can be achieved if some households from this category shift to EVs. Charger installations exceed EV grants for the '*Potential early adopters'* (Fig. 8), which is not the case for the other three clusters. Interestingly, the '*Potential early adopters'* cluster has the highest proportion of owner-occupiers. This is consistent with prior research indicating that homeowners are more inclined to invest in charging infrastructure (Campbell et al., 2012; Williams and Kurani, 2006). More public charging points may be offered to the cluster '*Potential early adopters needing infrastructure'* who might depend on cars to facilitate a smooth EV transition.

However, care must be taken to provide adequate low-emission alternatives for those in the other clusters. Shared bike stations, more stops, and increased bus frequencies may be provided to support low-emission modes, including active travel and public transport.

This study has several limitations, as discussed below. The presented algorithm for detecting driveways is limited by the thresholds set to identify un-vegetated and flat areas in the front yard of properties but was found to perform very well in the residential neighbourhoods of the study area. Replicating this study in a new location would need re-examining thresholds, but the basic logic behind the algorithm is expected to hold. The current driveway detection algorithm is set to find open driveways in the properties' front yards, which worked well for the study area in Dublin. This rule in the framework can be easily modified to include properties with parking areas on the side. For example, including connectivity of main roads/ streets to the parking area within a property boundary as an additional rule set could overcome the issue of detecting the front yard or side of properties. Regardless, buildings with underground and covered parking areas would still be left out since they are impossible to view from aerial images.

The driveway detection algorithm can also underperform in areas with wider roads. In such areas, a larger buffer from the main road is required to identify the front yards of residential properties. Therefore, selecting the buffer from the road's central line is important. One way to overcome this issue could be to use image segmentation techniques to identify the sides of the road that would serve as the reference for the buffer. However, the algorithm would still fail to identify parking spaces detached from property boundaries (these would be considered on-road parking and hence beyond the scope of this study). Additionally, the criteria of driveways being limited to simple geometries and car height being <2 m are some other rules that need to be adapted before application to newer regions.

The sociodemographic information of the study area is collated from the Census data 2016, which was the latest detailed information available at the time of the study. These limitations need to be considered when interpreting the results.

5. Conclusions

This study assesses the infrastructure suitability for private EV adoption in urban areas using sociodemographic parameters and access to driveways. The main contribution of this research lies in identifying the infrastructure available for the widespread transition of EVs. Infrastructure is measured in terms of driveways detected through a novel approach using geospatial techniques from multispectral remote sensing images.

The study results indicate the existence of distinctive sociodemographic clusters within the study area, which require different focus strategies for reducing transport emissions. Statistical modelling confirmed the influence of access to private driveways and favourable sociodemographic factors on EV adoption and home charger installation until now.

In the current deployment phase, several uncertainties can affect the mass roll-out of charging points and EVs. Hence, it is essential to identify strategic locations of charging points and profile Potential early adopters for targeted marketing and provision of charging infrastructure

Table 10
Results of the binary logistic regression model.

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step1[a]	Driveway	1.74	0.42	16.92	1	<0.001	5.70	2.49	13.07
	Cluster 1 (ref.)	–	–	2.97	3	0.40	–	–	–
	Cluster 2	0.55	0.38	2.17	1	0.14	1.74	0.83	3.62
	Cluster 3	−0.27	0.61	0.20	1	0.66	0.76	0.23	2.51
	Cluster 4	−0.31	0.73	0.18	1	0.67	0.74	0.18	3.08
	Constant	−6.60	0.42	243.9	1	<0.001	0.00		

while ensuring that this does not become discriminatory to any sector of the population. A successful transition to sustainable mobility requires that all have equal access to low-emission alternatives based on their travel needs. While increasing EV adoption is important, it should be accompanied by promoting a broader socio-demographic shift towards low-emission alternatives, such as public transport. Otherwise, the existing issues related to car dependency will persist.

The results from this study provide meaningful insights that could help identify ideal locations for deploying public charging infrastructure and shared mobility hubs. While the methodology can be adapted to other cities with minor adjustments to the driveway detection thresholds based on regional geography, it has limitations. These include set thresholds for identifying un-vegetated and flat areas in property front yards, which may require tweaking for different locations. Moreover, as discussed in the limitations section, the algorithm may not perform well in areas with wider roads, necessitating a larger buffer from the main road.

Declarations of competing interest

None.

CRediT authorship contribution statement

Anna Charly: Conceptualization, Methodology, Software, Formal analysis, Writing – original draft. **Gourav Misra:** Conceptualization, Software, Investigation, Data curation. **Shubham Sonarghare:** Software, Investigation, Data curation. **Rowan Fealy:** Conceptualization, Resources, Writing – review & editing, Supervision, Funding acquisition. **Tim McCarthy:** Conceptualization, Resources, Writing – review & editing, Supervision, Funding acquisition. **Brian Caulfield:** Conceptualization, Resources, Writing – review & editing, Supervision.

Data availability

The authors do not have permission to share data.

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