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Common practices and dissimilarities in greening residential routine mobility in selected countries of Europe, based on a comparative analysis

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This article aims at widening the knowledge about green mobility choices related consumer behaviour and attitudes of retail customers. The calculations rely on the dataset of a survey conducted in Hungary, Italy, Norway, Poland, and Spain between 2016 and 2019 by the ENABLE.EU team. The analysis revealed the potential enablers and disablers of environmentally friendly mobility by utilising linear regression, binary logistic regression, probit analysis, and multilayer perceptron networks on 39 predictors. Policymakers can improve the position of preferred travel modes by (i) disadvantaging traditional four-wheel vehicles, (ii) bolstering the spread of electric four-wheel vehicles, (iii) educating individuals regarding CO_2 emissions and their impacts, (iv) launching easy-to-popularise government actions affecting the transport system, (v) developing the infrastructure and accentuating the progress made, and targeting both (vi) economically active and (vii) rural citizens. Depending on the countries, supplementary areas are proposed for acting on. The scrutiny sheds light on country specificities (e.g. systemic dissimilarities, the advanced position of Norway on the electromobility pathway) and presumed paradoxes that must be addressed.

Keywords: green and smart mobility, electromobility, environmentally friendly mobility, sustainable mobility, mobility turn

Infrastructure (e.g. public roads, railways, and other fixed track networks, the electric charging network and hydrogen refuelling stations, the entire digital ecosystem, and pipelines in energy supply) is one of the main pillars of thriving economies and is analogous to the vascular, lymphatic, and nervous systems in a healthy human body. As a consequence of prevailing globalisation and concomitant technological development in the previous decades, distances have shrunk, even the farthest corners of Earth are within accessible reach in the 21st century. Not only products, services, workforce, and capital but also individuals, in general, have become more mobile. The progress made in the utilisation of more environmentally friendly vehicles has not counterbalanced the greenhouse gas (GHG) emissions stemming from the enhanced demand for transport in the European Union (EU). Although the Covid-19 pandemic caused a rupture in the steadily growing trend of GHG emissions due to transport perceived between 2013 and 2019 due to elevated passenger and inland freight transport, the increase in GHG emissions is likely to recrudesce in the coming years. Even with 'additional measures' (e.g. the penetration of public transport and electric vehicles and prioritisation of low-carbon fuels), sectoral GHG emissions in 2030 would hardly remain below their 1990 levels. In the next decades on EU level, GHG emissions arising from road transport are expected to fall, and those related to railway transport are likely to decrease, while the remaining emissions connected to other transport modes (both domestic and international aviation, maritime, and inland navigation) are projected to increase continuously *(EEA, 2023).* The 11th Sustainable Development Goal aims to create sustainable and resilient cities and communities by 2030. Its target 11.2 envisages safe transport systems with general access by putting more emphasis on public transport. By making use of preventive mitigation (inter alia in the field of transport), the augmentation in global average temperature in the 21st century can be limited not only to the jointly accepted 2°C but also to 1.5°C relative to pre-industrial levels in accordance with the Paris Agreement *(United Nations, 2015, pp. 1, 14, 21; 2023)*.

The European Climate Law – as part of the European Green Deal – stipulated at least 55% net reduction in total GHG emissions by 2030 compared to 1990 and set 2050 as the target year for obtaining carbon neutrality. The focus points are the energy and mobility turn. The transport-related aim is a 90% reduction in GHG emissions by 2050 compared to the base year of 1990. In 2019, the EU-28 was responsible for 7.3% of global GHG emissions; hence, its GHG emissions per capita exceeded the global average. In the territory of the EU, the share of transport was approximately 30% of total CO_2 emissions, of which 71.7% could be attributed to road transport, the majority being produced by passenger cars: cars and vans caused 12% and 2.5% of total CO_2 emissions respectively. By 2035, only carbon-neutral cars will be allowed in the EU when purchasing a new car. In line with the efforts to attain carbon neutrality, the EU decided to apply a sequence of measures (with stages in 2020, 2025, and 2030) leading to the penetration of zero- and low-emission vehicles. Correspondingly, imposing a series of performance standards on new passenger cars by setting EU fleet-wide CO_2 emission targets (i.e. absolute limitations expressed in CO_2/km) and introducing an incentive mechanism constitute the core of the regulation *(EC, 2023; EP, 2023a, 2023b, 2023c; World Bank, 2023)*. By assuming the energy intensity (MJ/passenger km) and GHG intensity (g CO_2-equivalent/passenger km) of passenger transport modes, valid for 2019, the indicators of public transport (rail, buses) and two-

/three-wheelers argue for reducing the use of both cars with fossil fuel combustion and aviation if reasonable parallel availability is ensured *(IEA, 2022a, 2022b)*.

In Hungary, the share of transport in final energy use showed a slight deviation from 27% between 2018 and 2020. Renewable energy sources in transport accounted for a low 11.6% share in the total energy use of 2020. Despite noteworthy modernisation of vehicles (e.g. spectacular growth in the number of railcars, see the self-propelled railway vehicles of Stadler) and infrastructure (e.g. electrification of the railway network, prolongation of the road network in favour of the expressway network, and prioritising asphalt and bitumen pavement), the number of passengers carried and passenger kilometres in public transport remained in 2021 below the 2015 levels due to the Covid-19 pandemic. Based on passenger kilometres, in 2019 (before Covid-19), trains and suburban railways were the cheapest means of public transport; aeroplanes – demonstrating dynamic growth in the number of passengers, excluding the period of the pandemic – were comparable to coaches in terms of cost, followed by underground trains, buses, and the common category of trams and trolleybuses. In spite of the lack of maintenance related to navigation routes, travelling by ship is ten times costlier than riding a train. The absolute majority of passengers (53–57%) chose the train for short distances (at most 30 km/travel), and the average distance ranged from 48 to 53 km between 2015 and 2021. The stock of passenger cars exceeded 4 million pieces in 2021 (71% of these were produced more than 10 years ago) and reached a share of 73% in road vehicles. Petrol cars accounted for 64.2%, diesel cars for 31.6%, hybrid cars for 2.9%, and electric cars for 0.5% of the total number of passenger cars. The remaining share of other fuels was 0.8% *(HCSO E-Shelf, 2022, Tables 4.5.4, 4.5.7, 5.6.5, 5.6.6, 5.6.9–5.6.13, 5.6.23; HCSO, 2023a)*.

1. Literature review

The research field of green mobility is frequently investigated; therefore, applying multiple refinements was required to reduce the number of articles to a manageable quantity. The filters encompassed (i) document type (open-access articles), (ii) publication year (published between 2019 and 2023), (iii) language (written in English), (iv) keywords, terms ('green mobility'), and (v) research area (environmental sciences ecology, transport, business economics, urban studies, energy fuels, and development studies). Relying on all databases offered by the Web of Science and the conjunction of filters resulted in 651 hits, which formed part of a simplified systematic literature review. Twenty-nine papers were considered relevant, based on the bibliographic analysis, and they encompassed a broad range of individual and collective influencers and measures promoting green mobility in the EU and other developed countries with regard to residential routine mobility. Their synthesised union with overlapping dimensions is listed below with a particular travel mode or general scope. The circle of decision-makers is not indicated for the specific cases, as it can be comprehensive (e.g. individuals, providers, manufacturers, municipalities, legislative bodies). The determinants that can promulgate not only green mobility but also pro-environmental behaviour are the following:

1. macroeconomic, infrastructural, and demographic indicators of countries, e.g. GDP, length of bike lanes network, charging infrastructure for electric vehicles, stock of private cars, population density and growth, and prolongation of life expectancy *(Echeverria et al., 2022a, p. 256),*
2. the socioeconomic profile of individuals, such as age, gender, family status, income, educational attainment, social-occupational group, nationality, and the area of residence *(Echeverria et al., 2022a, pp. 255–258; Enzler–Diekmann, 2019, p. 17; Herberz et al., 2020, p. 108; Hudde, 2022, p. 5)*,
3. environmental (e.g. striving for an ameliorated air quality), financial (e.g. incentives, subsidies, price of passes or future fuel consumption), independence, status, hedonic, health benefit, and safety motives of individuals in mobility purchase intentions, making use of shared vehicles, or buying public transport tickets *(Herberz et al., 2020, p. 108)*,
4. the psychological attachment to a private car, sharing it with members of the household, using multiple travel modes, the number of cars possessed by the household and their utilisation, and environmental aspects may induce the shift towards car sharing *(Briguglio–Formosa, 2023, pp. 1, 6, 9, 12)*,
5. recreational activities, environmental concerns (e.g. climate change), the convenience of opting for specific travel modes (e.g. e-scooter), perceived safety during their usage and on roads in general, reducing congestion and noise pollution (e.g. based on the engine noise level), lack of parking spaces, public transport shortcomings, and social influence (e.g. reference group, press) *(Kopplin et al., 2021, pp. 3–4, 8, 11),* complemented with the presumed causal chain of green attitudes, values, and loyalty *(Rodríguez-Correa et al., 2023, pp. 6, 13),*
6. previous experience gained in using travel modes *(Ko et al., 2021, p. 7)*,
7. opting for active transport in order to achieve higher levels of well-being during travel (i.e. physical activity, lack of air pollution, impacts on mental health, and social contacts coupled with walking and cycling) *(Echeverria et al., 2022b, pp. 1, 5)*,

8. corporate shared electric/hybrid cars for commuting to work (e.g. car sharing to events outside the firm) *(Julsrud–Standal, 2023, pp. 818–821)* and widening the composition of travellers, applying recommendation systems for ride sharing (e.g. matching commuters) *(Anagnostopoulos, 2021: p. 189)*,
9. popularising the P+R (park and ride) concept, restricting vehicle transport (e.g. prohibition of motor vehicles in a specific region), and improving public transport (e.g. new or modernised routes, enhanced capacity for more passengers, less polluting vehicles with higher speed - meaning less travel time) *(Oleskow-Szlapka et al., 2020, p. 14),*
10. trip attributes (e.g. purpose, travelling companions), parking management strategies (e.g. free on-street parking for electric cars and restrictions for the rest), priority lanes for public transport and environmentally friendly individual vehicles, creating low emission zones (e.g. bans on the use of polluting vehicles in order to generate a modal shift towards green mobility), and enhancing pedestrian areas by addressing the problems posed by the ground gaining of cleaner vehicles (e.g. congestion, not participating in public transport or active modes) *(Gonzalez et al., 2022, pp. 1, 5, 14)*,
11. the potential represented by applications (e.g. EcoAttivi smartphone application) in providing information about healthy and sustainable mobility along environmental (e.g. air pollution emissions), social (e.g. exchanging information, social media presence), organisational (e.g. trips, ticket purchase), and health (e.g. calorie intake for achieving an ideal weight, calories burned during physical activity, recommended duration and intensity of regular physical activity) dimensions *(Marquart–Schuppan, 2022, p. 6)*,
12. low-carbon fuels and electricity (e.g. colour palette of hydrogen depending on its source), renewable energies (e.g. residential photovoltaic electricity), innovations (e.g. amphibious/floating buses for sightseeing tours, setting up an innovation department in the organisation), technologies (e.g. hybrid cars, hydrogen fuel cell, decreasing prices of electric vehicles thanks to progress, autonomous driving), their integration with information and communication technology, the diffusion of digitalisation, technical readiness, availability of resources, economic viability, social acceptability, and environmental footprint *(Manakhov et al., 2022, pp. 1, 4, 12; Petrauskiene et al., 2020, p. 3),*
13. electricity storage (battery autonomy), creation and local industrial development of the automotive sector and/or other vehicle manufacturers (of trains, trams etc.), and battery recycling *(D'Adamo et al., 2023, pp. 848–849),*

14. green consumption values resulting in the reduction of pollution by changing mobility habits (e.g. a green band of manufacturers/providers triggers the intention to buy or rent their electric vehicles) *(Risitano et al., 2023, pp. 1096, 1105–1107)*,
15. possessing driving licences (e.g. prerequisite of driving an e-scooter), business models (e.g. bike- or car-sharing) and in a wider context the supply side (e.g. availability of green alternatives on the same route, access to more flexible demand responsive vehicles, profound knowledge about travel options and vehicle design, features, and specifications, subsequently, the opportunity to purchase suitable vehicles in terms of size, fuel efficiency and further environmental awareness, etc.), and imposing emission standards on vehicles *(Dijk et al., 2019, pp. 65, 73),*
16. political preferences (e.g. voting for green parties), spatial factors (e.g. frequented sites such as universities or cultural institutions, distance to the most often visited destinations, the density of public transport stops, greenness of urban areas, tram tracks, or the railway and road network) *(Münzel et al., 2020, p. 251; ten Dam et al., 2022, p. 3)* or their simultaneous presence in near distance (e.g. green areas, bike or pedestrian lanes, university facilities, and public parking space for cars) *(Campos-Sanchez et al., 2019, p. 14),*
17. redistributing fiscal revenues for green mobility investments *(Goers–Schneider, 2019, p. 454)*,
18. gender narratives by distinguishing between masculine (e.g. driving more and longer distances, power, speed, and status) and feminine (e.g. practical matters, less environmental harm and hence more openness for public transport and electric cars) stereotypical attributes associated with mobility *(Anfinsen et al., 2019, pp. 38, 45)*,
19. suitable combinations of travel mode, business model (e.g. car-sharing), and propulsion (e.g. fossil fuel internal combustion engine or electric motor) *(Turon et al., 2022, p. 1),*
20. the current phase of innovation diffusion (e.g. Norway is expected to achieve the peak of electric car sales in 2024) *(Brdulak et al., 2021, pp. 6, 8, 12)*,
21. the status quo, the relative strength of travel modes and business models (e.g. relative competitiveness of both the public transport system and traditional/electric two-wheelers compared to the private car regime or car-sharing in a larger city) *(Hjorteset et al., 2021, p. 8),*
22. disseminating knowledge, fostering participant networks and collaboration (e.g. industry alliances), planning and long-term commitments (e.g. roadmap with targets), establishing legitimisation and advocacy (e.g.

influencing public views, political lobbying), creating markets (e.g. urban air mobility by means of electric vertical take-off and landing /eVTOL/ aircraft), mobilising and allocating resources (e.g. funding for infrastructure, training transport and vehicle engineers, urban designers, and landscape architects), launching reforms (e.g. modifying or devising legislation with the purpose of improved energy and GHG intensity, initiatives targeted at energy savings, implementing green waves of traffic lights) *(Trencher et al., 2021, pp. 4–7)*,

23. using big data, simulation models (e.g. traffic congestion), optimisation problems (e.g. determining the timetable and the route of bus lines within a specific city), and machine learning techniques (e.g. predicting mobility patterns) *(de la Torre et al., 2021, pp. 5–6, 9, 12)*.

Many preceding studies utilised a common fixed set of predictors, while this article follows a different path by enabling prevailing country specificities by means of tailored predictor selection. In accordance with my objective, this study aims at addressing the following research question (RQ):

Based on the experiences gained in selected European countries and the timeshare of preferred travel modes, what are the main influencing factors of replacing individual vehicles that use fossil fuel combustion in the residential routine mobility field?

2. Methodology

2.1 Method

Quantitative analyses were carried out.

Ordinary least squares (OLS) linear regression, probit analysis, binary logistic regression, and artificial neural networks were used for prediction. Asymptotic independent samples z-tests were performed for comparing means.

OLS linear regression, probit analysis, binary logistic regression, and artificial neural networks were made in the statistical software IBM SPSS Statistics Version 27. The asymptotic independent samples z-tests were executed in Microsoft Excel.

2.2 Data collection

Between 2016 and 2019, the ENABLE.EU team undertook a project with the purpose of uncovering the drivers of individual energy choices and behaviours. The team compiled a questionnaire for conducting a household survey so that economic, social, cultural, geographical, and further institutional influencing factors could be revealed. The survey comprised seven sections: (i) home/building characteristics and household possessions, (ii) mobility, (iii) prosumers, (iv) heating and cooling, (v) electricity, (vi) governance, and (vii) social and economic characteristics. A total of 11,265 retail customers from eleven countries participated in the survey, of whom five (Hungary, Italy, Norway, Poland, and Spain) are relevant to this study owing to mobility data. The dataset contains 473, predominantly nominal and ordinal scale variables *(ENABLE.EU team, 2019)*. Table 1 recapitulates the sections split by country.

Table 1

Dataset: available combinations of sections and countries (extract)

Country (abbreviation)	Home	Mobility	Prosumers	Heating and cooling	Govern-ance	Socio-economic	Number of respon-dents
Hungary (HU)	x	x	–	x	x	x	1,022
Italy (IT)	x	x	x	–	–	x	1,025
Norway (NO)	x	x	x	–	x	x	1,221
Poland (PL)	x	x	–	–	x	x	1,000
Spain (ES)	x	x	–	x	–	x	760
Total number of countries/records	5	5	2	2	3	5	5,028

The sections on home/building characteristics and household possessions, mobility, governance, and social and economic characteristics bear importance for addressing the RQ. It is worth mentioning that amongst the five countries, Norway (5.504 million inhabitants at the end of the first quarter of 2023) is one of the countries with the highest number of electric vehicles in use worldwide. In 2022, the number of electric four-wheelers was 599 thousand units, and the stock of private cars was 2,917 thousand pieces. This implies that approximately 20.5% of the stock is composed of electric vehicles, corresponding to an estimate of 109 pieces per thousand inhabitants *(Statista, 2023; Statistics Norway, 2023a, 2023b)*. Due to the current share, Norway may serve as an appropriate case for illustrating the lessons learned during the penetration of electric cars.

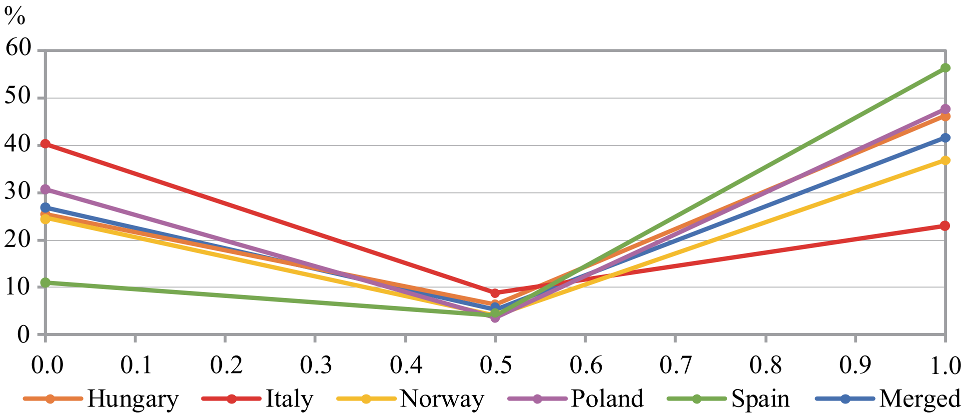
2.3 Data analysis

In order to prepare data suitable for investigation by using the mentioned quantitative techniques, data transformation was performed as shown in the Table of the online Annex.

The timeshare of preferred travel modes (TIME_SHARE_PREF_MODE) is a continuous variable ranging from 0 to 1. Only a subset of respondents (4,765 out of 5,028) indicated the needed data, necessary for the calculation of the variable. When analysing the dataset, three phenomena could be identified regarding single records. First, 37 Norwegian persons had at least one travel time field, where 1 day or more was registered. These fields are {M3(i)2_Time_(j)}, where i={A, B, C, D, E} and j={1, 2, ..., 11}. Second, the number of days was not known in the case of 33 Italian citizens; see the fields {M1(i)}, where i={A, B, C, D, E}. Third, the calculated destination-specific or total velocity was not plausible, as it exceeded the uniformly applied assumed speed limit of 140 km/h concerning 13 Norwegian or Spanish individuals. After removing 81 records[1] affected by at least one of these three limitations, 4,691 cases[2] remained in the dataset available for further analysis. Both Figure 1 and Table 2 characterise the distribution related to both the merged and the country-specific datasets. For the sake of transparency, Figure 1 illustrates the three most frequent values.

Figure 1

Partial histogram of the timeshare of preferred travel modes split by case



[1] The intersection of the limitations (i) and (iii) consists of 2 respondents, hence, the union comprises 37+33+13–2=81 elements.

[2] As mentioned earlier 5,028–4,765=263 persons did not fill in the needed questions entirely, thereof 7 Italians are part of the previously indicated 81 participants. Correspondingly, the final dataset incorporates 4,765–81+7=4,691 records.

Table 2

Descriptive statistics of the timeshare of preferred travel modes split by case

Statistics	Merged sample	Hungary	Italy	Norway	Poland	Spain
Mean	0.584	0.621	0.422	0.572	0.579	0.749
Median	0.667	0.833	0.429	0.640	0.750	1.000
Mode	1.000	1.000	0.000	1.000	1.000	1.000
Std. dev.	0.422	0.423	0.408	0.408	0.445	0.350
Sample size	4,691	991	878	1,110	969	743

Based on the asymptotic independent samples z-tests, the list of countries in decreasing order of timeshare of preferred travel modes begins with Spain (the timeshare amounts to 75% on average) followed by Hungary (62%) and the joint ranking of Poland and Norway (58%, 57%), while Italy (42%) lags behind. The dimension of the destination provided a ramification for research. Table 3 shows that travelling to the location of leisure activities (59.2%) and grocery/shopping (57.5%) has the highest timeshare of preferred modes, followed by the destinations of children's school (50.8%) and workplace/university (49.8%). Mobility decisions concerning the location of children's extra-school activities (42.2%) are the least conscious. Spaniards exemplify the most favourable country-destination pair in the comparative overview when they travel to the location of their leisure activities (82.0%).

Table 3

Mean of the timeshare of preferred travel modes by country and destination breakdown

Mean	Workplace/ university	Children's school	Children's activities	Grocery/ shopping	Leisure activities	General
Merged	0.498	0.508	0.422	0.575	0.592	0.584
Hungary	0.534	0.564	0.443	0.591	0.528	0.621
Italy	0.316	0.429	0.342	0.391	0.462	0.422
Norway	0.615	0.443	0.356	0.528	0.549	0.572
Poland	0.399	0.416	0.360	0.621	0.524	0.579
Spain	0.565	0.737	0.724	0.753	0.820	0.749

The available data render the prior formulation of the RQ more precise: Based on the experiences gained in Hungary, Italy, Norway, Poland, and Spain, and the timeshare of preferred travel modes, what are the main influencing factors of residential routine mobility choices promoting public transport, electromobility, mobility sharing business models, biking, walking, and further environmentally friendly mobility solutions?

The avoidance of the introduction of dummy variables in the case of social and economic characteristics restricted the number of independent variables to the original number of 7 instead of 7+17=24. Prior to the runs carried out in SPSS, the presence of multicollinearity was controlled based on two statistics coupled with linear regression: (i) variance inflation factor (reciprocal of tolerance) and (ii) condition index. By entering 39 predictors in the model, collinearity was observed in the case of 11 regressors: (i) M5_time, (ii) M5_comfort, (iii) M5_flexibility, (iv) M5_privacy, (v) M5_air_quality, (vi) M5_CO2_emissions, (vii) M6_car-sharing, (viii) M6_P2P_car-sharing, (ix) M7_financial_subsidy, (x) M7_tax_reduction, and (xi) M7_mobility_ improvement when applying the rule of thumb of 2 as an acceptable limit for the VIF *(Kovács, 2014, p. 94)*. After removing 6 variables that caused disturbing multicollinearity from the model, 33 independent variables remained for further investigation. In parallel, none of the condition indices exceeded 5, i.e. the ceiling referring to tolerable weak multicollinearity *(Kovács, 2014, p. 95).*

The timeshare of preferred travel modes can be modelled by **OLS linear regression** *(Kovács, 2014, pp. 87-91)*:

$$\hat{y} = \hat{\beta}_0 + \sum_{i=1}^{m} \hat{\beta}_i \cdot x_i = \underline{\hat{\beta}}^T \cdot \underline{x} \quad /1/$$

The total sum of squares is specified as: $SST = \sum_{j=1}^{n} (y_j - \overline{y})^2$ /2/

The sum of the squared estimate of errors (residuals) is set to:

$$SSE = \sum_{j=1}^{n} (y_j - \hat{y}_i)^2 \quad /3/$$

Adjusted R square is defined as follows: $R_{adj}^2 = 1 - \frac{SSE/(n-m-1)}{SST/(n-1)}$ /4/

where m represents the number of explanatory variables in the model and n is the sample size.

Testing the null hypothesis of zero beta coefficients relies on Student's t-distribution:

$t = {\hat{\beta}_k}/{s_{\hat{\beta}_k}}$ where k=0, 1, …, m and the number of degrees of freedom is ν=n–m–1. /5/

Both binary logistic regression *(IBM, 2016, pp. 557–566)* and probit analysis *(IBM, 2016, pp. 797–801)* are appropriate tools for binary classification. A dichotomous dependent variable is needed for logistic regression, ensured by eliminating the records differing from 0 or 1. In this study, the entire interval between 0 and 1 was investigated in order to reproduce the timeshare of preferred travel modes in the case of probit analysis. The regression parameters ($\underline{\beta}$ vector) are estimated in both cases with the maximum likelihood technique.

Binary logistic regression applies the logit transformation of the probability (i.e. the natural logarithm of the odds ratio), a linear function of the explanatory variables ($\underline{x}$ vector, which optionally contains 1 for the intercept), as shown below:

$$logit\ p(\underline{x}) = ln\left[\frac{p(\underline{x})}{1-p(\underline{x})}\right] = ln(odds) = \underline{\hat{\beta}}^T \cdot \underline{x} \quad /6/$$

Based on /6/, the model can be expressed as follows:

$$p(\underline{x}) = \frac{\exp(\underline{\hat{\beta}}^{\mathrm{T}} \cdot \underline{x})}{1+\exp(\underline{\hat{\beta}}^{\mathrm{T}} \cdot \underline{x})} \qquad /7/$$

The formula of the general likelihood function in the i[th] step (n is the sample size):

$$l(i) = \prod_{j=1}^{n} p(\underline{x}_{ij})^{y_j} \cdot \left[1 - p(\underline{x}_{ij})\right]^{1-y_j} \qquad /8/$$

By applying N(y=1)+N(y=0)=n, this is equivalent to:

$$l(i) = \prod_{j=1}^{N(y=1)} \left(\frac{e^{\underline{\hat{\beta}}_i^T \cdot \underline{x}_{ij}}}{1+e^{\underline{\hat{\beta}}_i^T \cdot \underline{x}_{ij}}}\right) \cdot \prod_{k=1}^{N(y=0)} \left(\frac{1}{1+e^{\underline{\hat{\beta}}_i^T \cdot \underline{x}_{ik}}}\right) \qquad /9/$$

If the constant is not included in the model, the initial likelihood function *l(0)* can be computed as:

$$l(0) = \left(\frac{1}{2}\right)^n \qquad /10/$$

If the constant is included in the model, the formula of the initial likelihood function can be written as follows:

$$l(0) = \left(\frac{e^{\beta_0}}{1+e^{\beta_0}}\right)^{N(y=1)} \cdot \left(\frac{1}{1+e^{\beta_0}}\right)^{N(y=0)} \text{where N(y=1)+N(y=0)=n.} \qquad /11/$$

Cox and Snell's R square in the i[th] step: $R_{CS}^2(i) = 1 - \left[\frac{l(0)}{l(i)}\right]^{\frac{2}{n}}$ /12/

Nagelkerke's R square in the i[th] step: $R_N^2(i) = \frac{R_{CS}^2(i)}{1-[l(0)]^{\frac{2}{n}}}$ /13/

Goodness-of-fit tests aim at assessing how accurately the predicted values represent the observations *(Canary et al., 2016, p. 675).* The Hosmer and Lemeshow goodness-of-fit statistic is a chi-square test:

$\chi_{HL}^2 = \sum_{k=1}^{g} \frac{(O_{1k}-E_{1k})^2}{E_{1k} \cdot \left(1-\frac{E_{1k}}{N_k}\right)}$ where k is the index of the group. /14/

O_{1k} and E_{1k} symbolise the number of observed cases with y=1 and that of expected cases with y=1 in the k[th] group. N_k stands for the total number of observations (both y=0 and y=1) in the k[th] group, and their sum is equal to n.

The p-value represents the following probability:

$p = \Pr(\chi^2 \geq \chi_{HL}^2)$ where the number of degrees of freedom is set to ν=g-2. /15/

Testing the null hypothesis of zero beta coefficients relies on the z^2 distribution, which is a chi-square distribution with the number of degrees of freedom equalling 1:

$$Wald_k = \hat{\beta}_k^2 \Big/ s_{\hat{\beta}_k}^2 \quad \text{where k=0, 1, …, m.} \qquad /16/$$

Probit analysis applies the cumulative distribution function of the standard normal distribution; transforms the sum of the intercept and the products of beta coefficients and predictors into a value between 0 and 1. The expected response $\hat{y}$ can be calculated as shown below:

$$\hat{y} = \Phi\left(\hat{\beta}_0 + \sum_{i=1}^{m} \hat{\beta}_i \cdot x_i\right) = \Phi\left(\underline{\hat{\beta}}^T \cdot \underline{x}\right) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\underline{\hat{\beta}}^T \cdot \underline{x}} e^{-\frac{z^2}{2}} dz \qquad /17/$$

By denoting the sample size with n, the Pearson goodness-of-fit test is a chi-square test whose test statistic is given by:

$$\chi^2 = \sum_{j=1}^{n} \frac{(y_j - \hat{y}_j)^2}{\hat{y}_j \cdot (1 - \hat{y}_j)} \qquad /18/$$

The null hypothesis of good model fit can be declined if the test statistic exceeds the right-tailed value of $\chi^2_{1-\alpha}(\nu)$, where α is the significance level and ν is the number of degrees of freedom determined as ν=n-m-1.

In addition to the previous techniques, an **artificial neural network** method was designed *(IBM, 2016, pp. 607–616).* It is a machine learning method fit to be applied for regression, too. The multilayer perceptron is a feedforward, supervised learning network, a function of one or more predictors that minimises the prediction error of the dependent variable. The general architecture of multilayer perceptron networks consists of the input layer, the hidden layer(s), and the output layer. SPSS restricts the number of possible hidden layers to two and offers three activation functions (hyperbolic tangent, sigmoid, and identity). The next notation was introduced: **x** vector of the predictors, *p* number of the independent variables, *q* number of the neurons in the 1st hidden layer, *r* number of the neurons in the 2nd hidden layer, *f* activation function of the hidden layer(s), *g* activation function of the output layer, *y* output, **w** matrix or vector of the synaptic weights (parameter estimates), b_0 scalar, and **b**, $\mathbf{b_1}$, or $\mathbf{b_2}$ vector of the parameter estimates for the biases (intercepts) in the 1st or 2nd hidden layer. The following formulae enable the calculation of the dependent variable:

Hyperbolic tangent: $h(x) = \tanh x = \frac{e^x - e^{-x}}{e^x + e^{-x}}$ /19/

Sigmoid: $h(x) = \frac{1}{1+e^{-x}}$ /20/

Identity: $h(x) = x$ /21/

The dependent variable for one hidden layer can be determined as follows:

$$y = g\left[\sum_{j=1}^{q} \mathbf{w}(\mathrm{j}) \cdot f\left(\sum_{i=1}^{p} \mathbf{w}(\mathrm{i},\mathrm{j}) \cdot \mathbf{x}(\mathrm{i}) + \mathbf{b}(\mathrm{j})\right) + b_0\right] \qquad /22/$$

In the case of two hidden layers:

$$y = g\left\{\sum_{k=1}^{r} \mathbf{w}(\mathrm{k}) \cdot f\left[\sum_{j=1}^{q} \mathbf{w}(\mathrm{j},\mathrm{k}) \cdot f\left(\sum_{i=1}^{p} \mathbf{w}(\mathrm{i},\mathrm{j}) \cdot \mathbf{x}(\mathrm{i}) + \mathbf{b_1}(\mathrm{j})\right) + \mathbf{b_2}(\mathrm{k})\right] + b_0\right\} \qquad /23/$$

The relative error is defined by the formula below (n is the sample size):

$$RE = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} = \frac{SSE}{SST} \qquad /24/$$

The normalised importance of the independent variables is computed in two steps. First, the average of the highest distances is determined for each predictor i=1, 2, …, p by denoting $S_i = \{x_i^{min}, \dots, x_i^{max}\}$ when using the input vector of the jth case: $\mathbf{x}_j = \left(x_j^1, \dots, x_j^{i-1}, x_j^{ik}, x_j^{i+1}, \dots, x_j^p\right)$:

$$d_i = \frac{1}{n} \cdot \sum_{j=1}^{n} \max_{x_{i1}, x_{i2} \in S_i} abs\left(\hat{y}_j^{i1} - \hat{y}_j^{i2}\right) \qquad /25/$$

Second, the normalised importance – as a relative indicator – is set to:

$$NI_i = \frac{d_i}{max(d_1,\dots,d_p)} \text{ where i=1, 2, …, p.} \qquad /26/$$

Both Kolmogorov-Smirnov and Shapiro-Wilk tests were applied for testing for normal distribution. The null hypothesis of the normal distribution can be declined in each case. For this reason, the results of independent samples z-, t- or Welch tests are not valid for comparing means. The asymptotic independent samples z-test *(Hunyadi et al., 2000, pp. 468–469)* proves to be a viable alternative for testing the equality of means thanks to the lack of such a prerequisite. This test requires merely finite standard deviations and large (sub)samples. In this study, (sub)sample sizes are above 600. A series of null hypotheses ($H_0: \bar{y} - \bar{x} = 0$) with the one-sided alternative hypotheses ($H_1: \bar{y} - \bar{x} > 0$) was carried out by dint of the formula of the asymptotic independent samples z-test. On the one hand, $\bar{y}$ denotes the higher value in question, and $\bar{x}$ refers to the corresponding lower value; on the other hand, $\delta_0 = 0$. Under the square root stand variances (s^2) and sample sizes (n) as specified in the formula below:

$$Z = \frac{\bar{y}-\bar{x}-\delta_0}{\sqrt{\frac{s_Y^2}{n_Y}+\frac{s_X^2}{n_X}}} \to N(0,1) \qquad /27/$$

3. Findings

In order to reproduce the timeshare of preferred travel modes ranging between 0 (0%) and 1 (100%), OLS linear regression, binary logistic regression, probit analysis, and an artificial neural network method proved to be the most appropriate technique. For the sake of comparability amongst these four methods, TIME_SHARE_PREF_MODE was selected as the dependent variable without standardisation, while the predictors were uniformly standardised variables in each run.

The analysis begins with the simplest technique, i.e. OLS linear regression. First, making use of the highest possible number of regressors (33 out of 38) limited the circle of countries to Hungary, Norway, and Poland. Second, the investigation was restricted to the respective five national datasets. In order to determine the final models, an algorithm was utilised by removing the records from the datasets that met at least one of the four criteria below *(Kovács, 2014, pp. 96, 99–101)*:

a) The standardised residual is outside 3 standard deviations, here [–3, +3], as reported in the casewise diagnostics.
b) The Cook's Distance exceeds 1.
c) The estimation can be considered risky if the Centred Leverage Value is above 0.2.
d) Observations with a covariance ratio below 1–3p/n or above 1+3p/n require special attention.

In general, a model may be considered final if further cleaning of the dataset does not result in a better model fit and/or the subsequent model demonstrates anomalies (e.g. the stepwise variable selection estimates the number of four-wheel electric vehicles with a negative beta parameter). When evaluating candidate models, a unified decision rule was not applicable; therefore, the model selection relies on different approaches, as described below.

Merged (Hungary, Norway, Poland): The run with the first local maximum of the adjusted R square was considered final, regardless of the number of standardised residuals outside 3 standard deviations.

Hungary: It was chosen considering that the adjusted R square exceeds 40% and the results are reasonably interpretable irrespective of the presence of standardised residuals outside 3 standard deviations.

Norway: The proportionally most abruptly waning sample size argued for achieving the first local minimum of the numbers of standardised residuals outside 3 standard deviations. In this particular case, the adjusted R square does not qualify as a local maximum.

Poland: The algorithm terminated when the first local maximum of the adjusted R square without any standardised residuals outside 3 standard deviations was attained.

Italy: Similarly, the first local maximum of the adjusted R square was sought, but the number of standardised residuals outside 3 standard deviations was disregarded.

Spain: The objective was simplified to obtain the first local maximum of the adjusted R square, as the issue of standardised residuals outside 3 standard deviations arose in none of the cases.

Table A1 in the Appendix recapitulates common phenomena and contrasts prevailing country specificities. Contradictory coefficients are marked with bold font type.

In spite of the effort to find models conform with reality and environmentally conscious consumer behaviour, four paradoxes can be identified from the models based on OLS linear regression. These are denoted with (i)-(iv). The intercept can be interpreted as a systemic starting point, where Spain occupies the most propitious position regarding the timeshare of preferred travel modes (71.2%), whereas Italy represents the opposite pole (44.1%). The lack or a low number of four-wheel traditional vehicles (petrol cars, diesel cars, methane-fuelled cars, LPG-fuelled cars[3], vans, trucks, caravans) is salutary in each country; however, its impact deviates substantially to the disadvantage of Hungary and Poland. Attempting to reduce cost or attributing less importance to flexibility promotes environmentally friendly transport (e.g. public vehicles, bicycles, walking). Supporting government actions affecting the transport system (e.g. reducing emissions, creating bike lanes), satisfaction with transport facilities (e.g. public transport, public bike-sharing and car-sharing), and consuming less energy thanks to environmentally friendly alternatives (e.g. public transport, car-sharing, biking) imply a more elevated level of environmental awareness. Socioeconomic characteristics such as employment status in favour of economically less active persons or gender in favour of women can contribute to greening mobility. (i) The first paradox is that the more a Hungarian agrees with negative statements about environmental issues (i.e. the readiness for acting now or making compromises in current lifestyle decreases), the higher the timeshare of preferred travel modes becomes. In contrast, the interrelationship in the case of Italy is exempt from it. Those who want to reduce CO_2 emissions give priority to greener travel modes. The wish for more availability supports the ownership of a vehicle with fossil fuel combustion; see the negative coefficient of Italy. (ii) Paradoxically, in Norway, the augmenting importance attributed to the availability of travel methods moderates the role of individual vehicles with fossil fuel combustion, presumably due to electric vehicles as a consequence of their high penetration. If travel time matters, the share of more air polluting modes is expected to rise, as in Norway. (iii) Nonetheless, in Poland, those who are evaluating travel time with a higher priority opt to a greater extent for preferred travel modes. The type of residence area can be a hindrance in the sense that living in rural areas can be coupled with less access to greener alternatives. (iv) As the fourth contradiction, the more citizens suffer from traffic problems (e.g. congestion, noise, local air quality), the less they travel by conveyances causing less environmental load. This assertion is valid for Poland and Spain. Assessing the infrastructure development positively over the last 3 years increases the inclination to choose public transport or electric vehicles, ride a bicycle, or walk. Both the number of two-wheel traditional vehicles (motorcycles, scooters, and non-electric bicycles) and that of four-wheel electric vehicles (electric cars and hybrid cars) are drivers. Younger customers are more likely to consider environmental concerns when making decisions about mobility. The good reputation of the methods of travel (e.g. public transport or electric

[3] LPG stands for liquefied petroleum gas.

vehicles) as an influencer may help in spreading attitudes beneficial for both nature and social well-being. Last but not least, financial difficulties support the transition, by renouncing the use of individual vehicles with fossil fuel combustion.

Binary logistic regression was performed by opting for the forward stepwise method based on conditional statistics. Only a subset of TIME_SHARE_PREF_MODE, i.e. the records, which equal 1 or 0, was apt for analysis. The algorithm applied to obtain the final model can be described as follows:

a) Primary criterion: The equation contains regressors and an intercept only if their beta coefficient can be considered significant at the 5% level. In addition, the null hypothesis of the Hosmer and Lemeshow test cannot be rejected.
b) If the primary criterion is met, the outliers outside 3 standard deviations have to be removed, and testing for the primary criterion is repeated.

The iteration is terminated when both criteria are fulfilled; hence, the final model is the first run with mere significant coefficients and an empty casewise list of standardised residuals. Table A2 in the Appendix aligns the results of the specific models. Again, bold font type refers to paradoxes.

By deviating from the OLS linear regression models, Polish (best) and Norwegian (worst performing) citizens occupy the two extreme positions regarding the intercept. Hungarians adhere the most to four-wheel traditional vehicles, while Spaniards are the most inclined to switch to more environmentally friendly alternatives even if they possess this type of vehicle. Possessing two-wheel traditional vehicles, considering travel cost and CO_2 emissions, supporting government actions affecting the transport system, and evaluating the household's current income less favourably exercise a positive impact. The unidirectional influence of flexibility varies between countries by cutting back on the timeshare of preferred travel modes, most strikingly in Poland. In contrast, if Polish customers are ready to consume less energy thanks to environmentally friendly alternatives, a higher timeshare can be achieved compared to their Hungarian counterparts. Negative assessment of infrastructure development, less urban type of residence area, attributing relevance to travel time, reputation, and availability of travel modes, and growing older are curbing the spread of environmentally friendly mobility. Being economically less active is an enabler, the gap between the economically active and inactive status is the narrowest in the case of Spanish citizens. Based on both the merged and Hungarian datasets, being female is nearly equivalent to consuming less energy thanks to environmentally friendly alternatives, while in Poland, the impact of the gender gap is moderated. The judgement of the safety of travel methods has conflicting effects: Polish people evaluate environmentally friendly mobility as safer both in direction and intensity than Hungarians. One of the previous paradoxes repeats itself: the more Polish individuals are confronted by the severity of traffic problems, the less the share of preferred travel modes becomes. In Norway, having four-wheel electric vehicles has the highest positive coefficient, which is only half of the absolute value of the coefficient of traditional four-wheelers (see a similar relationship in Table A1 in the Appendix amongst the linear regression models in the case of Italy). A possible interpretation of the Norwegian model is that without further support, the spread of electric cars purchased by individuals may not be the salvation in case of environmental problems stemming from transport. In addition, policymakers must reduce the time needed for travel with vehicles with less CO_2 emissions, improve their flexibility and reputation, and continue to widen the network of and increase access to environmentally friendly mobility in rural areas, according to the results.

The probit analysis was carried out in such a way that, first, the enter method was applied by relying on the maximum number of independent variables in order to select the regressors bearing significant beta parameters at the significance level of 10%. Second, the run was repeated by involving these significant predictors and keeping the enter method. The loop terminated when the model contained solely variables with significant beta coefficients at the significance level of 5%. Table A3 in the Appendix summarises the main results. No contradictions were detected. The constant is by default included in the equations, and SPSS does not enable running models without intercepts. The final model based on the algorithm cannot be considered valid neither for the merged dataset due to the declined null hypothesis of good model fit nor for the Hungarian sample because of the insignificant intercept (see the concerned values marked with bold font type). For this reason, these models are only disclosed but not interpreted.

The results of the probit analysis demonstrate many analogies with those of both the OLS linear regression and binary logistic regression. Considering the cumulative distribution function of the standard normal distribution helps in the interpretation of the beta parameters. Italy has the lowest average (42.2%, see Table 2), which provides an argument for its negative intercept. Four-wheel traditional vehicles function as the most important disabler, especially in Poland. Supporting government actions affecting the transport system (e.g. more attractive public transport) and consuming less energy thanks to environmentally friendly alternatives (e.g. abandoning the use of cars with fossil fuel combustion) propel the greening of the sector. Employment status proved to be the most important enabler in favour of economically less active persons, similar to binary logistic regression. As perceived in the relationship in earlier cases, driving four-wheel electric vehicles improves the timeshare of preferred travel modes, but it lags far behind the four-wheel traditional vehicles in outstripping their impact according to the model of Italy. Nevertheless, individual fossil fuel consumption comes in the foreground when paying more attention to the availability of methods of travel or travel time.

Subsequently, multilayer perceptron networks explored the most important factors by executing the algorithm as follows:

a) Carrying out all combinations of available settings offered by SPSS (number of hidden layers /1, 2/, activation function for the hidden layer(s) /hyperbolic tangent, sigmoid/, activation function for the output layer /hyperbolic tangent, sigmoid, identity/) based on the full dataset by entering 33 variables (see the description under OLS linear regression) into each model resulted in a total of 2·2·3=12 runs. Batch training with the scaled conjugate gradient optimisation algorithm and a training-test ratio of 100%-0% were applied.[4]
b) By making use of the decision rule of the lowest relative error, the architecture with (i) two hidden layers, (ii) the hyperbolic tangent activation function for the hidden layers, and (iii) the identity activation function for the output layer was selected as the most appropriate model, which was fixed for further runs.
c) The run was repeated on the trimmed dataset. The attribute 'trimmed' is used in the sense of keeping only the records whose residual is less than 0.2 in absolute value.
d) Country-specific runs based on trimmed datasets terminated the investigation by applying the previous rule for eliminating records.

Table A4 in the Appendix contains the normalised importance of all predictors by enabling cross-country comparisons so that country-specific phenomena can be identified. The percentages confirm the position of Norway as a forerunner, as it succeeded in interrupting the hegemony of four-wheel traditional vehicles as the most important influencer.

By setting a hypothetical minimum requirement of 40% for the normalised importance irrespective of countries (provided that the aspect is applicable and not counting the merged case of Hungary and Poland), (i) the number of four-wheel traditional vehicles, (ii) the assessment of infrastructure development, (iii) purchasing cars or motors from public means, (iv) supporting government actions affecting the transport system, (v) ascribing importance to the safety of travel methods, and (vi) making use of bike-sharing constitute the circle of the main common determinants of environmentally friendly mobility. The variables attaining at least 80% normalised importance in one of the countries as salient

[4] The reason for opting for 100%–0% was the fact that the application of various training-test ratios (90%–10%, 80%–20%, 70%–30%) did not improve the fit of the model.

influencers are the number of both (i) four-wheel traditional and (ii) four-wheel electric vehicles, (iii) the most typical current employment status, (iv) the severity of traffic problems, (v) placing emphasis on CO_2 emissions, (vi) the type of residence area, and (vii) utilising bike-sharing from the remaining predictors. The example of Norway suggests that factors such as the increasing endeavour of pairing down CO_2 emissions in mobility decisions and, correspondingly, both residential four-wheel electric vehicles and bike-sharing options will gain importance in the course of greening the transport sector.

4. Discussion

RQ: Based on the experiences gained in Hungary, Italy, Norway, Poland, and Spain, and the timeshare of preferred travel modes, what are the main influencing factors of residential routine mobility choices promoting public transport, electromobility, mobility sharing business models, biking, walking, and further environmentally friendly mobility solutions?

Table A5 in the Appendix shows the runs and clearly contrasts the results of valid models relying on different methods. The column of inconsistency indicates whether the variable in question is influenced by paradoxes, ambivalent impacts, or model dissimilarities along techniques.

Without reiterating the earlier disclosed interpretations, Table A5 in the Appendix outlines that seven areas form the intersection of the results through the lens of consistency:

(i) discouraging the possession (and use) of four-wheel traditional vehicles,
(ii) promoting the purchase of four-wheel electric vehicles,
(iii) raising awareness about CO_2 emissions so that individuals include this aspect in their mobility decisions,
(iv) supporting government actions affecting the transport system (e.g. by means of better communication),
(v) assessing the infrastructure development over the past couple of years in a positive way,
(vi) targeting and convincing employed people of the benefits of environmentally friendly mobility,
(vii) turning towards less urbanised territories and improving their access to green mobility.

Certain socioeconomic determinants, such as age, gender, completed studies, employment status, income, and residence, are present in the research of *Echeverria et al. (2022a, pp. 255–258)*, *Herberz et al. (2020, p. 108)*, and *Hudde (2022, p. 5)*. In addition, *Herberz et al. (2020, p. 108)* pointed to the role of environmental, financial, independence (here availability), and safety motives. Concordant with Table A5 in the Appendix, *Enzler–Diekmann (2019, p. 17)* concluded that income, economically active status, and owning traditional cars increase GHG emissions arising from mobility, while having environmental concerns (in this case, CO_2 emissions) and being female reduce them. Higher ages and living in a less urbanised area entail less GHG emissions, contrary to the findings related to the timeshare of preferred travel modes, by bearing in mind the dissimilarities between the two indicators. From a broader perspective, the low number of traditional four-wheelers and considering CO_2 emissions underpin the conclusions of *Briguglio–Formosa (2023, p. 12)* regarding car-sharing. By drawing on *Ko et al. (2021, p. 7)*, determinants of using shared mobility are car (non-)ownership, gender, and the satisfaction of such services (here a subset of SATIS_TRANS). *Oleskow-Szlapka et al. (2020, p. 14)* mentioned the improvement of public transport through investments, which is embodied in the score of supporting government actions affecting the transport system from an ecological viewpoint. Both *Kopplin et al. (2021, pp. 3, 11)* and *Marquart–Schuppan (2022, p. 6)* dealt with CO_2 emissions or environmental concerns. The aforementioned authors enumerated convenience (here to be interpreted as the mixture of time, flexibility, and availability), safety, traffic congestion and noise (see SEV_TRAF_PROB), and shortcomings in both parking spaces and public transport (as part of SATIS_TRANS). One of the technological advancements *(Petrauskiene et al., p. 3)* is manifested in four-wheel electric vehicles. *D'Adamo et al. (2023, p. 848)* ranked purchase cost as the most critical factor in buying an electric car. Based on the ambivalent impact of reputation, the present study does not confirm that purchasing an electric vehicle can be a green band response *(Risitano et al., 2023, pp. 1105–1107)*. The supply side (here the ambivalent availability) and business models (in the results restricted to bike-sharing) formed part of the conceptual framework of *ten Dam et al. (2022, p. 65)*.

In order to explore the role of destination in mobility decisions, the general destination-independent approach is replaced by the destination-specific best practice, i.e. the case with the highest mean of timeshares. This is represented by Spain if the destination is leisure activities. Neither OLS linear regression nor probit analysis produced adequate models apt for use in merit. By applying the previous algorithm related to linear regression and keeping at least 55% of the records of the initial dataset, a low adjusted R^2, a non-informative model due to an intercept above 0.9, and the persistent presence of outliers in the dataset caused the failure. In the case of probit analysis, a model with one single significant predictor (agreeing with negative statements about environmental issues) and a significant intercept at the significance level of 5% was generated. Carrying out binary logistic regression repeated quasi-identical results (both in composition and coefficients) with those computed for the general timeshare of preferred travel modes: the number of four-wheel traditional vehicles and the score expressing the support of government actions affecting the transport system as independent variables complemented with an intercept. As the partial correct classification rate related to y=0 is slight (6.8%), this model is not appropriate for classification. The results of multilayer perceptron networks elucidate that general attitudes change when Spanish citizens travel to the location of their leisure activities, as shown in Table A6 in the Appendix. In addition, it contains the figures related to the other destinations, but these are no more interpreted.

Regarding leisure activities, at least a 15% point improvement (marked with bold font type) in normalised importance can be captured in the field of (i) supporting government actions affecting the transport system, (ii) agreeing with negative statements about environmental issues, (iii) the role of safety and (iv) flexibility in mobility decisions, (v) benefitting from a financial subsidy, and (vi) having four-wheel electric vehicles. Owning two-wheel electric vehicles and ascribing importance to the reputation of travel methods demonstrated at least the same level of shrinking (see figures written in italic font type) of the normalised importance. As Table A6 in the Appendix demonstrates, the normalised importance may vary in the function of the destination.

5. Conclusion, limitations, and further research

By performing OLS linear regression, enablers of green mobility are lower travel fares (decision based on cost), more supportive stance on government actions affecting the transport system, higher satisfaction with transport facilities, less energy consumption thanks to environmentally friendly alternatives, an economically less active employment status, being female, occupying a supportive position regarding environmental issues, considering CO_2 emissions and the reputation of preferred travel modes, citizens dwelling in urban areas, positive assessment of infrastructure development, possessing four-wheel electric and two-wheel traditional vehicles, younger age groups, and financial difficulties shifting people towards less air polluting modes. In contrast, the number of four-wheel traditional vehicles, less flexibility, less availability, and more travel time of preferred travel modes hinder the expansion of environmentally friendly transport. The impact of a few variables (e.g. owning four-wheel traditional vehicles) and the intercept deviates considerably amongst countries. The investigation revealed a few paradoxes, such as the way the severity of traffic problems is evaluated.

Binary logistic regression models demonstrated bold dissimilarities in the systemic initial point, the curbing impact of both possessing four-wheel traditional vehicles and the attachment to the flexibility of travel methods; furthermore, there were beneficial implications of the triad of consuming less energy thanks to environmentally friendly alternatives, economically less active status, and being female. By applying this technique, the safety of travel methods as the sole predictor proved to have conflicting effects. Additional enablers are having both two-wheel traditional and four-wheel electric vehicles, finding travel cost and CO_2 emissions important, supporting government actions affecting the transport system, and encountering financial difficulties with regard to the household's current income. Conversely, disregard of infrastructure development, considering traffic problems more seriously, less urban type of residence area, accentuation of travel time, reputation, and availability of travel modes, and increasing age are slowing down the spread of environmentally friendly mobility.

Probit analysis demonstrated that the intensity of supporting government actions affecting the transport system, consuming less energy thanks to environmentally friendly alternatives, shifting towards an economically less active employment status, and having four-wheel electric vehicles are determinants with a positive impact. Possessing four-wheel traditional vehicles and the increasing role of both availability and travel time related to travel modes exercise a negative influence. In addition, noteworthy differences can be perceived in the systemic initial point: Italy and Spain represent the two opposite poles.

Multilayer perceptron networks revealed, based on the normalised importance, that the number of four-wheel traditional vehicles, the assessment of infrastructure development, purchasing cars or motors from public means, supporting government actions affecting the transport system, ascribing importance to the safety of travel methods, and making use of bike-sharing can be considered as the six main country-independent factors. In addition, the set of country-specific outstanding determinants consists of the number of four-wheel electric vehicles, the most typical current employment status, how severe traffic problems are perceived, the impact of CO_2 emissions on mobility decisions, and the type of residence area, complemented with the intersection of the two lists: number of four-wheel traditional vehicles and bike-sharing.

The general assertion that disablers can be transformed into enablers is valid in each case (e.g. enhancing the availability of public transport lines outside peak hours through an improved frequency and reducing the travel time by means of express bus lines and dedicated traffic lanes).

The results have some limitations. The set of predictors may not contain relevant variables. Such unobserved variables can be, e.g. values of the reference group related to owning four-wheel vehicles, objective circumstances such as health impairment, average number of passengers in four-wheel vehicles, professions requiring immediate access in emergency, impact of travel modes on health, and availability of alternative greener travel modes. The objective was the comparison of beta coefficients between both variables and methods; therefore, no interactions between variables were considered (e.g. interaction between gender and air quality impact or between employment status and company car). Further model types (e.g. quadratic) may improve the fit of the model. The dataset may bear deficiencies, e.g. the low proportion of positive or affirmative answers in the case of specific variables of blocks M6 and M7. The commencement of the survey dates back to 2016; hence, the proliferation of preceding alternative electric or new electric vehicles such as Segways, unicycles, skateboards (e.g. hoverboards), skates, wheelchairs, furthermore, niche markets covering any type of water transport (e.g. motorboats) and air transport vehicles (e.g. planes of Texel, the largest Wadden Island in the Netherlands) owned by citizens were out of the scope of the survey. None of the questions targeted explicitly the national or international nature of travel. By estimating the total travel distance per week expressed in kilometres, it can be assumed that mostly urban and national interurban passenger transport was investigated. Less than 30 respondents indicated a total travel distance per week exceeding 1,000 km, which may qualify as national interurban transport in large countries such as Norway or as international transport in the case of persons residing in countries such as Hungary. The section on mobility did not consider holiday travels, while these holiday trips (especially by aeroplane) may cause a considerable part of the individual carbon footprint and thus could offer leeway for reduction. The weak fit of certain models, paradoxes, ambivalent impacts, and model dissimilarities along techniques mitigate validity. The sample cannot be considered representative, e.g. the citizens of Budapest are overrepresented based on the real distribution of the resident population *(HCSO, 2023b)*. Finally, as country-specific phenomena prevail and the validity of assertions is restricted to the investigated countries, their broader applicability should be treated with reservation.

Within electromobility, a future research opportunity could be the spread of both four-wheel and two-wheel electric vehicles in the circle of residuals investigated from a broader perspective of environmentally conscious consumer behaviour (e.g. involving the section on prosuming or heating and cooling habits).

Mobility impacts the future development of societal well-being, environmental health, economic prosperity, and science. Deploying green and smart technologies in a citizen- and nature-centred way (e.g. social inclusiveness, improving the share of active modes as a remedy for sedentary lifestyles), engaging public opinion, and fading the hegemony of traditional vehicles with fossil fuel combustion promise to take the most benefit out of the mobility turn. By anticipating the future of carbon-neutral vehicles, the aspect of energy intensity may lose its relevance as a consequence of harnessing inexhaustible energy sources. Autonomous vehicles may reshape the mobility scene into driverless roads, and by taking flight, urban air mobility may revolutionise human transport (e.g. shorter distances, higher speed, lack of congestion, no need for a built road network and its costly maintenance). By applying pro-environmental motivators, residential routine mobility can be transformed into regular active enjoyment with a plethora of benefits.

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Appendix

Table A1

Coefficients of the OLS linear regression models, cases excluded listwise, method: stepwise, dependent variable: TIME_SHARE_PREF_MODE

Countries involved in the final model	Merged (HU, NO, PL)			Hungary			Norway		
Initial set of independent variables	33			33			32[a)]		
Adjusted R square (%)	38.55			40.27			47.57		
Final sample size	585			364			86		
Number of regressors in the final model	8			6			5		
Variable	Beta	t-test	Sig.	Beta	t-test	Sig.	Beta	t-test	Sig.
Intercept	0.576	33.383	0.000	0.491	26.337	0.000	0.560	15.137	0.000
Zscore(NUM_FOUR_WHEEL_TRAD_VEH)	–0.265	–12.820	0.000	–0.332	–12.033	0.000	–0.136	–3.021	0.003
Zscore(M5_cost)	0.071	4.618	0.000	0.069	3.480	0.001			
Zscore(M5_flexibility)	–0.081	–5.022	0.000	–0.088	–3.994	0.000			
Zscore(SCORE_TRANS_SYS)	0.055	3.605	0.000				0.155	4.200	0.000
Zscore(SATIS_TRANS)	0.058	4.014	0.000						
Zscore(LESS_ENERGY_CONS)	0.064	3.357	0.001						
Zscore(S3-employment status)	0.080	5.028	0.000						
Zscore(S5-gender)	0.063	4.508	0.000	0.079	4.614	0.000			
Zscore(AGR_NEG_STAT)				**0.058**	2.703	0.007			
Zscore(M5_CO_2_emissions)				0.077	3.650	0.000			
Zscore(M5_availability)							**0.083**	2.222	0.029
Zscore(M5_time)							–0.128	–3.217	0.002
Zscore(S6-type of residence area)							–0.095	–3.052	0.003
Zscore(SEV_TRAF_PROB)									
Zscore(ASSESS_INFRASTR)									
Zscore(NUM_TWO_WHEEL_TRAD_VEH)									
Zscore(NUM_FOUR_WHEEL_ELEC_VEH)									
Zscore(age_2019)									
Zscore(M5_reputation)									
Zscore(S8-subjective evaluation of household's current income)									

(Table continues on the next page.)

(Continued.)

Countries involved in the final model	Poland			Italy			Spain		
Initial set of independent variables	33			28b)			28c)		
Adjusted R square (%)	53.00			23.37			38.20		
Final sample size	149			406			242		
Number of regressors in the final model	8			7			7		
Variable	Beta	t-test	Sig.	Beta	t-test	Sig.	Beta	t-test	Sig.
Intercept	0.707	16.006	0.000	0.441	20.441	0.000	0.712	34.386	0.000
Zscore(NUM_FOUR_WHEEL_TRAD_VEH)	–0.218	–5.837	0.000	–0.130	–5.772	0.000	–0.081	–3.800	0.000
Zscore(M5_cost)									
Zscore(M5_flexibility)	–0.155	–3.975	0.000						
Zscore(SCORE_TRANS_SYS)	0.090	2.720	0.007				0.118	6.314	0.000
Zscore(SATIS_TRANS)									
Zscore(LESS_ENERGY_CONS)	0.159	4.417	0.000	x			x		
Zscore(S3-employment status)	0.147	5.161	0.000	0.124	7.199	0.000	0.085	4.172	0.000
Zscore(S5-gender)									
Zscore(AGR_NEG_STAT)				–0.056	–2.735	0.007			
Zscore(M5_CO_2_emissions)									
Zscore(M5_availability)				–0.057	–3.223	0.001			
Zscore(M5_time)	**0.095**	2.725	0.007						
Zscore(S6-type of residence area)							–0.100	–5.492	0.000
Zscore(SEV_TRAF_PROB)	**–0.152**	–3.224	0.002				**–0.107**	–6.068	0.000
Zscore(ASSESS_INFRASTR)	–0.087	–4.113	0.000	x			x		
Zscore(NUM_TWO_WHEEL_TRAD_VEH)				0.042	2.316	0.021			
Zscore(NUM_FOUR_WHEEL_ELEC_VEH)				0.056	2.951	0.003			
Zscore(age_2019)				–0.048	–2.735	0.007			
Zscore(M5_reputation)							0.077	3.795	0.000
Zscore(S8-subjective evaluation of household's current income)							0.042	2.650	0.009

a) M7_financial_subsidy was discarded.
b) The five removed variables are LESS_ENERGY_CONS, PUBLIC_FIN_VEH, ASSESS_INFRASTR, PREF_TREAT_CARS, and NAT_POL_EFF.
c) The five removed variables coincide with those listed under the previous footnote.

Table A2

Coefficients of the binary logistic regression models, method: forward – conditional, dependent variable: TIME_SHARE_PREF_MODE with 0 and 1 values

Countries involved in the final model	Merged (HU, PL)			Hungary			Norway		
Initial set of independent variables	32[a)]			31[b)]			27[c)]		
Cox & Snell R square (%)	56.54			58.03			58.06		
Nagelkerke R square (%)	75.38			77.38			78.82		
Hosmer and Lemeshow test (p-value)	0.618			0.175			0.558		
Partial correct classification rate related to y=0 (%)	84.91			90.23			80.36		
Partial correct classification rate related to y=1 (%)	88.37			89.73			93.26		
Total correct classification rate (cut value=0.5) (%)	86.94			89.94			88.28		
Final sample size	513			318			145		
Number of regressors in the final model	10			9			7		
Variable	Beta	Wald	Sig.	Beta	Wald	Sig.	Beta	Wald	Sig.
Intercept	x	x	x	x	x	x	–1.532	5.386	0.020
Zscore(NUM_FOUR_ WHEEL_TRAD_VEH)	–3.783	79.245	0.000	–4.924	45.822	0.000	–3.088	14.786	0.000
Zscore(NUM_TWO_ WHEEL_TRAD_VEH)	0.668	13.534	0.000	0.812	12.066	0.001			
Zscore(M5_cost)	0.412	4.812	0.028	0.795	10.286	0.001			
Zscore(M5_flexibility)	–1.013	26.343	0.000	–0.807	10.318	0.001	–1.340	5.757	0.016
Zscore(SCORE_TRANS_ SYS)	0.561	9.343	0.002	0.796	11.515	0.001			
Zscore(LESS_ENERGY_ CONS)	0.856	19.165	0.000	0.801	8.656	0.003			
Zscore(ASSESS_ INFRASTR)	–0.390	8.144	0.004						
Zscore(S3-employment status)	1.122	38.217	0.000	0.927	14.392	0.000			
Zscore(S5-gender)	0.834	24.642	0.000	0.879	15.802	0.000			
Zscore(S8-subjective evaluation of house-hold's current income)	0.712	11.923	0.001						
Zscore(M5_safety)				–0.578	4.674	0.031			
Zscore(SEV_TRAF_PROB)									
Zscore(S6-type of residence area)							–1.563	15.016	0.000
Zscore(NUM_FOUR_ WHEEL_ELEC_VEH)							1.580	11.297	0.001
Zscore(M5_time)							–1.014	5.354	0.021
Zscore(M5_ CO_2 emissions)							0.672	3.920	0.048
Zscore(M5_reputation)							–1.573	7.856	0.005
Zscore(M5_availability)									
Zscore(age_2019)									

(Table continues on the next page.)

(Continued.)

Countries involved in the final model	Poland			Italy			Spain		
Initial set of independent variables	31[d)]			27[e)]			27[f)]		
Cox & Snell R square (%)	56.55			39.39			16.32		
Nagelkerke R square (%)	76.64			56.99			25.43		
Hosmer and Lemeshow test (p-value)	0.105			0.271			0.707		
Partial correct classification rate related to y=0 (%)	87.65			93.69			24.49		
Partial correct classification rate related to y=1 (%)	91.27			69.05			97.30		
Total correct classification rate (cut value=0.5) (%)	89.86			86.93			82.05		
Final sample size	207			306			234		
Number of regressors in the final model	8			4			3		
Variable	Beta	Wald	Sig.	Beta	Wald	Sig.	Beta	Wald	Sig.
Intercept	2.500	21.237	0.000	–1.007	26.300	0.000	1.397	53.090	0.000
Zscore(NUM_FOUR_ WHEEL_TRAD_VEH)	–3.159	28.982	0.000	–1.937	37.722	0.000	–0.742	12.930	0.000
Zscore(NUM_TWO_ WHEEL_TRAD_VEH)									
Zscore(M5_cost)									
Zscore(M5_flexibility)	–1.921	15.123	0.000						
Zscore(SCORE_TRANS_ SYS)							0.685	13.323	0.000
Zscore(LESS_ENERGY_ CONS)	1.388	15.329	0.000						
Zscore(ASSESS_INFRASTR)									
Zscore(S3-employment status)	1.607	25.928	0.000	1.462	49.515	0.000	0.776	12.221	0.000
Zscore(S5-gender)	0.542	4.279	0.039						
Zscore(S8-subjective evaluation of house-hold's current income)									
Zscore(M5_safety)	1.043	6.734	0.009						
Zscore(SEV_TRAF_PROB)	**–1.069**	5.224	0.022						
Zscore(S6-type of residence area)	–1.380	10.153	0.001						
Zscore(NUM_FOUR_ WHEEL_ELEC_VEH)									
Zscore(M5_time)									
Zscore(M5_CO_2_emissions)									
Zscore(M5_reputation)									
Zscore(M5_availability)				–0.665	13.759	0.000			
Zscore(age_2019)				–0.842	19.592	0.000			

a) SATIS_TRANS was discarded.
b) NUM_TWO_WHEEL_ELEC_VEH and SATIS_TRANS were discarded.
c) NUM_TWO_WHEEL_TRAD_VEH, AGR_NEG_STAT, M6_company_car, M7_financial_subsidy, SATIS_TRANS, and PREF_TREAT_CARS were discarded.
d) SATIS_TRANS and S8 were discarded.
e) The six removed variables are SATIS_TRANS, LESS_ENERGY_CONS, PUBLIC_FIN_VEH, ASSESS_INFRASTR, PREF_TREAT_CARS, and NAT_POL_EFF.
f) The six removed variables are identical with those enumerated in the previous footnote.

Table A3

Coefficients of the probit models, method: enter, dependent variable: TIME_SHARE_PREF_MODE

Countries involved in the final model	Merged (HU, NO, PL)			Hungary			Norway		
Initial set of independent variables	32[a)]			31[b)]			32[c)]		
Pearson goodness-of-fit test (p-value)	**0.000**			1.000			1.000		
Final sample size	2,310			990			1,082		
Number of regressors in the final model	8			3			2		
Variable	Beta	z-test	Sig.	Beta	z-test	Sig.	Beta	z-test	Sig.
Intercept	0.254	8.296	0.000	0.060	1.280	**0.201**	0.136	3.399	0.001
Zscore(NUM_ FOUR_WHEEL_ TRAD_VEH)	–0.703	–17.857	0.000	–0.985	–13.938	0.000			
Zscore(M5_cost)	0.098	3.282	0.001						
Zscore(M5_ flexibility)	–0.250	–7.670	0.000						
Zscore(SCORE_ TRANS_SYS)	0.116	3.829	0.000						
Zscore(LESS_ ENERGY_CONS)	0.176	5.894	0.000						
Zscore(S3-employment status)	0.193	6.258	0.000						
Zscore(S5-gender)	0.159	5.418	0.000	0.257	5.670	0.000			
Zscore(S6-type of residence area)	–0.148	–5.113	0.000						
Zscore(NUM_ TWO_WHEEL_ TRAD_VEH)				0.109	2.266	0.023			
Zscore(NUM_ FOUR_WHEEL_ ELEC_VEH)							0.208	6.740	0.000
Zscore(M5_ availability)									
Zscore(M5_time)							–0.090	–2.121	0.034
Remark	invalid model			invalid model					

(Table continues on the next page.)

(Continued.)

Countries involved in the final model	Poland			Italy			Spain		
Initial set of independent variables	31[d)]			28[e)]			28[f)]		
Pearson goodness-of-fit test (p-value)	0.939			1.000			1.000		
Final sample size	948			851			566		
Number of regressors in the final model	3			4			3		
Variable	Beta	z-test	Sig.	Beta	z-test	Sig.	Beta	z-test	Sig.
Intercept	0.214	4.479	0.000	–0.105	–2.014	0.044	0.665	10.340	0.000
Zscore(NUM_ FOUR_WHEEL_ TRAD_VEH)	–0.866	–12.879	0.000	–0.350	–6.507	0.000	–0.393	–5.382	0.000
Zscore(M5_cost)									
Zscore(M5_ flexibility)									
Zscore(SCORE_ TRANS_SYS)							0.199	3.069	0.002
Zscore(LESS_ ENERGY_CONS)	0.188	3.530	0.000	x			x		
Zscore(S3-employment status)	0.364	7.899	0.000	0.365	7.932	0.000	0.357	4.912	0.000
Zscore(S5-gender)									
Zscore(S6-type of residence area)									
Zscore(NUM_ TWO_WHEEL_ TRAD_VEH)									
Zscore(NUM_ FOUR_WHEEL_ ELEC_VEH)				0.172	2.972	0.003			
Zscore(M5_ availability)				–0.153	–3.390	0.001			
Zscore(M5_time)									

a) SATIS_TRANS was discarded.
b) SEV_TRAF_PROB and SATIS_TRANS were discarded.
c) M7_financial_subsidy was discarded.
d) SEV_TRAF_PROB and age_2019 were discarded.
e) The five removed variables are LESS_ENERGY_CONS, PUBLIC_FIN_VEH, ASSESS_INFRASTR, PREF_TREAT_CARS, and NAT_POL_EFF.
f) The aforementioned list of Italy is a duplicate of that applied to Spain.

Table A4

Normalised importance of the independent variables, architecture with two hidden layers, the hyperbolic tangent activation function for the hidden layers, and the identity activation function for the output layer, dependent variable: TIME_SHARE_PREF_MODE, 100% training dataset

Variables↓/Countries→	Hungary, Poland	Hungary	Norway	Poland	Italy	Spain
Number of variables	32	32	32	31	28	28
Relative error	0.090	0.066	0.019	0.026	0.083	0.038
Training sample size	532	374	99	162	347	305
Zscore(NUM_FOUR_WHEEL_TRAD_VEH) (%)	100.0	100.0	93.3	100.0	100.0	100.0
Zscore(ASSESS_INFRASTR) (%)	67.8	60.9	41.3	60.3	x	x
Zscore(NUM_TWO_WHEEL_ELEC_VEH) (%)	56.8	68.5	51.3	25.0	79.7	67.7
Zscore(AGR_NEG_STAT) (%)	56.7	49.1	45.8	19.7	71.7	67.7
Zscore(M6_private_car_rental) (%)	51.1	20.4	47.5	59.3	72.4	74.4
Zscore(S2-highest level of completed studies) (%)	48.5	31.3	46.4	38.3	79.6	50.4
Zscore(M7_financial_subsidy) (%)	47.6	54.5	x	31.2	64.4	43.7
Zscore(M5_flexibility) (%)	46.9	32.0	19.4	75.2	56.2	36.0
Zscore(NUM_TWO_WHEEL_TRAD_VEH) (%)	45.7	38.5	16.6	29.1	60.9	41.7
Zscore(PREF_TREAT_CARS) (%)	45.0	40.5	58.1	36.1	x	x
Zscore(SATIS_TRANS) (%)	44.1	38.3	5.5	31.6	53.0	52.2
Zscore(PUBLIC_FIN_VEH) (%)	42.6	42.9	60.2	70.1	x	x
Zscore(M6_company_car) (%)	40.1	30.4	12.0	40.0	60.4	46.4
Zscore(M5_time) (%)	40.0	35.6	15.0	28.9	41.9	49.4
Zscore(S8-evaluation of household’s income) (%)	37.6	48.7	15.8	28.7	60.3	54.4
Zscore(NAT_POL_EFF) (%)	37.3	25.0	50.4	14.5	x	x
Zscore(S3-current employment status) (%)	37.0	31.9	14.7	64.2	82.2	41.4
Zscore(M5_cost) (%)	36.5	51.3	48.9	35.7	64.1	44.3
Zscore(age_2019) (%)	36.3	37.3	15.3	26.0	67.5	56.8
Zscore(SEV_TRAF_PROB) (%)	34.6	37.5	46.2	82.3	68.5	62.7
Zscore(NUM_FOUR_WHEEL_ELEC_VEH) (%)	34.2	22.4	100.0	x	80.5	30.7
Zscore(SCORE_TRANS_SYS) (%)	32.2	52.9	62.7	58.0	73.3	68.0
Zscore(M5_reliability) (%)	31.5	33.8	29.5	49.5	68.3	45.5
Zscore(LESS_ENERGY_CONS) (%)	30.9	32.5	46.8	53.8	x	x
Zscore(S5-gender) (%)	29.5	23.1	8.2	13.0	39.9	19.1
Zscore(M5_CO_2_emissions) (%)	29.1	32.3	89.7	41.2	49.8	42.5
Zscore(M5_reputation) (%)	29.0	29.4	53.0	28.7	40.0	49.0
Zscore(M6_car-sharing) (%)	27.5	33.2	65.8	19.3	61.4	61.7
Zscore(S1-persons living in the household) (%)	27.3	46.4	29.6	44.5	37.4	65.6
Zscore(M5_safety) (%)	27.0	41.6	42.0	42.4	58.2	46.5
Zscore(S6-type of residence area) (%)	27.0	27.7	98.6	50.9	71.8	42.3
Zscore(M5_availability) (%)	22.1	45.7	16.7	21.4	73.1	50.2
Zscore(M6_bike-sharing) (%)	x	x	87.6	x	66.1	45.4

Table A5

Range of coefficients, main common and salient determinants arising from the multilayer perceptron networks, and perceived inconsistencies

Zscore of variables (monotonicity of favourable values)↓/Technique→	Linear regression	Binary logistic regression	Probit analysis	Multilayer perceptron		Inc.
Regressand or type of determinant→	TIME_SHARE_PREF_MODE			Main common	Salient	
Set of values→	range: [0,1]	values: {0, 1}	range: [0,1]			
Intercept	[+0.441, +0.712]	[–1.532, +2.500]	[–0.105, +0.665]			
NUM_FOUR_WHEEL_TRAD_VEH	[–0.332, –0.081]	[–4.924, –0.742]	[–0.866, –0.350]	x	x	
NUM_TWO_WHEEL_TRAD_VEH	+0.042	[+0.668, +0.812]	–			
NUM_FOUR_WHEEL_ELEC_VEH	+0.056	+1.580	[+0.172, +0.208]		x	
AGR_NEG_STAT (decreasing)	[–0.056, +0.058]	–	–			x
M5_cost	[+0.069, +0.071]	[+0.412, +0.795]	–			
M5_time	[–0.128, +0.095]	–1.014	–0.090			x
M5_flexibility	[–0.155, –0.081]	[–1.921, –0.807]	–			
M5_safety	–	[–0.578, +1.043]	–	x		x
M5_CO_2_emissions	+0.077	+0.672	–		x	
M5_availability	[–0.057, +0.083]	–0.665	–0.153			x
M5_reputation	+0.077	–1.573	–			x
SCORE_TRANS_SYS (increasing)	[+0.055, +0.155]	[+0.561, +0.796]	+0.199	x		
SEV_TRAF_PROB (increasing)	[–0.152, –0.107]	–1.069	–		x	x
SATIS_TRANS (increasing)	+0.058	–	–			
LESS_ENERGY_CONS (increasing)	[+0.064, +0.159]	[+0.801, +1.388]	+0.188			
ASSESS_INFRASTR (decreasing)	–0.087	–0.390	–	x		
S3-employment status	[+0.080, +0.147]	[+0.776, +1.607]	[+0.357, +0.365]		x	
age_2019	–0.048	–0.842	–			
S5-gender	[+0.063, +0.079]	[+0.542, +0.879]	–			
S6-type of residence area	[–0.100, –0.095]	[–1.563, –1.380]	–		x	
S8-subjective evaluation of household's current income	+0.042	+0.712	–			
M6_bike-sharing	–	–	–	x	x	
PUBLIC_FIN_VEH (increasing)	–	–	–	x		

Note: Inc.=Inconsistency.

Table A6

Normalised importance of the independent variables split by destination, architecture with two hidden layers, the hyperbolic tangent activation function for the hidden layers, and the identity activation function for the output layer, 100% training dataset, Spain

Variables↓/Destination of travel→	General (i)	LA (ii)	Change in percentage points [(ii)–(i)]	W/U (iii)	CS (iv)	CA (v)	GS (vi)
Mean of timeshare of preferred travel modes	0.749	0.820	–	0.565	0.737	0.724	0.753
Number of variables	28	28	–	28	26	25	28
Relative error	0.038	0.016	–	0.028	0.301	0.001	0.045
Training sample size	305	258	–	211	55	41	273
Zscore(NUM_FOUR_WHEEL_TRAD_VEH) (%)	100.0	89.6	–10.4	78.4	48.1	3.6	83.9
Zscore(M6_private_car_rental) (%)	74.4	66.7	–7.7	100.0	x	x	80.6
Zscore(SCORE_TRANS_SYS) (%)	68.0	100.0	**+32.0**	97.7	61.6	85.3	90.1
Zscore(NUM_TWO_WHEEL_ELEC_VEH) (%)	67.7	48.4	*–19.3*	66.2	38.1	54.9	74.0
Zscore(AGR_NEG_STAT) (%)	67.7	95.2	**+27.5**	69.6	5.9	15.4	72.9
Zscore(S1-persons living in the household) (%)	65.6	60.5	–5.1	63.2	64.1	46.5	56.0
Zscore(SEV_TRAF_PROB) (%)	62.7	59.8	–2.9	72.7	35.2	57.8	58.0
Zscore(M6_car-sharing) (%)	61.7	56.8	–5.0	76.0	24.5	11.1	100.0
Zscore(age_2019) (%)	56.8	68.1	+11.4	47.7	1.3	3.6	39.8
Zscore(S8-subjective evaluation of household's current income) (%)	54.4	53.2	–1.2	60.7	100.0	100.0	50.0
Zscore(SATIS_TRANS) (%)	52.2	61.3	+9.1	73.9	34.2	4.4	51.8
Zscore(S2-highest level of completed studies) (%)	50.4	61.4	+11.0	67.3	48.1	90.2	61.4
Zscore(M5_availability) (%)	50.2	60.9	+10.7	64.6	25.5	1.0	22.2
Zscore(M5_time) (%)	49.4	56.5	+7.1	57.0	3.0	38.5	47.1
Zscore(M5_reputation) (%)	49.0	28.2	*–20.8*	42.7	16.8	16.6	58.4
Zscore(M5_safety) (%)	46.5	67.0	**+20.5**	46.6	8.8	73.8	50.3
Zscore(M6_company_car) (%)	46.4	41.4	–5.1	78.1	1.3	x	60.3
Zscore(M5_reliability) (%)	45.5	49.6	+4.1	68.0	48.6	59.5	44.9
Zscore(M6_bike-sharing) (%)	45.4	50.7	+5.3	94.5	0.6	0.3	55.4
Zscore(M5_cost) (%)	44.3	46.9	+2.6	48.6	3.6	28.1	42.0
Zscore(M7_financial_subsidy) (%)	43.7	88.2	**+44.6**	97.5	54.2	6.3	63.1
Zscore(M5_CO_2_emissions) (%)	42.5	40.2	–2.3	67.0	25.4	1.6	68.6
Zscore(S6-type of residence area) (%)	42.3	46.3	+4.1	47.9	31.1	2.2	51.3
Zscore(NUM_TWO_WHEEL_TRAD_VEH) (%)	41.7	31.6	–10.0	49.9	33.6	10.6	44.6
Zscore(S3-employment status) (%)	41.4	37.6	–3.7	30.2	2.2	1.1	41.5
Zscore(M5_flexibility) (%)	36.0	54.5	**+18.5**	45.7	36.3	50.8	51.8
Zscore(NUM_FOUR_WHEEL_ELEC_VEH) (%)	30.7	45.8	**+15.1**	64.7	x	x	33.1
Zscore(S5-gender) (%)	19.1	28.2	+9.1	48.1	1.9	12.6	31.5

Note: LA = Leisure activities, W/U = Workplace/university, CS = Children's school, CA = Children's activities, GS = Grocery/shopping.

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