Transportation Research Part F: Psychology and Behaviour 115 (2025) 103328

Contents lists available at ScienceDirect

Transportation Research Part F: Psychology and Behaviour

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

# Exploring the role of Technophilia on electric vehicle use: a structural equation modelling approach

Rongqiu Song [a], Paul Haggar [a], Dimitrios Xenias [b], Dimitris Potoglou [a,*]

[a] School of Geography and Planning, Cardiff University, CF10 3WA Cardiff, UK
[b] School of Psychology, Cardiff University, CF10 3AT Cardiff, UK

ARTICLE INFO

*Keywords:*
Electric vehicle adoption
Technophilia
Socio-demographics
Structural equation modelling
Mediation

ABSTRACT

The transition to electric vehicles (EVs) plays a crucial role in achieving sustainable transport and reducing greenhouse gas emissions. However, EV adoption rates in the UK remain relatively low compared to some other European nations. Understanding the factors influencing individuals' EV adoption behaviour is essential for shaping effective policies to encourage EV uptake. This study focuses on the role of technophilic consumer attitudes, 'an individual's openness to, and enthusiasm for, technological innovation'. The study analysed data from 302 EV and 279 non-EV users who were sampled across Great Britain. Logistic regression models, examine the relationship between EV vehicle adoption and socio-demographic characteristics and Technophilia; that latter was quantified by different specifications of Generalised Structural Equation Models (GSEM). The findings indicated that younger, wealthier individuals, and those with children were more likely to use EVs. Technophilia was a significant factor in the likelihood of EV use and mediated the effects of socio-demographic characteristics. Specifically, younger individuals, males, with higher levels of income, having more children, living in London, tended to have higher levels of Technophilia, and thus were more likely to use EVs. By highlighting the mediating role of Technophilia in EV use, this study fills a critical research gap and offers novel insights into socio-demographic and attitudinal patterns specific to the British context. The findings underscore the importance of integrating socio-demographic and psychological factors into strategies aimed at accelerating EV adoption.

## 1. Introduction

The transition to Electric Vehicles (EVs) is a critical step in global efforts to combat climate change and reduce carbon emissions in the road transport sector (Hill et al., 2019). Recognising that moving away from fossil fuel-powered vehicles may be a way to achieve long-term sustainable development goals, many countries have proposed their own EV-related strategies (Song & Potoglou, 2020). However, despite efforts to encourage EV uptake, EV adoption rate in Britain remains relatively low compared to Nordic countries, for example. In 2023, only around 25 % of all cars sold in the UK were electric, while other countries such as the Netherlands (30 %), Sweden (60 %), and Norway (95 %) achieved much higher adoption rates (International Energy Agency, 2024).

* Corresponding author at: School of Geography and Planning, Cardiff University, Glamorgan Building, Room: 2.79, King Edward VII Avenue, Cardiff CF10 3WA, Wales, UK.

*E-mail addresses:* songr3@cardiff.ac.uk (R. Song), HaggarPC@cardiff.ac.uk (P. Haggar), xeniasd@cardiff.ac.uk (D. Xenias), potogloud@cardiff.ac.uk (D. Potoglou).

https://doi.org/10.1016/j.trf.2025.103328
Received 19 February 2025; Received in revised form 29 July 2025; Accepted 29 July 2025
Available online 5 August 2025
1369-8478/

The key challenges regarding EV uptake in Great Britain (UK) centre around two areas: (a) infrastructure and (b) consumer behaviour. In terms of infrastructure, the current GB electricity system would face limitations in meeting the new demand for EV charging. Thus, it is debatable whether GB electricity infrastructure can match very high renewable power penetration rates, like those in Nordic countries; or whether it can integrate supporting technologies like vehicle-to-grid (V2G) before pushing for large-scale EV adoption (Mehdizadeh et al., 2023; Mehdizadeh et al., 2024). Having said that, the UK still has a lot of untapped renewable energy potential and grid upgrades are actively pursued (e.g., Department for Energy Security & Net Zero, 2024; National Grid, 2024). Another challenge is the availability of public charging infrastructure, as the charging network is not yet sufficiently developed or evenly distributed across regions (CMA, 2021). For example, data from the Department for Transport (DfT) showed that from 2019 to 2022, the ratio of public charging points to EVs worsened across all regions in the UK (UK Parliament, 2024). This issue is particularly evident in Northern Ireland, the South West, the South East, and the North West, where the ratio of EVs to charging points exceeds 100 to 1.

Regarding consumer behaviour, there have been efforts towards targeted policies and strategies that support EV adoption. For example, some measures included tax exemptions for EV purchases and monetary incentives and investments towards charging point installations, or non-monetary measures such as travel or parking priority (Song & Potoglou, 2020). Other measures have included banning the sale of new petrol and diesel cars by 2030 (Office for Zero Emission Vehicles, 2025). Tailoring such policies, however, requires a thorough understanding of motivations and barriers to EV consumer adoption. Relevant studies have considered both EV-specific attributes (e.g., financial and technical features, infrastructure, and policy conditions) and individual-related factors (e.g., socio-economic status and psychological traits) as correlates of EV adoption (Liao et al., 2017). While EV-specific attributes provide valuable insights into EV preferences, they tend to be context-dependent, varying according to local EV charging infrastructure (Miele et al., 2020; Potoglou et al., 2023) and policy environments (Song & Potoglou, 2020). By contrast, it is important to look closer into the attitudinal aspects of consumers and their relationship with individual-level characteristics as they may also provide a better insight regarding EV adoption.

Much of the existing research on (consumer) individual-level factors has primarily focused on EV adoption intentions rather than actual EV adoption – i.e., differences between EV and non-EV users. Findings on the association of socio-demographic factors with EV adoption have varied across geographic regions (Wicki et al., 2022). Despite these variations, the overall trend suggests that it is often younger, wealthier, educated men who are more likely to express an intention to adopt EVs (Wicki et al., 2022). Intentions, however, do not always translate into adoption behaviour (Sovacool et al., 2019; Jia & Chen, 2021). For example, a study in Virginia, USA (Jia & Chen, 2021), found that at the individual level, younger people (35 years of age and under) showed stronger intentions to adopt non-Internal Combustion Electric Vehicles (ICEVs) – namely, Hybrid Electric Vehicles (HEVs), Plug-in Hybrid Electric Vehicles (PHEVs), and Battery Electric Vehicles (BEVs), while older individuals (55 and over) were less likely to adopt such vehicles. However, at the country level, those who actually adopted EVs tended to be older than 55 years of age. Similarly, research in the Nordic countries suggested that while urban residents showed greater interest in EVs, rural residents were more likely to own EVs (Sovacool et al., 2019). Therefore, it is important to consider the differences between individuals who have adopted EVs and those who have not, as opposed to considering intentions only. Such an analysis can provide valuable insights into the overall characteristics of early EV adopters, as well as highlight the practical barriers and enablers that motivate individuals to commit to an EV purchase rather than just express interest. It is also important to report on empirical evidence from different contexts (countries), given existing differences reported in the literature.

Very few studies have specifically focused on actual EV adoption, and those that have done so have reported mixed results, especially regarding the relationship between socio-demographics and EV adoption (see in Table A1 in the Appendix). For example, Sovacool et al. (2018) conducted a study in the Nordic countries (Denmark, Finland, Iceland, Norway and Sweden) and found that EV owners were typically younger than non-EV owners, with the majority falling within the middle-aged range of 25–44 years of age. By contrast, Westin et al. (2018) reported that EV adopters in Sweden were generally older than non-adopters. Despite these differences, several socio-demographic trends consistently emerge across studies. For example, individuals with higher-level education qualifications (Sovacool et al., 2018; Westin et al., 2018), higher income (Sovacool et al., 2019; Brückmann et al., 2021), males (Sovacool et al., 2018; Brückmann et al., 2021), married (Renaud-Blondeau et al., 2023; Dai & Yang, 2024), living in larger households (Sovacool et al., 2018; Dai and Yang, 2024), and residing in suburban or rural areas (Westin et al., 2018) were more likely to be EV owners. Interestingly, while women were more likely than men to recognise the benefits of EVs, they were still significantly less likely to express interest in or adopt them (Sovacool et al., 2018). These findings highlight the complexity of the impact of socio-demographic factors on EV adoption, with variations likely to be shaped by local contexts, infrastructure availability, and cultural factors.

In addition to individual socio-demographic characteristics, several other psychological factors can affect individual EV adoption such as range anxiety (e.g., Zatsarnaja et al., 2025) or ease of charging (e.g., Mehdizadeh et al., 2024). The influence of attitudes in particular, as described by the Theory of Planned Behaviour (TPB), is critical to accelerating the transition to EV ownership (Harinath et al., 2021). The TPB suggests that technology adoption intentions are affected by attitudes, subjective norms, and perceived behavioural control (Ajzen, 2011). Unlike the mixed and inconsistent effects of socio-demographic factors on EV adoption, the positive effects of certain attitudes could be more consistent across studies. Individuals with high levels of Technophilia, characterised by openness to innovations, are more inclined to adopt EVs (Brückmann et al., 2021; Renaud-Blondeau et al., 2023; Dai & Yang, 2024). Technophilia is a positive attitude towards new technologies and innovations, while it also reflects the innovativeness construct in

Rogers' Diffusion of Innovations Theory (Rogers, 2003), in which innovations diffuse, spreading between different groups over time according to their levels of innovativeness.[1] Hence, more innovative early adopters typically acquire innovations sooner than less innovative late adopters due to their technophilic affinity for cutting-edge innovations. Evidence on the extent to which this attitude applies to the context of Great Britain (GB) and how it relates to socio-demographic factors remains sparse.

Many studies have focused only on socio-demographics (Sovacool et al., 2018; Westin et al., 2018), or else considered socio-demographics and attitudes as independent factors influencing actual EV adoption (Brückmann et al., 2021; Dai & Yang, 2024). These approaches overlook the possibility that socio-demographic factors, such as age, income, or education, may be associated with attitudes like environmental concern or technophilia, which in turn affect EV adoption. Exploring these two dimensions (socio-demographics and attitudes) in different ways, can provide a deeper understanding of the individual-level factors influencing actual EV adoption, and help lead to targeted strategies for encouraging EV adoption across different demographic groups. Of the studies conducted on EV adoption in the UK, very few compare EV adopters to non-adopters. Two UK studies have been made of innovativeness (akin to Technophilia) and EV preferences, previously, but they used general consumer samples rather than comparing adopters to non-adopters (Morton et al., 2016; Morton et al., 2017). These studies used registration data at the area level (e.g., Morton et al. (2018), but they tend to be limited to socio-demographics, and attitudes are rarely considered. Beyond the UK, there are more studies comparing adopters and non-adopters (Haustein & Jensen, 2018; Jin et al., 2020; Fevang et al., 2021), and there is one study comparable to the present work (Iogansen et al., 2023), but this was undertaken in California, where EV-diffusion, public policy, culture, and charging infrastructure are considerably different, making a GB-focused study valuable.

Given the context of Great Britain, and the gaps in existing literature, this study aimed to examine the individual-level factors that correlate with EV use,[2] focusing on socio-demographic characteristics and technology affinity attitudes (Technophilia). Specifically, this paper examines how these factors affect EV use in Great Britain, and it aims to highlight the role of Technophilia in EV use both as a determinant, and as a mediator of EV adoption. It is the first time that this mediation effect is studied in the UK (e.g., Morton et al., 2017; Iogansen et al., 2023). Given the unique dynamics of EV adoption patterns in the UK, the research enriches the empirical discourse on EV use.

Guided by these research objectives, this study aimed to address the following research questions:

(1) What are the socio-demographic profiles of individuals who use EVs compared to those who do not use EVs in Great Britain?
(2) To what extent does Technophilia influence individuals' decisions to use EVs?
(3) Do socio-demographic factors influence individuals' Technophilia, and how does this relate to EV use?
(4) Do the effects of socio-demographics and Technophilia both drive EV use, and, if so, does Technophilia mediate socio-demographic effects?

The originality of this research lies in its focus on the interplay between socio-demographic factors, Technophilia, and EV adoption in Great Britain. While previous studies have explored socio-demographic influences on EV use or the role of technology attitudes in isolation, this study innovatively integrates these dimensions to compare simple, partial direct and indirect (mediated) effects[3]. Specifically, it investigates how socio-demographic factors influence individuals' Technophilia and how this attitude might mediate EV use. Additionally, it analyses the partialdirect effects of socio-demographics and Technophilia on EV adoption, providing a better understanding of the decision-making process. This represents a novel contribution to the literature, offering fresh insights into the complex dynamics driving EV adoption in a GB context.

The significance of this research is multifaceted. By identifying the socio-demographic profiles of EV users and the role of Technophilia, this study provides actionable insights for policymakers to design targeted interventions for EV adoption. For example, understanding whether and how Technophilia mediates EV use can help tailor communication strategies that target individuals with varying levels of technology affinity based on their socio-demographics. Second, this research advances the theoretical understanding of EV adoption by integrating socio-demographic and attitudinal factors into a unified framework. It examines the mediating role of Technophilia, offering a new perspective on whether and how individual attitudes and characteristics interact to influence the adoption of cleaner technologies. Finally, findings can also guide automakers and infrastructure planners in developing EV technologies and charging solutions that align with the preferences and attitudes of different socio-demographic groups, ultimately accelerating the transition to sustainable mobility. For example, an automaker or infrastructure planner might develop versions of appropriately framed and simpler – vs. more nuanced- user interfaces, which are adapted to different audiences, thus overcoming a barrier in the adoption and use of these technologies.

The remainder of this article is organised as follows: the following section (Section 2) provides a detailed description of the methodology used, outlining the survey design, data collection process and analysis strategy. Section 3 presents the results of these models. Section 4 highlights the key findings from the analysis and offers a discussion of these findings, suggesting areas for future study, and suggests potential policy implications. Section 5 summarises the main contributions of the study and its conclusions.

[1] The term 'Technophilia' can refer to an enduring personality trait, like 'innovativeness'. We instead use 'Technophilia' as a synonym for positive attitude towards technology.

[2] In this study, 'EV use' and 'EV adoption' are used interchangeably in this paper depending on how EV ownership/use/intention to adopt was phrased in previous studies. In general, the terms imply those individuals who most often drove a BEV or a PHEV.

[3] Simple effects refer to univariate (simple) correlation (e.g., a B coefficient in simple/univariate regression); partial correlation (e.g., a B coefficient in multiple regression).

## 2. Data and methods

### 2.1. Survey questionnaire and implementation

This study implemented a web-based survey questionnaire that included a stated choice experiment (Song & Potoglou, 2024), and was administered via the Qualtrics Survey Platform (https://www.qualtrics.com) survey platform, between September and October 2023. The survey questionnaire included a range of socio-demographic questions about age, gender, education level, income, rurality of participants' residential area, ethnicity, housing type, geographic region (of their residence), household size, and the number of children in their household. In terms of attitudes, the questionnaire measured each respondent's technology affinity attitudes, termed "Technophilia". This attitudinal measure was designed using Globisch et al.'s (2019) framework, and utilised three statements (attitudinal indicators) rated on a 5-point Likert scale (from "strongly disagree" to "strongly agree"):

- T1: "I am very interested in the latest technology developments",
- T2: "It doesn't take me long to learn to like new technology developments", and
- T3: "I am always keen to use the latest technological devices".

The target population for the survey comprised individuals over the age of 18 years who lived in Great Britain (England, Scotland, and Wales), and held a full driving license. Participants identified as non-EV users were those who had access to a petrol or diesel car, whereas EV users were those with access to, and who most often used, a BEV or a PHEV. Northern Ireland was not included in our sample as its electricity grid is separate from that of Great Britain, and it is subject to separate regulation and management. This has different implications for customers in the two regions (e.g. different incentives or electricity tariffs) and for the grid (e.g. different network balancing or V2G readiness). We could not accommodate these nuances in this study.

The recruitment process for non-EV users employed a quota sampling approach to ensure that – following the screening questions above – the sample reflected the population in Great Britain in terms of age, gender, and regional representation in line with the latest Census data (i.e., 2021 for England and Wales; 2022 for Scotland). The quotas for the EV user group were relaxed to allow for more flexibility in the recruitment process due to the low proportions of EV owners in the general population. Following screening questions and completeness of the survey questionnaire, the final sample consisted of 581 respondents, with 279 non-EV users and 302 EV users. The mean and median duration to complete the survey were 10.45 and 7.79 min, respectively. The recruitment of both EV and non-EV users was conducted via the Qualtrics Online Panel Research Services platform,[4] which allowed to specify the quotas as detailed above.

### 2.2. Analytical approach

The primary scope of the analysis in this study is to examine the role of Technophilia and socio-economic characteristics in the likelihood of an individual being an EV or non-EV user. As shown in Eq. (1), the probability of an individual being an EV user is represented as $P(Y = 1|X)$, with Y being a binary outcome (1 for EV users; 0 for non-EV users) (Hosmer et al., 2013):

$$P(Y = 1|X) = \frac{e^{(\beta_0+\beta_1X_1+\beta_2X_2+\cdots+\beta_nX_n)}}{1 + e^{(\beta_0+\beta_1X_1+\beta_2X_2+\cdots+\beta_nX_n)}} \tag{1}$$

where $\beta_0$ is the intercept term, and $\beta_1, \beta_2, \ldots, \beta_n$ are the coefficients of the variables $X_1, X_2, \ldots, X_n$ such as individual socio-demographic factors including age, gender, and their level of Technophilia.

As shown in Fig. 1, this study tested four model specifications, which aligned with the following hypotheses and are in line with the research questions in Section 1:

- H1: Socio-demographic characteristics are associated with EV use (Model A).
- H2: Technophilia is positively associated with EV use, after controlling for socio-economic characteristics (Model B).
- H3: Technophilia positively mediates an indirect association between socio-demographic characteristics and EV use (Model C).
- H4: Technophilia positively mediates an indirect association between socio-demographic characteristics and EV use, after controlling for the direct effect of socio-demographic characteristics (Model D).

The plan of analysis in this study is formed as follows. Models A, B, C, and D were estimated to provide a more detailed, step-by-step understanding of the different layers of association with EV use. Specifically, Model A isolates the direct effects of socio-demographics, Model B adds Technophilia as a latent variable but without being determined by socio-demographic variables, Model C examines the likelihood of an individual being an EV user by only modelling Technophilia as a function of socio-demographics (via a MIMIC model) thus examining the role of Technophilia and its internal structure. Finally, Model D examines both the direct and indirect effects of socio-demographics and Technophilia. This stepwise approach adds clarity, validity and theoretical rigour to the reported findings. It also allows one to observe the contributions of each variable within each model and their mediation, e.g., how socio-demographic and psychological factors are associated with EV adoption. Methodologically, using this series of models demonstrates the complexity of

[4] https://www.qualtrics.com/research-services/.

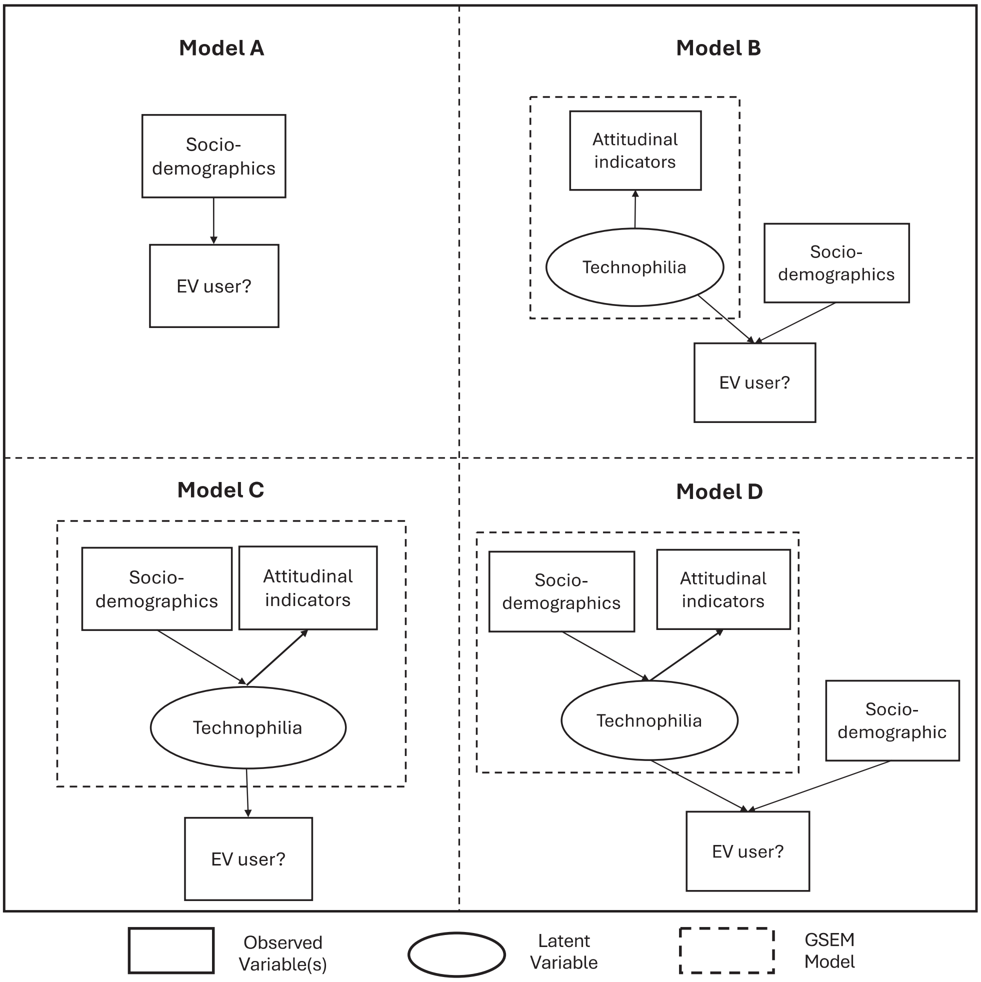


**Fig. 1.** Alternative model specifications to explain the likelihood of being an EV user.

these relationships and helps build a more comprehensive evaluation of the role of Technophilia in determining EV adoption.

Model A (Hypothesis 1) explores how socio-demographics alone explain EV use. This provides a baseline understanding of how factors like age, gender, and income relate to EV use. Previous research (e.g., Brückmann et al., 2021; Renaud-Blondeau et al., 2023), however, suggests that Technophilic attitudes also play a key role in EV adoption. These attitudes may explain additional variance in EV adoption that socio-demographics alone cannot capture. Theories like Rogers' (2003) Diffusion of Innovations, and Ajzen's (2011) Theory of Planned Behaviour, further support this idea. They highlight how individual attitudes, such as openness towards innovation, can significantly influence the adoption of new technologies, such as EVs.

To explore this assertion, Hypothesis 2 was introduced to examine the effect of Technophilic attitudes on EV use, building on the baseline model established by socio-demographics. Model B therefore expands on Model A by incorporating Technophilia as a latent variable in the logistic regression model (see, Fig. 1). Model B was estimated in a two-stage process. Firstly, a Generalised Structural Equation Model (GSEM) was employed to construct the latent variable Technophilia. This involved estimating the latent construct – Technophilia through a constant (structural model) and the three observed attitudinal indicators (measurement model) (Bagozzi & Yi, 2012).[5] A Principal Component Analysis (PCA; see Section 3.2) confirmed that the observed indicators (T1, T2, and T3) consistently loaded onto a single underlying dimension. This supported the validity and coherence of the latent variable and reinforced the construct validity. In the second stage, a logistic regression model was applied to estimate the probability of being an EV user as a function of Technophilia and key socio-demographic variables. This sequential modelling approach facilitated the integration of psychological disposition and observable demographic characteristics in explaining the likelihood of EV adoption, while maintaining the conceptual clarity of the latent construct.

Models C and D also used a two-step sequential approach. Firstly, a special form of GSEM known as the Multiple Indicator Multiple

[5] Models B, C and D first estimate 'Technophilia' scores, a step that may be referred as 'a (generalised) confirmatory factor analysis (CFA), followed by a logistic regression.

**Table 1**
Socio-demographic characteristics of the sample split into EV and non-EV users.

| Variable | Level | Frequency (column%) | | Chi-Square | Cramer's V |
|---|---|---|---|---|---|
| | | Non-EV-Users | EV users | | |
| Age | 18–24 | 20 (7.2) | 20 (6.6) | 285.200*** | 0.701 |
| | 25–34 | 7 (2.5) | 94 (31.1) | | |
| | 35–44 | 19 (6.8) | 101 (33.4) | | |
| | 45–54 | 18 (6.5) | 55 (18.2) | | |
| | 55–64 | 98 (35.1) | 12 (4.0) | | |
| | 65–74 | 73 (26.2) | 12 (4.0) | | |
| | 75+ | 44 (15.8) | 8 (2.6) | | |
| Gender | Male | 135 (48.4) | 179 (59.5) | 7.161*** | −0.111 |
| | Female | 144 (51.6) | 122 (40.5) | | |
| Education qualification | Lower than university degree | 166 (59.5) | 75 (24.8) | 71.787*** | 0.352 |
| | University degree or higher | 113 (40.5) | 227 (75.2) | | |
| Household income | ≤15 K | 38 (13.6) | 7 (2.3) | 163.256*** | 0.530 |
| | 15–25 K | 58 (20.8) | 16 (5.3) | | |
| | 25–35 K | 63 (22.6) | 28 (9.3) | | |
| | 35–45 K | 42 (15.1) | 30 (9.9) | | |
| | 45–55 K | 24 (8.6) | 35 (11.6) | | |
| | 55–65 K | 16 (5.7) | 23 (7.6) | | |
| | 65–75 K | 13 (4.7) | 27 (8.9) | | |
| | 75–85 K | 10 (3.6) | 7 (2.3) | | |
| | 85–95 K | 5 (1.8) | 13 (4.3) | | |
| | 95–105 K | 8 (2.9) | 46 (15.2) | | |
| | >105 K | 2 (0.7) | 70 (23.2) | | |
| Rurality | Urban area | 70 (25.1) | 150 (49.7) | 37.239*** | −0.253 |
| | Rural area | 209 (74.9) | 152 (50.3) | | |
| House | Not detached | 171 (61.3) | 135 (44.7) | 16.008*** | 0.166 |
| | Detached | 108 (38.7) | 167 (55.3) | | |
| Ethnicity | White | 260 (93.5) | 245 (81.4) | 19.076*** | 0.182 |
| | Non-white | 18 (6.5) | 56 (18.6) | | |
| Region of residence | London | 22 (7.9) | 86 (28.5) | 72.985*** | 0.354 |
| | North East | 11 (3.9) | 8 (2.7) | | |
| | North West | 30 (10.8) | 32 (10.6) | | |
| | Yorkshire and The Humber | 22 (7.9) | 20 (6.6) | | |
| | East Midlands | 16 (5.7) | 32 (10.6) | | |
| | West Midlands | 28 (10.0) | 19 (6.3) | | |
| | East of England | 27 (9.7) | 45 (14.9) | | |
| | South East | 42 (15.1) | 26 (8.6) | | |
| | South West | 27 (9.7) | 13 (4.3) | | |
| | Scotland | 36 (12.9) | 12 (4.0) | | |
| | Wales | 18 (6.5) | 9 (3.0) | | |
| Number of children | 0 | 229 (82.1) | 91 (30.1) | 159.217*** | 0.524 |
| | 1 | 30 (10.8) | 105 (34.8) | 10.196*** | 0.133 |
| | 2 or more | 20 (7.2) | 106 (35.1) | | |
| Household size | 1 | 67 (24.2) | 53 (17.6) | | |
| | 2 | 160 (57.8) | 162 (53.8) | | |
| | 3 or more | 50 (18.0) | 86 (28.6) | | |
| Number of cars | 0 | 1 (0.4) | 0 | 28.175*** | 0.220 |
| | 1 | 222 (79.6) | 181 (59.9) | | |
| | 2 or more | 56 (20.0) | 121 (40.1) | | |

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Cause (MIMIC) models was used to estimate the latent construct Technophilia. These models allow for the analysis of latent variables (e.g., Technophilia) while incorporating the relationship with external factors, such as socio-demographics (Nayum et al., 2023). Secondly, as with Model B, a logistic regression was subsequently performed in Models C and D, following the MIMIC model, to estimate the likelihood of EV adoption based on the latent variable Technophilia. Hypothesis 3 examines whether socio-demographic factors are associated with attitudes to technology adoption, like Technophilia. In Model C, Technophilia is the only explanatory variable, again estimated through an GSEM within the logistic-regression model of EV use (vs. non-EV use). Socio-demographic characteristics were introduced only indirectly in Model C (*through* Technophilia). This model tests whether differences in EV use across socio-demographic groups are entirely explained by varying levels of Technophilia. Hypothesis 4 further considers the possibility that socio-demographic factors are linked to EV use both directly and indirectly. For example, higher education may foster positive attitudes towards technology (indirect effect) while also providing a more rounded knowledge of the science behind technology (direct effect), both of which increase the likelihood of EV adoption. Model D captures this dual relationship by allowing socio-demographics to explain EV use *directly* and *indirectly* through Technophilia.

The reason for not including attitudinal indicators directly in the regression model is that indicators are usually derived from survey responses, assuming that all items contribute equally and consistently to the measured latent attitude. However, this may not be accurate due to measurement errors or variations in respondents' interpretations of individual items (Bagozzi & Yi, 2012). This can lead to biased or inconsistent model estimates. GSEM addresses such limitations by estimating the underlying constructs, which is accomplished by taking into account measurement error and separating the shared variance between observed indicators (Weston & Gore, 2006). This approach improves both reliability and validity, while allowing a more detailed exploration of theoretical relationships, such as those between attitudes and behaviour.

## 3. Findings

### 3.1. Socio-demographic profiles of EV-users and non-EV-users

Table 1 summarises socio-demographic characteristics for EV users and non-EV users. These two groups had significantly different socio-demographic characteristics and Technophilia attitudinal indicators (item scores). EV users were generally younger, with a higher representation in the 25–34 (31.1 %) and 35–44 (33.4 %) age ranges. In contrast, non-EV users were older, with the majority aged 55–64 (35.1 %) and 65–74 (26.2 %). More EV users were male (59.5 %), compared to non-EV users (48.4 %). Ethnic differences were also observed, with more non-EV users identifying as white (93.5 %), compared to EV users (81.4 %). More EV users reported having university degrees (75.2 %) compared to non-EV users (40.5 %). Similarly, income was positively associated with EV use, as more EV users reported higher income, particularly those earning over £105 K (23.2 %). Conversely, non-EV users were more evenly distributed across lower income ranges.

In addition, the socio-demographic characteristics of EV and non-EV users suggested there were significant differences in terms of family structure, household size, car ownership, region, and type of domicile. As shown in Table 1, non-EV users were more likely to have no children (82.1 %) compared to EV users (30.1 %), while EV users were more likely to have one or more children, with 34.8 % having one child and 35.1 % having two or more. Non-EV users were more likely to live alone (24.2 %), whereas EV users were more likely to reside in larger households, with 28.6 % living in households of three or more people. Non-EV users predominantly owned a single car (79.6 %), while EV users were more likely to own multiple vehicles, with 40.1 % reporting two or more cars. Non-EV users lived predominantly in rural areas (74.9 %), while EV users were nearly equally split between urban and more rural areas (50.3 %).

**Table 2**
Technophilia indicators and responses by EV and non-EV users.

| Variables | Technophilia indicators | | Strongly disagree | Somewhat disagree | Neither | Somewhat agree | Strongly agree | Chi-Squared | Cramer's V |
|---|---|---|---|---|---|---|---|---|---|
| T1 | I am very interested in the latest technology developments | Non-EV-users | 31 (11.1 %) | 55 (19.7 %) | 51 (18.3 %) | 107 (38.4 %) | 35 (12.5 %) | 152.335*** | 0.512 |
| | | EV-users | 2 (0.7 %) | 9 (3.0 %) | 18 (5.9 %) | 115 (38.1 %) | 158 (52.3 %) | | |
| T2 | It doesn't take me long to learn to like new technology developments | Non-EV-users | 21 (7.5 %) | 48 (17.2 %) | 75 (26.9 %) | 103 (36.9 %) | 32 (11.5 %) | 104.668*** | 0.424 |
| | | EV-users | 5 (1.7 %) | 12 (4.0 %) | 30 (9.9 %) | 136 (45.0 %) | 119 (39.4 %) | | |
| T3 | I am always keen to use the latest technological devices | Non-EV-users | 36 (12.9 %) | 62 (22.2 %) | 72 (25.8 %) | 75 (26.9 %) | 34 (12.2 %) | 153.385*** | 0.514 |
| | | EV-users | 5 (1.6 %) | 16 (5.3 %) | 25 (8.3 %) | 102 (33.8 %) | 154 (51.0 %) | | |

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Domicile type also differed significantly, with EV users more likely to reside in detached houses (55.3 %), while a larger proportion of non-EV users lived in other types of housing (61.3 %). Region was also associated with EV use patterns, with a significant number of EV users located in London (28.5 %), while non-EV users were more spread out across other regions, with a greater proportion of non-EV users than EV users in the South of England and Scotland.

EV users exhibited a notably higher level of Technophilia compared to non-EV users across all three indicators (Table 2). Specifically, EV users were more likely to express strong enthusiasm for the latest technological developments (52.3 % strongly agree), whereas non-EV users showed a more neutral or less enthusiastic stance, with only 12.5 % strongly agreeing. Similarly, EV users were quicker to embrace and learn to like new technologies, with 39.4 % strongly agreeing, compared to 11.5 % of non-EV users. Finally, EV users were more inclined to use the latest technological devices, with 51.0 % strongly agreeing, in contrast to just 12.2 % of non-EV users. These differences were statistically significant ($p < 0.01$) with moderate effect sizes, which suggested that EV users exhibited a significantly higher level of Technophilia than non-EV users.

Therefore, in response to the question posed in Section 1, "what are the socio-demographic profiles of individuals who drive EVs most often compared to those who do not drive EVs in GB?": EV users were generally younger and more likely to be male. They also tended to have higher education and income compared to non-EV users, and were more likely to live in detached houses, particularly in urban areas such as London. Additionally, EV users typically resided in larger households, with more children and more cars. Finally, EV users displayed a higher level of Technophilia compared to non-EV users.

### *3.2. Validity testing of Technophilia in the data*

Prior to introducing the findings of the logistic regression model, this section provides the validity testing results of the latent Technophilia construct using PCA. The purpose of this step is to ensure that the three Technophilic indicators (T1, T2, and T3) adequately represent the latent construct of Technophilia. This validation is a critical prerequisite for the subsequent SEM analysis, where Technophilia is estimated as a latent variable. The results of the PCA, summarised in Table 3, confirm that the three observed attitudinal indicators (T1, T2, and T3) were all valid and reliable measures of the latent construct, Technophilia. All indicators had strong factor loadings exceeding the acceptable threshold of 0.70, demonstrating a robust relationship with the latent construct. Furthermore, the high Cronbach's α value (0.891) indicated excellent internal consistency among the indicators. These findings collectively validated that the three attitudinal indicators effectively measured Technophilia with minimal error, justifying their use in the subsequent models.

### *3.3. Estimation results on EV /non-EV user models*

The estimated coefficients from the GSEM models specified to determine Technophilia and the four subsequent logistic-regression model specifications aligning with Fig. 1 are reported in Tables 4 and 5, respectively. The socio-demographic variables included in the logistic regression were carefully selected to ensure both relevance and robustness. The selection process prioritised highly associated variables, such as education and income, which also resulted in models with higher goodness-of-fit (pseudo-$R^2$). The step-by-step specification of variables in the models and the rationale behind these decisions are documented in Table A3 in the Appendix.

A comparison of the four models highlights the value of a stepwise modelling approach. Model A showed that socio-demographics alone explained a moderate portion of EV use (pseudo-$R^2 = 0.383$), while Model B demonstrated that adding Technophilia significantly improved model fit (pseudo-$R^2 = 0.418$; $\chi^2$ (1) = 27.49, $p < 0.001$). Model C, which tested only the indirect effects of socio-demographics via Technophilia, and EV use was explained by Technophilia alone, had the weakest fit (pseudo-$R^2 = 0.259$). Thus, this led to Model D specification, which included socio-demographics as direct and indirect effects. Interestingly, Models D and B had the same goodness-of-fit (pseudo-$R^2 = 0.418$). This meant that introducing socio-demographic characteristics as mediators for 'predicting' Technophilia had no difference in the resulting explanatory power of the model explaining EV use. The conclusion of the model comparisons is that socio-demographics only had a significant (in terms of model fit) direct effect onto explaining EV use (Model B) and there was no difference relative to a model that included socio-demographics within a GSEM model (Model D). Therefore, the progression of estimating Models A to D illustrates the value of integratingtesting different model structures to better capture the determinants of EV adoption. Given cultural and technology progression differences, this pattern may be different across different countries and settings, which emphasises the value of context-specific research.

This stepwise model building approach not only improved explanatory power but also helped to uncover different patterns regarding the significance and association of explanatory variables across models. For example, as shown in Table 5, the effect of Technophilia nearly doubled in Model C (0.812) relative to Models B (0.399) and D (0.445) – that is when model specification included socio-demographics. This suggests that part of the variance previously explained by Technophilia was then attributed to socio-demographic variables. Also, the significance of 'Type of Housing' dropped between Model A (significant at 99 % confidence level)

**Table 3**
Results of Principal Component Analysis.

| Construct | Indicator | Loading | Cronbach's alpha |
|---|---|---|---|
| Technophilia | T1 (Interest in technology) | 0.848 | 0.891 |
| | T2 (Technology liking) | 0.782 | |
| | T3 (Technology use) | 0.876 | |

**Table 4**
GSEM model coefficients.

| **Variables** | **Model A** Coefficient (sig.) | **Model B** Coefficient (sig.) | **Model C** Coefficient (sig.) | **Model D** Coefficient (sig.) |
|---|---|---|---|---|
| *MIMIC model* | N/A | | | |
| * Measurement equation | | | | |
| T1 (Interest in tech.) | | 1 (constrained) | 1 (constrained) | 1 (constrained) |
| T2 (Technology liking) | | 0.683 *** | 0.665 *** | 0.665 *** |
| T3 (Technology use) | | 1.426 *** | 1.601 *** | 1.601 *** |
| * Structural equation | | | | |
| Age | | | −0.375 *** | −0.375 *** |
| Gender (Female) | | | −0.626 *** | −0.626 *** |
| Income | | | 0.114 *** | 0.114 *** |
| Ethnicity (Non-white) | | | 0.275 | 0.275 |
| Number of children | | | 0.282 *** | 0.282 *** |
| Type of housing (Detached house) | | | 0.130 | 0.130 |
| Region of residence (Living in London) | | | 0.667 *** | 0.667 *** |
| * Threshold parameters | | | | |
| T1 Threshold parameters | | | | |
| Threshold 1 | | −3.717 | −4.752 | −4.752 |
| Threshold 2 | | −2.192 | −3.283 | −3.283 |
| Threshold 3 | | −1.243 | −2.345 | −2.345 |
| Threshold 4 | | 0.990 | −0.100 | −0.100 |
| T2 Threshold parameters | | | | |
| Threshold 1 | | −2.983 | −3.616 | −3.616 |
| Threshold 2 | | −1.837 | −2.518 | −2.518 |
| Threshold 3 | | −0.739 | −1.463 | −1.463 |
| Threshold 4 | | 1.107 | 0.354 | 0.354 |
| T3 Threshold parameters | | | | |
| Threshold 1 | | −4.632 | −6.811 | −6.811 |
| Threshold 2 | | −2.524 | −4.579 | −4.579 |
| Threshold 3 | | −0.936 | −2.818 | −2.818 |
| Threshold 4 | | 1.421 | −0.144 | −0.144 |
| Observations | N/A | 581 | 573 | 573 |
| Final Log-likelihood | | −2013.096 | −1854.207 | −1854.207 |
| df | | 15 | 22 | 22 |
| AIC | | 4056 | 3752 | 3752 |
| BIC | | 4121 | 3848 | 3848 |

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

**Table 5**
Logistic regression model coefficients.

| Variables | Model A Coefficient (sig.) | Model B Coefficient (sig.) | Model C Coefficient (sig.) | Model D Coefficient (sig.) |
|---|---|---|---|---|
| Age | −0.576*** | −0.485*** | | −0.457*** |
| Gender (Female) | −0.233 | −0.023 | | 0.020 |
| Household income | 0.258*** | 0.233*** | | 0.224*** |
| Ethnicity (Non-white) | −0.180 | −0.337 | | −0.348 |
| Number of children | 0.542*** | 0.451*** | | 0.431*** |
| Type of housing (Detached house) | 0.475** | 0.448* | | 0.435* |
| Region of residence (Living in London) | 0.452 | 0.101 | | 0.032 |
| Constant | 1.091** | 0.798 | 0.968*** | 1.219** |
| Technophilia | | 0.399*** | 0.812*** | 0.445*** |
| Observations | 573 | 573 | 573 | 573 |
| Pseudo R-squared | 0.383 | 0.418 | 0.259 | 0.418 |
| Log-likelihood (0) | −396.8 | −396.8 | −396.8 | −396.8 |
| Log-likelihood (Final) | −244.8 | −231.0 | −294.0 | −231.0 |
| df | 8 | 9 | 2 | 9 |
| AIC | 506 | 480 | 592 | 480 |
| BIC | 540 | 519 | 601 | 519 |

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

and Models B and D (significant at 90 % confidence level), suggesting that part of its effect was mediated through Technophilia. Similarly, the association of age and number of children slightly diminished when Technophilia was introduced in Models B and D, indicating partial mediation. Although the region of residence (living in London), variable was not significant in explaining EV use across all models, it emerged as a significant predictor of Technophilia in the GSEMs (Models C and D). This finding highlights an important indirect explanatory pathway. Therefore, estimating Models A to D enabled a better understanding of how Technophilia interacts with structural variables, and allowed detecting of different patterns of statistical significance, clarified mediation effects, and built a comprehensive explanation of EV adoption behaviour. The following subsections present the results of the four models in detail.

#### 3.3.1. The effects of socio-demographics on EV use (Model A)

As shown in Table 5, the baseline logistic regression model, which included only socio-demographic variables, explained about 38.3 % of the variance in EV use. Among all the socio-demographics, younger people (coefficient: −0.576, $p < 0.01$), those with higher income (coefficient: 0.258, $p < 0.01$), or more children in the household (coefficient: 0.542, $p < 0.01$) were more likely to drive an EV. Living in a detached house also showed a significant positive effect (coefficient: 0.475, $p < 0.05$). However, other socio-demographic factors, such as gender, ethnicity, and living in London, were not significant in this model. These results support the first hypothesis that "socio-demographic characteristics are statistically significantly associated with EV use". Specifically, age, income, number of children, and housing type are key factors explaining the variation, while gender, ethnicity, and location (e.g., London) do not significantly contribute. This contrasts with simple (univariate) relationships, where all sociodemographic factors were associated with EV use (see also Section 3.1 and Table A2).

#### 3.3.2. The direct effect of socio-demographics and Technophilia on EV use (Model B)

When Technophilia was added to the original logistic regression model while controlling for socio-demographics, the logistic regression results in Model B (see, Table 5) showed that Technophilia significantly increased the likelihood of driving an EV among UK driver's license holders (coefficient: 0.399, $p < 0.01$). This finding supports the second hypothesis that "Technophilia is positively associated with EV use, after controlling for socio-economic characteristics". This finding suggests that individuals with a higher level of Technophilia were more likely to adopt EVs.

In comparison to the logistic regression results of Model A (see, Table 5), socio-demographic factors like age (coefficient: −0.485, $p < 0.01$), income (coefficient: 0.233, $p < 0.01$), number of children (coefficient: 0.451, $p < 0.01$), and detached housing (coefficient: 0.448, $p < 0.10$) remained significant or marginally significant predictors of EV use, though their coefficients were slightly reduced. This suggests that part of the effect these variables had on EV use may be explained through their relationship with Technophilia. As in Model A, gender, ethnicity, and city of residence were not significant predictors in Model B, indicating that these factors did not significantly affect EV use when Technophilia was controlled for.

#### 3.3.3. The indirect effect of socio-demographics via Technophilia on EV use (Model C)

Building on the findings from Model B, which suggested that socio-demographics may relate to EV use through Technophilia, Model C introduced a more complex structure using the MIMIC model. The logistic regression estimates in Model C (see Table 5) indicated that individuals with higher Technophilia were significantly more likely to use EVs (coefficient: 0.812, $p < 0.01$), which again supported Hypothesis 2 "Technophilia is positively associated with EV use, after controlling for socio-economic characteristics". Unlike Model B, where socio-demographic variables were included directly in the logistic regression, Model C treated these variables as correlating with EV use indirectly through their impact on Technophilia. As shown in Table 4 (Model C), younger individuals (coefficient: −0.375, $p < 0.01$), men (coefficient: −0.626, $p < 0.01$), those with higher income (coefficient: 0.114, $p < 0.01$), more children (coefficient: 0.282, $p < 0.01$), and those living in London (coefficient: 0.667, $p < 0.01$) had higher levels of Technophilia, which in turn increased the likelihood of using EVs.

#### 3.3.4. Direct and indirect effects of socio-demographics and Technophilia on EV use (Model D)

The logistic regression results in Model D (Table 5) suggested that Technophilia remained statistically significant and positively associated with EV use, with a coefficient of 0.445 ($p < 0.01$). However, this coefficient is smaller compared to Model C (coefficient: 0.812, $p < 0.01$), suggesting that the effect of socio-demographic factors on EV use in Model C is partially mediated by Technophilia, in Model D. These results support the fourth hypothesis: "Technophilia positively mediates an indirect association between socio-demographic characteristics and EV use, after controlling for the direct effect of socio-demographic characteristics".

As shown in Table 5, socio-demographics remained significant predictors of EV use: age (coefficient: −0.457, $p < 0.01$), income (coefficient: 0.224, $p < 0.01$), number of children (coefficient: 0.431, $p < 0.01$), and detached housing (coefficient: 0.435, $p < 0.10$). This suggests that these factors continue to have a direct effect on EV use, independent of Technophilia. Additionally, the GSEM results for Model D (Table 4) showed that socio-demographics were associated with Technophilia – i.e., younger individuals (coefficient: −0.375, $p < 0.01$), males (coefficient: −0.626, $p < 0.01$), those with higher incomes (coefficient: 0.114, $p < 0.01$), more children (coefficient: 0.282, $p < 0.01$), and those living in London (coefficient: 0.667, $p < 0.01$) tended to have higher levels of Technophilia. This positive technophilic attitude, then, in turn, increased the likelihood of EV use through a positive association between Technophilia and EV use. Detached housing was the only variable that showed a direct effect on EV use without also being associated with Technophilia.

## 4. Discussion

### 4.1. The role of Technophilia (and socio-demographics) on EV use

This study examined the effects of Technophilia and socio-demographics on EV use in Great Britain, and how these factors may be related through statistical mediation. Using a stepwise model-specification approach, it was possible to specify Technophilia as a latent construct and examine its mediating role in the relationship between socio-demographic factors and EV use. By investigating these relationships, this study provides an original contribution to EV adoption research as one of the first to reveal the complex ways in which individual-level Technophilia is associated with the adoption of EVs. In line with previous studies, individuals who were inclined towards technological innovation were more likely to use EVs (Brückmann et al., 2021; Dai & Yang, 2024). This finding is in line with the Diffusion of Innovations Theory (Rogers, 2003) – which posits that those with positive attitudes towards innovation are more likely to be earlier adopters of new technologies – and resembles attitude-based theories, such as the Theory of Planned Behaviour (Ajzen, 2011) thus confirming that individual attitudes are associated with behaviour. A detailed summary of the findings relative to the initially specified hypotheses in this study is presented in Table 6.

This study also provides evidence that Technophilia mediates the effect of socio-demographic variables upon EV use. This implies that socio-demographics impact an individual's Technophilia, which in turn affects their likelihood of using EVs. Specifically, men who were younger, wealthier, parents, and those who lived in London exhibited higher level of Technophilia, which, in turn, increased their likelihood of using EVs. This finding suggests that specific socio-demographics had both a direct and an indirect association with EV use via Technophilia. Previous studies have recognised the role of psychological factors like Environmental Awareness and Technophilia on EV ownership (Brückmann et al., 2021). Some studies have also confirmed that psychosocial factors mediated the effect of policy incentives on EV adoption (Xue et al., 2023). Also, this study is consistent with socio-demographic differences in innovations proposed by the Diffusion of Innovations Theory (Rogers, 2003).

Technophilia was modelled within a GSEM framework and was determined either by constants (Model B) or socio-demographic characteristics (Models C and D). In the latter case, younger, men, with higher incomes, more children and who live in London are more likely to express higher levels of Technophilia. Income-differences are consistent with the higher socio-economic status of innovative early adopters described by Rogers (2003), as in previous studies (e.g., Morton et al., 2017). Age and gender results are consistent with empirical associations with Technophilia/innovativeness in previous studies (Tellis et al., 2009; Seebauer et al., 2015; Velazquez et al., 2018). The association between higher Technophilia and residence in London aligns with the study by Menezes Amorim and Abreu e Silva (2025), which also emphasised the importance of place. Specifically, Technophilia is spatially distributed and higher in neighbourhoods with mixed land use and strong transit infrastructure. Households with more children tended to have higher level of Technophilia, which aligns with Choi and Lee (2023), who found that older adults in multi-person households had higher digital literacy. This suggests that household composition may generally influence technology engagement across different age groups.

Examining the direct effects of socio-demographics on EV use regardless of Technophilia levels, this study confirmed patterns identified in previous research – i.e., EV users are typically younger (Sovacool et al., 2018), wealthier (Brückmann et al., 2021), or are parents (Sovacool et al., 2018). Higher-income individuals were more likely to use EVs, with a wider explanation being their higher disposable income and thus increased level of affordability towards the upfront costs associated with EV ownership (e.g., vehicle purchase and home charging infrastructure) relative to those owning conventional vehicles (Sovacool et al., 2019). However, the findings on age in this study differ from those of Jia and Chen (2021), who reported that EV owners in the US were predominantly older (vs. younger in this study). In their study, younger individuals expressed strong intentions to adopt EVs, but these intentions did not translate into (actual) behaviour. Possible reasons for this discrepancy may be financial constraints, psychological factors, and regional differences in infrastructure provision (Chu et al., 2019). This comparison points towards the gap between EV interest/intention to own an EV, and actual EV adoption. It also confirms the importance of investigating differences between non-EV and EV users, which is the case of this study. Interestingly, all models showed that gender, ethnicity, and living in London were not significantly associated with EV use. These findings were not in line with previous evidence. For example, Sovacool et al. (2018) reported that EV adopters in Nordic countries were mostly males. Regarding ethnicity, Winikoff (2024) reported higher EV adoption rates among non-white populations in California, US. Finally, Morton et al. (2018) identified London as a UK 'hotspot' for EV registrations; this is possibly due to London-specific factors, such as availability of charging infrastructure and emissions zoning policies, but is also consistent with urban environments facilitating EV adoption (Westin et al., 2018; Fevang et al., 2021; Winikoff, 2024).

Upon reflection, it is possible that the association between socio-demographic characteristics and EV adoption could be entirely accounted for through the measurement of the right attitudes or other cognitions (e.g., norms, efficacy-beliefs, values, perceptions, etc)

**Table 6**
Summary of results for hypotheses and research questions.

| Model | Hypothesis | Result |
|---|---|---|
| A | H1: Socio-demographic characteristics are associated with EV use. | Confirmed |
| B | H2: Technophilia is positively associated with EV use, after controlling for socio-economic characteristics. | Confirmed |
| C | H3: Technophilia positively mediates an indirect association between socio-demographic characteristics and EV use | Confirmed |
| D | H4: Technophilia positively mediates an indirect association between socio-demographic characteristics and EV use, after controlling for the direct effect of socio-demographic characteristics. | Confirmed |

(Nayum & Klöckner, 2014). This study only considered Technophilia, so it is possible that other mediating cognitions are reflected in the findings with respect to socio-demographics. However, some cognitions (e.g., social norms, perceived behavioural control) also reflect social realities and practical constraints that may be captured succinctly through socio-demographics (Ajzen, 2011; Westin et al., 2018; Iogansen et al., 2023). This study found that individuals who were younger, wealthier, and had larger households were more likely to adopt EVs regardless of their attitudes towards technology. It is possible that, for example, younger individuals may naturally lean towards EV use due to factors such as greater exposure to innovative products in the earlier stages of their lifecycle (Tully, 2003) and lifestyle-alignment with sustainability trends (Poortinga et al., 2023). For example, wealthier individuals often have the financial capacity to afford the higher upfront costs associated with EV ownership, which constitute an important practical barrier to EV adoption. Similarly, households with more children might opt for EVs as a practical choice to accommodate family mobility needs while aligning with environmental values.

### 4.2. Strengths and limitations

This study makes several original contributions. Firstly, this study provides timely empirical evidence concerning EV adoption during this decisive phase in its diffusion within Great Britain. EV adoption, as a field of study, is not uniform but instead varies, across time and between contexts – e.g., locations, societies, and national and regional policy frameworks (Sierzchula et al., 2014; Novotny et al., 2022). This study's evidence bears comparison with similar studies, present and future, within other contexts. This may be especially informative when considering that attitudes to technology may vary between cultures and institutional contexts, and -compared to Britain- may be decisive in anticipating EV adoption decisions. The evidence reported in this study was generated from actual EV and non-EV users, as opposed to eliciting hypothetical opinions, preferences or future intentions. The latter have been the mainstay in the past and thus have been abundant in the literature due to the infrequency of EV adoption in the population. However, stated intentions risk becoming increasingly imprecise as markets evolve and therefore, there is value in the potentially increased accuracy of the present study. Moreover, this study's theoretical contribution is also considerable. Through GSEM with differing specifications, this study has revealed interesting relationships concerning the unique and mediating explanatory role of Technophilia upon EV-use. Through stepwise and varying model specifications, these relationships become manifest, and can be given careful consideration individually, facilitating comparison with other ongoing research and informing the specifics of policy instrumentation concerning key socio-demographic population segments.

It is also important to reflect on this study's limitations. Cross-sectional surveys provide insufficient evidence for causal inference, though, in many cases, the associative evidence they provide is a necessary condition for causal links (Altman & Krzywinski, 2015). However, one cannot exclude the possibility that the EV use may itself affect more malleable aspects of household socio-demography (e.g., number of cars, house type, or rurality) or the technophilic attitudes of EV-owners. Likewise, a single survey of motorists in Great Britain is necessarily time- and place-specific, and results may not fully generalise. While this study aimed to recruit EV-users and non-EV users as population-stratified groups through quota sampling, to better facilitate inference to the British population, it is likely that the necessity of relaxing the stratifying-quotas for EV-user recruitment arose due to EV ownership continuing to be more common within certain early adopter segments of the population. This being so, a natural sample of EV users remains valuable for comparisons, and stratified comparisons may be more realistic as the market matures. On the other hand, the study was based on 581 EV (302) and non-EV users (279), which exceeded the minimum recommended thresholds for confirmatory factor analysis (CFA) and structural equation modelling (SEM), a ratio of cases to free parameters being between '10 observations over 1 estimated parameter' and'20 observations over 1 estimated parameter thus, providing enough sample to be able to observe 'meaningful patterns of association' across the tested variables (Wolf et al., 2013; Klein, 2016).

### 4.3. Policy implications

This study has several policy implications. The strong effects of Technophilia underscore the importance of cultivating a cultural openness toward technology as a strategy for promoting EV adoption, especially as EV technology continues to evolve. Those who view sustainable technological advancements positively are more likely to recognise the advantages of EVs in reducing environmental impacts and utilising potentially cleaner energy sources. For example, studies showed that people with positive perceptions of innovations like rooftop solar photovoltaics are often early adopters of complementary technologies such as EVs, as they view them as part of a broader ecosystem of sustainable living (Kaufmann et al., 2021). Similarly, early exposure to advanced EV features like autonomous driving (Potoglou et al., 2020) or fast-charging capabilities (Greene et al., 2020) can shape positive attitudes towards their usability and convenience, which can mitigate concerns such as range anxiety or unfamiliarity with EV technology. To capitalise on these insights, public initiatives could focus on increasing awareness of EV benefits and dispelling misconceptions. For example, campaigns emphasising advancements in charging infrastructure, such as ultra-fast chargers now available along major highways, can reduce range anxiety; thus, concerns about battery life, range anxiety, and charging station availability may be reduced (Adnan et al., 2017). It is also worth considering that innovativeness and environmental values may not always coincide, so emphasising the innovativeness of EVs may be necessary to reach groups for whom the technology, rather than the sustainability, is perceived to be the primary advantage.

The indirect effect of socio-demographic characteristics on EV use, through Technophilia, emphasises the importance of fostering positive attitudes towards technology, especially among people with lower levels of Technophilia in general. This study suggests that, in general, these might include older individuals, women, those without children in the household, people living outside London, and lower-income groups. Hence, to encourage greater EV adoption, efforts should focus on overcoming technological scepticism, particularly among groups that may have less exposure to new technologies. A practical approach to addressing these challenges when communicating about EVs could involve highlighting real-world success stories of individuals or families who have successfully transitioned to EVs or making technologies user friendly. These relatable examples can build trust and inspire confidence among consumers who may be hesitant to adopt new technology (Pettifor et al., 2017). These efforts can help bridge the gap between interest in and actual adoption of EVs, broadening their appeal across a range of socio-demographic groups.

## 5. Conclusion

This study contributes to the EV adoption literature by highlighting how Technophilia is associated with EV adoption decisions, directly or by mediating socio-demographic characteristics of motorists. Exploring this intersection in detail, establishes a useful precedent for future research of EV adoption attitudes. The mediation effects identified here do not seem to have been examined before in a British context (e.g., Morton et al., 2018; Iogansen et al., 2023). While the focus upon motorists in Great Britain at a single moment in time may limit the temporal and geographical generalisation of these findings, the comparison of actual EV users to non-EV users is valuable in a field often reliant on assessing only the future intentions or (stated) preferences of motorists rather than their actions.

The findings of this study suggest that while Technophilia plays a key role in shaping EV adoption decisions, socio-demographic characteristics could, in themselves, have a fundamental role on EV adoption. This reinforces the importance of considering both socio-demographic characteristics and attitudes, such as Technophilia, when developing strategies to encourage broader adoption of EVs. Future studies could examine the role of different socio-demographic factors across a wider range of EV adoption stages, including intention, awareness, and post-purchase behaviour. Inspired by Roger's Diffusion of Innovation Theory (Rogers, 2003), repeated cross-sectional or longitudinal research could also offer insights into how these factors affect EV adoption over time; as well as whether moments of significant household-lifecycle changes (e.g., graduating university, starting a family, retirement) and/or changes in technology attitudes correlate with shifts in adoption patterns. Past research indicates that new behaviours can be adopted during such key 'moments of change' in life (Verplanken et al., 2018), and tracking them over time could be a fertile further step of this research.

These results imply the need for targeted interventions to address barriers to EV adoption, like tailored information/messaging to specific socio-demographic segments. This could involve dispelling persisting misconceptions around battery life, range anxiety, and charging infrastructure amongst less technophilic groups. EV and EV charging technologies are novel and evolve rapidly away from conventional vehicle technology; they are fundamentally different from it (e.g., charging, range) and incorporate novel digital technologies. Fair and equitable decarbonisation through EV use obligates policymakers and designers to consider not only the "tech-savvy" but also those whose technological attitudes and ability are challenged.

Should EV ownership become more commonplace, there may be more opportunity to make more thorough distinctions in research between owners of different vehicle-technologies than were drawn in this study. For example, this study combined BEV and PHEV users into a single group, a common practice in many studies; however, different levels of Technophilia and other types of heterogeneity (e.g., motivations for use, vehicle-usage patterns) may exist between these two groups. Future research could also investigate the extent to which other psychological factors (e.g., environmental concern or sustainability values) mediate the relationship between socio-demographic characteristics and EV use whilst also allowing for technophilic attitudes (Noppers et al., 2015).

## CRediT authorship contribution statement

**Rongqiu Song:** Writing – review & editing, Writing – original draft, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Paul Haggar:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation, Conceptualization. **Dimitrios Xenias:** Writing – review & editing, Writing – original draft, Conceptualization. **Dimitris Potoglou:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

## Funding

This study was supported by the UKRI's Engineering and Physical Sciences Research Council [EP/S032053/1 and EP/Y026233/1]. The first author also acknowledges the financial support of the China Scholarship Council.

## Declaration of competing interest

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

## Appendix

**

**Table A1**
The effects of individual socio-demographics and attitudes on EV adoption.

| Reference | Context | Data | Methodology | Significant individual level variables |
|---|---|---|---|---|
| Sovacool et al. (2018) | EV ownership | 5,067 respondents across Denmark, Finland, Iceland, Norway, and Sweden | Bivariate statistical tests | Gender (Male) +, education +, age −, household size + |
| Westin et al. (2018) | The probability of being EV and non-EV owners | All private car owners in Sweden (N = 4,447,118) | Logistic regression models | Age +, education +, weekly driving distance +, suburban + and rural + (ref. metropolitan), charging poles + |
| Morton et al. (2018) | Spatial EV registration rate | 374 local authorities | Spatial regression models | Direct effects: University degree +, self-employed +, median income +, semi-detached +, mean residents −, one car household −, HEVs per 1,000 cars +, the number of charge points +, spatial interaction + Indirect effects: Population density + |
| Sovacool et al. (2019) | EV ownership | 5,067 respondents across Denmark, Finland, Iceland, Norway, and Sweden | Bivariate statistical tests | Urbanisation −, income + |
| Brückmann et al. (2021) | The probability of individuals' BEV adoption or no BEV adoption | 557 BEV holders and 1776 ICEV holders, Switzerland | Generalised linear mixed model | Tech +, environmental concern +, female −, >65 years old −, income +, green party preferences +, house-own +, multiple car +, multiple people in the household −, car sharing + |
| Fevang et al. (2021) | Household characteristics of BEV owners | Registered private car drivers, Norway | Regression analysis | Income+, education+, household with kids+, living in large cities+, age- |
| Renaud-Blondeau et al. (2023) | EV ownership for car owners | 100 EV owners, 366 CV owners, Montreal, Canada | Logistic regression models | Marital status (single) −, age group: 55–64 years old +, # of days per week using a car +, perceived insufficient charging stations around their residence −, attract to new technologies +, insufficient EV range −, EVs perform better than gas-powered cars +, high purchase price −, high charging cost − |
| Dai and Yang (2024) | EV owners and potential consumers | 1,186 participants in China | Logistic and stepwise regression analyses | First- and second-tier cities: age −, household size +, married +, car ownership +, social norm +, financial benefits −; Third-tier cities and below: age −, married +, car ownership+, technological interest + |
| Winikoff (2024) | Zip-code characteristics and BEV purchase | California Energy Commission's 'New ZEV (Zero Emission Vehicles) Sales in California' data | Zip-code regressions | University degree +, income+, white share −, rural share −, median age + |

**Table A2**
The effect of each variable alone on EV use in the logistic regression.

| Variable | Logistic regression coefficient | Standard error | p-value | Pseudo $R^2$ |
|---|---|---|---|---|
| Age | −0.817 | 0.069 | 0.000 | 0.254 |
| Gender (Female) | −0.448 | 0.168 | 0.008 | 0.009 |
| Household income | 0.391 | 0.036 | 0.000 | 0.211 |
| Education (University degree or higher) | 1.492 | 0.181 | 0.000 | 0.091 |
| Ethnicity (Non-white) | 1.194 | 0.285 | 0.000 | 0.025 |
| Number of children | 1.376 | 0.139 | 0.000 | 0.182 |
| Household size | 0.326 | 0.097 | 0.001 | 0.015 |
| Type of housing (Detached house) | 0.672 | 0.169 | 0.000 | 0.020 |
| Cars owned in the household | 0.825 | 0.163 | 0.000 | 0.036 |
| Rurality (Rural area) | −1.081 | 0.1798 | 0.000 | 0.047 |
| Region of residence (Living in London) | 1.537 | 0.256 | 0.000 | 0.054 |

**Table A3**
Variable exclusion to avoid multicollinearity.

| Variable pair | Logistic Regression Coefficients and Pseudo $R^2$ of the first (1) variable | Logistic Regression Coefficients and Pseudo $R^2$ of the second (2) variable | Exclude the variable out of the model |
|---|---|---|---|
| Household income (1) vs. Education (2) | 0.391*** (Pseudo $R^2 = 0.211$) | 1.492*** (Pseudo $R^2 = 0.091$) | Education |
| Household income (1) vs. Number of cars (2) | 0.391*** (Pseudo $R^2 = 0.211$) | 0.825*** (Pseudo $R^2 = 0.036$) | Number of cars |
| Income (1) vs. Gender (2) | 0.391*** | −0.448*** | Gender |

(*continued on next page*)

**Table A3** (*continued*)

| Variable pair | Logistic Regression Coefficients and Pseudo $R^2$ of the first (1) variable | Logistic Regression Coefficients and Pseudo $R^2$ of the second (2) variable | Exclude the variable out of the model |
|---|---|---|---|
| | (Pseudo $R^2 = 0.211$) | (Pseudo $R^2 = 0.009$) | |
| Number of children (1) vs. Household size (2) | 1.376*** (Pseudo $R^2 = 0.182$) | 0.326*** (Pseudo $R^2 = 0.015$) | Household size |
| Rurality (1) vs. Region of residence (2) | −1.081*** (Pseudo $R^2 = 0.047$) | 1.537*** (Pseudo $R^2 = 0.054$) | Rurality |

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

## Data availability

The authors do not have permission to share data.

## References

Adnan, N., Nordin, S. M., Rahman, I., Vasant, P. M., & Noor, A. (2017). A comprehensive review on theoretical framework-based electric vehicle consumer adoption research. *International Journal of Energy Research, 41*(3), 317–335. https://doi.org/10.1002/er.3640

Ajzen, I. (2011). The theory of planned behaviour: Reactions and reflections. *Psychology and Health, 26*(9), 1113–1127. https://doi.org/10.1080/08870446.2011.613995

Altman, N., & Krzywinski, M. (2015). Points of significance: Association, correlation and causation. *Nature Methods, 12*(10), 899–900. https://doi.org/10.1038/nmeth.3587

Bagozzi, R. P., & Yi, Y. (2012). Specification, evaluation, and interpretation of structural equation models. *Journal of the Academy of Marketing Science*. https://doi.org/10.1007/s11747-011-0278-x

Brückmann, G., Willibald, F., & Blanco, V. (2021). Battery Electric Vehicle adoption in regions without strong policies. *Transportation Research Part D: Transport and Environment, 90*(2020). https://doi.org/10.1016/j.trd.2020.102615

Choi, J. Y., & Lee, M. J. (2023). Household type, gender, and digital literacy among older adults in South Korea. *Universal Access in the Information Society, 24*(1), 425–433. https://doi.org/10.1007/s10209-023-01064-0

Chu, W., Im, M., Song, M. R., & Park, J. (2019). Psychological and behavioral factors affecting electric vehicle adoption and satisfaction: A comparative study of early adopters in China and Korea. *Transportation Research Part D: Transport and Environment, 76*, 1–18. https://doi.org/10.1016/j.trd.2019.09.009

CMA, 2021. *Electric Vehicle Charging market study*. Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1012617/EVC_MS_final_report_–.pdf.

Dai, G., & Yang, S. (2024). A comparative study of motivations driving EV purchases in different-tier Chinese cities. *Transportation Research Part D: Transport and Environment, 126*(2023). https://doi.org/10.1016/j.trd.2023.103993

Department for Energy Security & Net Zero. 2024. *Open letter from DESNZ and Ofgem: Aligning grid connections with strategic plans*. Available at: https://www.gov.uk/government/publications/aligning-grid-connections-with-strategic-plans/open-letter-from-desnz-and-ofgem-aligning-grid-connections-with-strategic-plans-5-november-2024.

Fevang, E., Figenbaum, E., Fridstrøm, L., Halse, A. H., Hauge, K. E., Johansen, B. G., & Raaum, O. (2021). Who goes electric? The anatomy of electric car ownership in Norway. *Transportation Research Part D: Transport and Environment, 92*(February), 1–20. https://doi.org/10.1016/j.trd.2021.102727

Globisch, J., Plötz, P., Dütschke, E., & Wietschel, M. (2019). Consumer preferences for public charging infrastructure for electric vehicles. *Transport Policy, 81*, 54–63. https://doi.org/10.1016/j.tranpol.2019.05.017

Greene, D. L., Kontou, E., Borlaug, B., Brooker, A., & Muratori, M. (2020). Public charging infrastructure for plug-in electric vehicles: What is it worth? *Transportation Research Part D: Transport and Environment, 78*(2019). https://doi.org/10.1016/j.trd.2019.11.011

Harinath, V., Teja, V., & Kadali, B. R. (2021). Does perceived technology and knowledge of maintenance influence purchase intention of BEVs. *Transportation Research Part D, 93*. https://doi.org/10.1016/j.trd.2021.102759

Haustein, S., & Jensen, A. F. (2018). Factors of electric vehicle adoption: A comparison of conventional and electric car users based on an extended theory of planned behavior. *International Journal of Sustainable Transportation, 12*(7), 484–496. https://doi.org/10.1080/15568318.2017.1398790

Hill, G., Heidrich, O., Creutzig, F., & Blythe, P. (2019). The role of electric vehicles in near-term mitigation pathways and achieving the UK's carbon budget. *Applied Energy, 251*(March). https://doi.org/10.1016/j.apenergy.2019.04.107

Hosmer, D.W., Lemeshow, S. and Sturdivant, R.X. 2013. *Applied Logistic Regression: Third Edition*. doi: 10.1002/9781118548387.

International Energy Agency. 2024. *Global EV Outlook 2024: Moving towards increased affordability*. Available at: https://iea.blob.core.windows.net/assets/a9e3544b-0b12-4e15-b407-65f5c8ce1b5f/GlobalEVOutlook2024.pdf.

Iogansen, X., Wang, K., Bunch, D., Matson, G., & Circella, G. (2023). Deciphering the factors associated with adoption of alternative fuel vehicles in California: An investigation of latent attitudes, socio-demographics, and neighborhood effects. *Transportation Research Part A: Policy and Practice, 168*(2022). https://doi.org/10.1016/j.tra.2022.10.012

Jia, W., & Chen, T. D. (2021). Are Individuals' stated preferences for electric vehicles (EVs) consistent with real-world EV ownership patterns? *Transportation Research Part D: Transport and Environment, 93*. https://doi.org/10.1016/j.trd.2021.102728

Jin, F., Yao, E., & An, K. (2020). Understanding customers' battery electric vehicle sharing adoption based on hybrid choice model. *Journal of Cleaner Production, 258*. https://doi.org/10.1016/j.jclepro.2020.120764

Kaufmann, R. K., Newberry, D., Xin, C., & Gopal, S. (2021). Feedbacks among electric vehicle adoption, charging, and the cost and installation of rooftop solar photovoltaics. *Nature Energy, 6*(2019). https://doi.org/10.1038/s41560-020-00746-w

Klein, R.B. 2016. Principles and Practice of Structural Equation Modeling, fourth edition.

Liao, F., Molin, E., & van Wee, B. (2017). Consumer preferences for electric vehicles: A literature review. *Transport Reviews, 37*(3), 252–275. https://doi.org/10.1080/01441647.2016.1230794

Mehdizadeh, M., Nayum, A., Nordfjærn, T., & Klöckner, C. A. (2024). Are Norwegian car users ready for a transition to vehicle-to-grid technology? *Transport Policy, 146*(2023), 126–136. https://doi.org/10.1016/j.tranpol.2023.11.014

Mehdizadeh, M., Nordfjaern, T., & Klöckner, C. A. (2023). Estimating financial compensation and minimum guaranteed charge for vehicle-to-grid technology. *Energy Policy, 180*(June). https://doi.org/10.1016/j.enpol.2023.113649

Menezes Amorim, J. de; and Abreu e Silva, J. de; 2025. The influence of residential location and public transit options on commuters' intention to use travel apps for different travel purposes. 38(July 2024).

Miele, A., Axsen, J., Wolinetz, M., Maine, E., & Long, Z. (2020). The role of charging and refuelling infrastructure in supporting zero-emission vehicle sales. *Transportation Research Part D: Transport and Environment, 81*. https://doi.org/10.1016/j.trd.2020.102275

Morton, C., Anable, J., & Nelson, J. D. (2016). Exploring consumer preferences towards electric vehicles: The influence of consumer innovativeness. *Research in Transportation Business and Management, 18*, 18–28. https://doi.org/10.1016/j.rtbm.2016.01.007

Morton, C., Anable, J., & Nelson, J. D. (2017). Consumer structure in the emerging market for electric vehicles: Identifying market segments using cluster analysis. *International Journal of Sustainable Transportation, 11*(6), 443–459. https://doi.org/10.1080/15568318.2016.1266533

Morton, C., Anable, J., Yeboah, G., & Cottrill, C. (2018). The spatial pattern of demand in the early market for electric vehicles: Evidence from the United Kingdom. *Journal of Transport Geography, 72*(2016), 119–130. https://doi.org/10.1016/j.jtrangeo.2018.08.020

National Grid, 2024. *How we're innovating at National Grid to boost the energy transition*. Available at: https://www.nationalgrid.com/electricity-transmission/how-were-innovating-national-grid-boost-energy-transition.

Nayum, A., & Klöckner, C. A. (2014). A comprehensive socio-psychological approach to car type choice. *Journal of Environmental Psychology, 40*, 401–411. https://doi.org/10.1016/j.jenvp.2014.10.001

Nayum, A., Nordfjærn, T., Bhaduri, E., & Goswami, A. K. (2023). Examining user attitudes towards ride-hailing services – A SEM-MIMIC Ordered Probit approach. *Travel Behaviour and Society, 22*(2021), 41–59. https://doi.org/10.1016/j.tbs.2022.08.008

Noppers, E. H., Keizer, K., Bockarjova, M., & Steg, L. (2015). The adoption of sustainable innovations: The role of instrumental, environmental, and symbolic attributes for earlier and later adopters. *Journal of Environmental Psychology, 44*, 74–84. https://doi.org/10.1016/j.jenvp.2015.09.002

Novotny, A., Szeberin, I., Kovács, S., & Máté, D. (2022). National culture and the market development of battery electric vehicles in 21 countries. *Energies, 15*(4), 1–16. https://doi.org/10.3390/en15041539

Office for Zero Emission Vehicles. 2025. *Office for zero emission vehicles*. Available at: https://www.gov.uk/government/organisations/office-for-zero-emission-vehicles.

Pettifor, H., Wilson, C., Axsen, J., Abrahamse, W., & Anable, J. (2017). Social influence in the global diffusion of alternative fuel vehicles – A meta-analysis. *Journal of Transport Geography, 62*(June), 247–261. https://doi.org/10.1016/j.jtrangeo.2017.06.009

Poortinga, W., Demski, C., & Steentjes, K. (2023). Generational differences in climate-related beliefs, risk perceptions and emotions in the UK. *Communications Earth and Environment, 4*(1). https://doi.org/10.1038/s43247-023-00870-x

Potoglou, D., Song, R., & Santos, G. (2023). Public charging choices of electric vehicle users: A review and conceptual framework. *Transportation Research Part D: Transport and Environment, 121*. https://doi.org/10.1016/j.trd.2023.103824

Potoglou, D., Whittle, C., Tsouros, I., & Whitmarsh, L. (2020). Consumer intentions for alternative fuelled and autonomous vehicles: A segmentation analysis across six countries. *Transportation Research Part D: Transport and Environment, 79*. https://doi.org/10.1016/j.trd.2020.102243

Renaud-Blondeau, P., Boisjoly, G., Dagdougui, H., & He, S. Y. (2023). Powering the transition: Public charging stations and electric vehicle adoption in Montreal, Canada. *International Journal of Sustainable Transportation, 17*(10), 1097–1112. https://doi.org/10.1080/15568318.2022.2152403

Rogers, E. M. (2003). *Diffusion of innovations* (fifth ed.). New York: Free Press.

Seebauer, S., Stolz, R., & Berger, M. (2015). Technophilia as a driver for using advanced traveler information systems. *Transportation Research Part C: Emerging Technologies, 60*, 498–510. https://doi.org/10.1016/j.trc.2015.10.009

Sierzchula, W., Bakker, S., Maat, K., & Van Wee, B. (2014). The influence of financial incentives and other socio-economic factors on electric vehicle adoption. *Energy Policy, 68*, 183–194. https://doi.org/10.1016/j.enpol.2014.01.043

Song, R., & Potoglou, D. (2020). Are existing battery electric vehicles adoption studies able to inform policy? A review for policymakers. *Sustainability, 12*(16), 6494. https://doi.org/10.3390/su12166494

Song, R., & Potoglou, D. (2024). Electric vehicle public charging choices: a qualitative investigation. *Transportation Planning and Technology., 1–23*. https://doi.org/10.1080/03081060.2024.2367754

Sovacool, B. K., Kester, J., Noel, L., & de Rubens, G. Z. (2018). The demographics of decarbonizing transport: The influence of gender, education, occupation, age, and household size on electric mobility preferences in the Nordic region. *Global Environmental Change, 52*, 86–100. https://doi.org/10.1016/j.gloenvcha.2018.06.008

Sovacool, B. K., Kester, J., Noel, L., & de Rubens, G. Z. (2019). Income, political affiliation, urbanism and geography in stated preferences for electric vehicles (EVs) and vehicle-to-grid (V2G) technologies in Northern Europe. *Journal of Transport Geography, 78*, 214–229. https://doi.org/10.1016/j.jtrangeo.2019.06.006

Tellis, G. J., Yin, E., & Bell, S. (2009). Global consumer innovativeness: Cross-country differences and demographic commonalities. *Journal of International Marketing, 17*(2). https://doi.org/10.1509/jimk.17.2.1

Tully, C. J. (2003). Growing up in technological worlds: How modern technologies shape the everyday lives of young people. *Bulletin of Science, Technology and Society, 23*(6). https://doi.org/10.1177/0270467603260812

UK Parliament, 2024. *EV strategy: rapid recharge needed*. Available at: https://publications.parliament.uk/pa/ld5804/ldselect/ldenvcl/51/51.pdf.

Velazquez, G., Kaplan, S., & Monzon, A. (2018). Ex-ante and ex-post evaluation of a new transit information app: Modeling use intentions and actual use. *Transportation Research Record, 2672*(50). https://doi.org/10.1177/0361198118792753

Verplanken, B., Roy, D. and Whitmarsh, L. 2018. Cracks in the wall: Habit discontinuities as vehicles for behaviour change. In: *The Psychology of Habit: Theory, Mechanisms, Change, and Contexts*. doi: 10.1007/978-3-319-97529-0_11.

Westin, K., Jansson, J., & Nordlund, A. (2018). The importance of socio-demographic characteristics, geographic setting, and attitudes for adoption of electric vehicles in Sweden. *Travel Behaviour and Society, 13*, 118–127. https://doi.org/10.1016/j.tbs.2018.07.004

Weston, R., & Gore, P. A. (2006). A brief guide to structural equation modeling. *The Counseling Psychologist*. https://doi.org/10.1177/0011000006286345

Wicki, M., Brückmann, G., Quoss, F., & Bernauer, T. (2022). What do we really know about the acceptance of battery electric vehicles?–Turns out, not much. *Transport Reviews*, 1–26. https://doi.org/10.1080/01441647.2021.2023693

Winikoff, J. B. (2024). Economic specialization, infrastructure, and rural electric vehicle adoption. *Energy Policy, 195*. https://doi.org/10.1016/j.enpol.2024.114380

Wolf, E. J., Harrington, K. M., Clark, S. L., & Miller, M. W. (2013). Sample size requirements for structural equation models: An evaluation of power, bias, and solution propriety. *NIH Public Access, 76*(6). https://doi.org/10.1177/0013164413495237.Sample

Xue, Y., Zhang, Y., Wang, Z., Tian, S., Xiong, Q., & Li, L. Q. (2023). Effects of incentive policies on the purchase intention of electric vehicles in China: Psychosocial value and family ownership. *Energy Policy, 181*. https://doi.org/10.1016/j.enpol.2023.113732

Zatsarnaja, J., Reiter, K., Mehdizadeh, M., Nayum, A., & Nordfjærn, T. (2025). Charged up with peace in mind: Unraveling the factors of range anxiety among Norwegian electric vehicle drivers. *Transportation Research Part F: Traffic Psychology and Behaviour, 110*(2024), 15–28. https://doi.org/10.1016/j.trf.2025.02.006