Testing diffusion of innovation theory for decarbonisation using heat pumps and electric vehicles

Shane Timmons, Diarmaid Ó Ceallaigh, Philip Carthy & Fionn Rogan

ESRI Working Paper No. 844

September 2026

Author Affiliation:

Shane Timmons[a,b*]

Diarmaid Ó Ceallaigh[a,c]

Philip Carthy[a]

Fionn Rogan[d, e]

a. Economic and Social Research Institute, Dublin, Ireland.

b. School of Psychology, Trinity College Dublin, Dublin, Ireland.

c. *Present affiliation:* Coimisiún na Meán (Media Commission), Dublin, Ireland.

d. School of Engineering and Architecture, University College Cork, Cork, Ireland

e. Sustainability Institute, University College Cork, Cork, Ireland

* Corresponding Author: shane.timmons@esri.ie

Abstract

Decarbonisation requires adoption of low-carbon technologies for residential heating and transport, and Diffusion of Innovations theory has strongly influenced modelling approaches and policy. We test central propositions of the theory Diffusion for two priority technologies: residential heat pumps and electric vehicles (EVs). Using a nationally representative survey (N = 1,000), we analyse adoption intentions for each technology and examine the associations between adopter category and three classes of theory-specified predictors: technology perceptions, communication exposure and individual characteristics. We employ pre-registered generalised ordered logistic regression, complemented by exploratory structural equation modelling. Across both technologies, observed distributions of intentions differ from the S-curve predicted by the theory, with higher proportions of those most resistant to adoption. Positive technology perceptions are generally associated with greater adoption intentions, while communication exposure and individual characteristics are more weakly associated once perceptual factors are taken into account. Structural equation models indicate that communication exposure and individual characteristics primarily influence adoption indirectly, through their effects on perceptions. Comparing heat pumps and EVs reveals broadly similar patterns. By empirically testing Diffusion of Innovations constructs across two technologies within the same population, the study strengthens the evidence base underpinning diffusion modelling and policy analysis, and highlights the importance of addressing perceptual barriers to accelerate residential decarbonisation.

Acknowledgements

This paper was funded by MaREI Research Ireland Centre for Energy, Climate and Marine. The last author was supported by the Department of Climate, Energy and the Environment through the Climate and Energy Modelling Services to the Climate Energy Modelling Group (CEMG) (grant no. RFT2022/S164-466018). The authors would like to thank attendees at the 2025 MaREI Climate & Energy Research Seminar, the 16th International Sustainability Transitions (IST) Conference 2025 and Behave 2025 (the European Energy Network's biannual conference on the application of behavioural insights in energy efficiency and climate mitigation) for feedback on initial findings. We also thank staff at the Sustainable Energy Authority of Ireland's Behavioural Economics Unit for helpful comments.

JEL codes (optional):

Keywords: diffusion of innovations; technology adoption; heat pumps; electric vehicles

1 Introduction

Rapidly decarbonising residential heating and private transport remains a central challenge for climate and energy policy (Knobloch et al., 2020). Achieving the European Commission's (2026) Electrification Action Plan target of 46% by 2040 depends on widespread adoption of heat pumps and electric vehicles (EVs). Although stock of both technologies has increased in recent years, adoption remains highly uneven across Europe. EVs account for over one-fifth of the vehicle fleet in some countries (Denmark, 21.3%) but less than 1% in others (Poland and Cyprus, both 0.8%), while heat pump penetration in the Nordic countries remains several times higher than other EU member states.

Recent energy-modelling literature reaches a similar conclusion: adoption of low-carbon technologies is accelerating, but unevenly and well short of policy targets and scenario models (Adamo et al, 2024; Chitchyan, 2025; Hardman & Tal, 2024). Structural constraints contribute to this gap, but evidence increasingly points to the importance of psychological and social processes in shaping how households evaluate and respond to new technologies (Eppe, Niehoff, Albers & Bouman, 2025; Günther et al., 2025; Pettifor et al., 2017; Roberts et al., 2018).

Understanding these behavioural processes matters, because they are frequently represented in energy-system and agent-based models used to project decarbonisation pathways. Such models commonly assume that adoption follows a normal distribution, that psychological traits such as risk aversion act as stable determinants of early uptake and that information campaigns shift behaviour more or less directly (e.g., McCoy & Lyons, 2013; Meles & Ryan, 2022; Sopha, Klöckner & Hertwich, 2013). These assumptions are often necessary because comparable empirical evidence is scarce. However, testing them directly can improve projections of adoption trajectories and the policies informed by them. For this reason, researchers have begun to call for closer integration of empirically validated behavioural mechanisms into diffusion modelling (Rietkerk-van der Wijngaart et al., 2025). The present study responds to that call by examining the behavioural propositions of a leading theory of technology diffusion.

1.1 Diffusion of Innovations

Several theories seek to explain patterns of social decision-making, consumer choice and technology diffusion over time (Wilson & Dowlatabadi, 2012; Peres et al, 2010). Among the most influential is Diffusion of Innovations theory (Rogers, 1962, 2003). A core claim is that cumulative adoption follows an S-shaped diffusion curve. Uptake is slow at first, occurring initially only among ‘innovators’ (who comprise 2.5% of the population) followed by ‘early adopters’ (13.5% of the population). Adoption then accelerates among the ‘early majority’ (34%) becoming more visible and socially validated, before eventually saturating the market as the ‘late majority’ (34%) join. ‘Laggards’ (16%) are those last to adopt, only doing so if forced by market conditions. As a result, the distribution of new adopters over time is expected to be approximately normal. This pattern has been observed across a wide range of technologies, particularly consumer durables and telecommunications technologies (Meade & Islam, 2006). Because this S-curve shape is frequently assumed when calibrating technology-diffusion and energy-scenario models, whether it holds for low-carbon residential technologies is an empirical question with direct implications for such models (Mahajan et al, 1995; Sharp & Miller, 2016; Kumar et al, 2022)

Beyond describing aggregate diffusion patterns, Diffusion of Innovation theory proposes mechanisms through which adoption varies across individuals and social groups. These can be organised into three broad classes of predictors that influence where individuals are likely to sit along the adoption curve. Together, they provide a testable set of drivers that diffusion and agent-based models can employ for simulation uptake of heat pumps and EVs.

The first class of predictors concerns perceptions of the innovation itself (Rogers, 2003). These include perceived advantages over incumbent alternatives, for example in terms of cost, convenience, comfort or environmental impact (relative advantage); whether it fits with existing practices, routines and values (compatibility); and its perceived ease of understanding and use (simplicity). Adoption is also shaped by whether the innovation can be tested prior to commitment (trialability) and whether others are seen using it (observability or visibility). Empirical research shows that these evaluations, particularly relative advantage, predict energy-efficient technology adoption among firms (Anderson & Newell, 2004; Fleiter, Hirzel & Worrell, 2012; Völlnik, Meertens & Midden, 2002).

The second class concerns exposure to communication about the technology (e.g., Eppstein, Grover, Marshall & Rizzo, 2011; Räihä & Ruokamo, 2021). Diffusion of Innovation theory distinguishes between mass-media, which primarily creates awareness and legitimacy at early stages of diffusion, and interpersonal communication, which becomes increasingly influential as adoption spreads. Interpersonal sources, such as family, friends, neighbours, installers or other trusted contacts, are argued to provide social proof and reassurance that move potential adopters from awareness to action, particularly among the early and late majority.

The third class comprises individual characteristics that shape responses to information and uncertainty. These include personal innovativeness, defined as a tendency to adopt new technologies sooner (Aggarwal & Prasad, 1998; Emmann, Arens & Theuvsen, 2013), and opinion leadership, the propensity to influence others' adoption decisions (Childers, 1986; Seebauer, 2015). Environmental concern may promote adoption of sustainable technologies through sooner perceived benefits or willingness to accept trade-offs (Erdem, Şentürk & Şimşek, 2010; Smith, Olaru, Jabeen & Greaves, 2017), while concern with social status may encourage earlier adoption where technologies act as visible status signals (Anderson, Hildreth & Howland, 2015). Risk aversion is theorised to distinguish later adopters, who are more reluctant to adopt until uncertainty is reduced through others' experience (Eckel & Grossman, 2008). Income and broader socio-economic resources operate as contextual enablers, shaping whether favourable dispositions translate into actual adoption (Wilson, Hargreaves & Hauxwell-Baldwin, 2017).

1.2 Relevant Applications of Diffusion of Innovation Theory

Diffusion of Innovation theory has been widely applied to the study of green technology adoption, including EVs and heating systems (e.g., Frenceshinis et al., 2017; Noppers, Keizer, Bockarjova & Steg, 2015). Empirical applications have often emphasise individual characteristics, especially risk aversion and innovativness, partly because they are readily measured through surveys and lend themselves to the construction of consumer archetypes used in policy and communication strategy (e.g., Egmond, Jonkers & Kok, 2006; Mac Uidhir et al., 2020; Strazzera, Meleddu, Contu & Fornara, 2024). Psychological traits derived from survey data have also been incorporated into agent-based diffusion models to simulate the spread of EVs and related technologies, although such models vary in how psychological processes are operationalised (e.g., Kangur, Jager, Verbrugge & Bockarjova, 2017; McCoy & Lyons, 2014; Meles & Ryan, 2022; Sopha, Klöckner & Hertwich, 2013).

A related strand of research uses market segmentation techniques to identify distinct groups of current and prospective EV consumers (e.g., Axsen, Goldberg & Bailey, 2016; Du et al., 2018; Lee, Hardman & Tal, 2019; Jaiswal, Deshmukh & Thaichon, 2022; Ramadoss et al., 2025). These studies typically generate consumer archetypes or latent segments from observed data and have contributed important insights into heterogeneity among adopters and pathways toward mass-market uptake. While conceptually related to Diffusion of Innovations theory, such segments are generally derived inductively rather than corresponding directly to Rogers' adopter categories.

While this literature has yielded important insights into consumer heterogeneity and technology uptake, fewer studies have tested whether the predictors specified by Diffusion of Innovations theory systematically distinguish adopter categories. Even where models are informed by observed population attributes, assignment to adopter categories often reflects theoretical expectations or qualitative classification rather than statistical validation (Domarchi & Cherchi, 2023; Gnann et al., 2022; Kangur, Jager, Verbrugge & Bockarjova, 2017). Empirical studies that formally test the association between Diffusion of Innovations predictors and adopter category therefore remain relatively limited, particularly across multiple classes of predictors considered simultaneously (Wolf, Schröder, Neumann & de Haan, 2015; Zhang & Vorobeychik, 2019).

Despite their widespread use, adopter categories are often treated as established benchmarks rather than propositions requiring empirical validation. For example, Hardman and Tal (2024) note the emergence of terms such as ‘mass market adoption’ and ‘tipping points’ in media coverage of electric vehicle sales. Drawing on vehicle fleet data and Rogers’ 16% threshold separating ‘early adopters’ and ‘early majority,’ they argue that such commentary frequently misinterprets the distinction between early and mainstream adopters. While their analysis demonstrates the ongoing influence of Diffusion of Innovations theory, it does not evaluate the empirical validity of the adopter categories themselves.

The present study builds on this literature by empirically testing the associations between Diffusion of Innovations-specified predictors and adopter category. In doing so, it responds to recent calls for work that moves beyond descriptive archetyping toward formal evaluation of multiple predictor classes across adoption stages and technologies (Chadwick, Russell-Bennett & Biddle, 2022).

While Diffusion of Innovation has been applied separately to both EV and heat-pump adoption, the two technologies have rarely been analysed simultaneously within the same sample. This is notable given their central role in decarbonising residential heating and private transport (frequently in the same households) and their exposure to similar policy instruments such as grants, tax incentives and public information campaigns. If adoption predictors differ substantially across technologies, this has implications for how policy and communication strategies should be differentiated; if they are broadly consistent, this supports the use of integrated frameworks and potentially co-adoption modelling approaches (Du, Han & de Vries, 2022).

There are reasons to expect both similarities and differences. Both technologies involve high upfront costs and uncertainty linked to unfamiliarity and perceived risk. However, EVs are highly visible, potentially increasing the importance of observability and social influence relative to heat pumps, which are largely invisible once installed. Symbolic and identity-related dimensions may therefore be more salient for EV ownership than for heat pumps (Schuitema, Anable, Skippon & Kinnear, 2013). Heat pump adoption is also more dependent on housing tenure and building characteristics, creating different structural constraints (Timmons, Shier & Ó Ceallaigh, 2026). Empirically testing whether these differences translate into distinct Diffusion of Innovation predictor profiles is therefore analytically important.

1.3 The Present Study

This study examines the application of Diffusion of Innovation theory to heat pump and EV adoption. Specifically, we examine: (RQ1) whether adoption intentions are consistent with the S-curve proposed by the theory; (RQ2) whether and which technology perceptions are associated with stronger adoption intentions; (RQ3) whether positive communications exposure is associated with stronger adoption intentions; (RQ4) whether theory-specified individual characteristics predict stronger adoption intentions; and (RQ5) whether these classes of predictors independently explain variation in adoption intentions. To address these research questions, we use data from a nationally representative survey of adults in Ireland, in which respondents reported their openness to adopting each technology along a stage-of-change continuum corresponding to Diffusion of Innovation adopter categories.

To test RQs 2-5, we employ generalised ordered logistic regression models, using respondents' adopter category as an ordinal outcome variable. Individuals are classified along the full diffusion spectrum, from innovators and early adopters through to the early majority, late majority and laggards, allowing adoption to be modelled as a sequential process. The generalised ordered logistic approach allows predictors to vary in their influence at different thresholds of adopter category (i.e., moving from laggard to late majority, late majority to early majority or early majority to early adopter), recognising that factors associated with movement between adjacent stages of adoption may depend on the consumer's current adopter category (Anderson et al., 2024; Chadwick et al., 2022). Predictor classes are first examined separately before being combined to assess their independent associations with adopter category and potential attenuation effects. We complement these regressions with an exploratory structural equation model examining whether the association between communication exposure and adoption operates indirectly through technology perceptions.

Ireland provides a useful test case for these questions. Ireland combines ambitious decarbonisation goals (including a legally binding target to reach 51% reduction in emissions by 2030), with among the highest levels of support for heat pump and EV adoption in Europe. Households have also experienced substantial volatility in heating and transport fuel costs in recent years, increasing the salience of energy-related decisions. Although these conditions are not shared uniformly across Europe, they are increasingly characteristic of countries pursuing rapid residential decarbonisation. Findings that reflect general psychological processes should therefore extend beyond the Irish context, while findings that depend on particular market conditions or policy arrangements can be interpreted as context-specific. The Discussion returns to this distinction.

The study makes four contributions. First, it provides a direct empirical test of whether Diffusion of Innovations-specified predictors distinguish adopter categories for two key residential decarbonisation technologies, addressing a validation gap in the diffusion literature. Second, it jointly evaluates technology perceptions, communication exposure and individual characteristics, allowing their independent and overlapping associations with adoption stage to be assessed. Third, it applies a generalised ordered logistic regression framework that models adoption as an ordinal process rather than a binary outcome. Fourth, by analysing heat pumps and electric vehicles within the same nationally representative sample, it enables a direct comparison of predictor profiles across technologies, with implications for the coordination and targeting of policy and communication interventions.

2 Method

2.1 Participants

One thousand adults in Ireland were recruited by a market research agency using stratified quota sampling to be nationally representative by age, gender, living region and socio-economic status (Table 1).[a] Participants were paid €5 for completing this study alongside a second study on time-of-use tariffs (Carthy, Farrell, Harold & Timmons, 2026). The combined median completion time was 25 minutes. Participants were also enrolled in a raffle for a €100 Mastercard voucher, with additional entries available dependent on choices in our measure of risk aversion (described below). Data were collected in April 2025, following the Russian invasion of Ukraine and subsequent spikes in fuel prices but prior to the US-Iran war. The study was undertaken in accordance with institutional ethics policy.

Table 1. Sample socio-demographics.

		n	%	Census Estimate
Gender	Men	484	48.4	49.0
	Women	510	51.0	51.0
	Non-Binary/Other	6	0.6	-
Age	18-39 years	394	39.4	36.8
	40-59 years	346	34.6	36.5
	60+ years	260	26.0	26.7
Education	Secondary or below	332	33.2	43.9
	Tertiary below degree	359	35.9	28.6
	Degree or above	309	30.9	27.5
Region	Leinster (incl. Dublin)	554	55.4	55.7
	Munster	275	27.5	26.7
	Connacht/Ulster	171	17.1	17.6

Note: The Census does not record non-binary as a gender. We proxied socio-economic status through "social grade," a market research measure based on the occupation of the chief income earner in the household. However, the Census does not record social grade, so we instead use educational attainment. The Census record for educational attainment excludes those who did not report their attainment (i.e., who reported their status as 'other', who did not state a level or who reported being in education without stating the level of education attained), whereas these groups are retained in our sample.

[a] A further 242 participants met quota criteria but did not complete the study. Ninety-five failed one of two forced-response attention checks, 33 exited during the heat pump or EV surveys and a further 114 exited at other stages of the study. Data from these participants were not accessed.

Participants reported information on housing and vehicle ownership relevant to heat pump and EV adoption (Table 2). Most respondents (61.9%) owned their home outright or with a mortgage. The most common primary or supplementary heating systems were oil boilers (43.4%), solid fuel systems (37.3%) and gas boilers (33.8%), noting that homes may have more than one system. Just 8.5% reported having an air or ground source heat pump (air or ground source). Approximately one-third (34.7%) expected to replace their current heating system within 10 years, while a similar proportion were unsure of their replacement timeline and almost one quarter believed they will never need to do so. Among non-homeowners, many (37.1%) expected to purchase a home within 10 years, while a comparable proportion (37.4%) were unsure of their timeline.

Most participants (87.7%) held a driving licence. Of those, the vast majority reported access to a vehicle they own outright or with finance. Internal combustion engine (ICE) vehicles predominated, with just 6.6% driving an EV (PHEV or BEV).

Table 2. Sample home and car ownership characteristics

Home Ownership Characteristics			Car Ownership Characteristics		
Home Ownership	Own Home	61.9	*Licence Status*	Full	81.0
	Renting	27.8		Provisional	6.7
	Living rent-free	10.1		None	12.3
	No fixed abode	0.2			
			Car Access (Of those with a licence)	Car/van	96.8
Heating System	Oil Boiler	43.4		Motorcycle	0.4
	Solid Fuel	37.3		None	2.8
	Gas Boiler	33.8			
	Electric Radiators	13.3	*Ownership Status (Of those with access)*	Owns Outright	81.3
	Heat Pump	8.5		Owns with Finance	10.7
	Storage Heater	4.2		Someone Else Owns	7.3
	Other	1.0		Company car	0.8
Replace Current System (Own Home Only)	Within 2 years	8.8	*Engine (Of those with access)*	Diesel	44.1
	In 2 to 5 years	13.6		Petrol	39.5
	In 5 to 10 years	12.3		Hybrid	9.8
	In 10 years or more	6.3		EV	4.3
	Unsure	35.4		PHEV	2.3

	Unlikely to ever	23.6			
			Next Car Purchase	Within 1 year	9.8
Purchase Own Home (Non-homeowners Only)	Within 2 years	13.8		In 1 to 2 years	22.0
	In 2 to 5 years	11.4		In 2 to 4 years	24.9
	In 5 to 10 years	11.9		In 4 years or more	10.3
	In 10 years or more	8.2		Unsure	21.1
	Unsure	37.4		Unlikely	12.1
	Unlikely to ever	17.2			

2.2 Measures and Design

The study was administered using Gorilla Experiment Builder (Anwyl-Irvine et al., 2020). Participants were informed that the study concerned home heating and driving. Home heating and driving questions were presented in separate, counterbalanced modules, with conditional branching to tailor questions to participants' housing and vehicle circumstances. Full materials are available on the project's Open Science Framework page (https://osf.io/4zgwh/?view_only=522b47f23418452793ab6a253116b302).

2.2.1 Heat Pumps

The heat pump module began with questions on home ownership and heating systems. Homeowners without a heat pump reported when they expected to next replace their heating system and their intention to adopt a heat pump using response options aligned with Diffusion of Innovations adopter categories: *I intend to install one* (early adopter), *I am open to installing one* (early majority), *I would only install one after most other people have* (late majority) or *I don't see myself ever installing one* (laggard). Non-homeowners reported their likelihood of purchasing a home and, conditional on non-negligible purchase intentions, their intentions regarding heat pump installation.

Perceptions of heat pumps were measured using Diffusion of Innovations theory constructs of relative advantage, compatibility, simplicity, trialability and visibility. Relative advantage was assessed by comparing heat pumps with participants' current or previous heating systems across six dimensions: purchase and installation cost, running costs, maintenance, heating comfort, reliability and environmental impact. Ratings were made on seven-point scales from 1 ("current or previous system much better") to 7 ("heat pump much better"). Where respondents selected the scale midpoint, follow-up questions distinguished perceived equivalence from uncertainty.

Compatibility was measured using two items assessing perceived installation hassle and disruption to existing heating routines. Simplicity was assessed using three items capturing self-reported understanding of heat pump operation, use and running costs. Trialability was operationalised as a binary variable indicating whether respondents had ever used a heat pump or visited a dwelling equipped with one. Visibility was measured using a seven-point scale assessing how frequently participants notice heat pumps installed in homes in their local area.

Communication exposure was assessed across four sources: family or friends, mass media, social media and industry professionals (e.g. installers, engineers, builders). For each source, respondents rated the overall valence of communication on a seven-point scale ranging from "mostly negative" to "mostly positive."

2.2.2 Electric Vehicles

The EV module followed the same structure. Participants reported driving licence status, vehicle access and vehicle engine type. Non-drivers reported their intentions to learn to drive. Participants with any intention to drive reported their likelihood of purchasing a future vehicle and, conditional on this, their intentions regarding BEV or PHEV adoption.

Relative advantage was assessed across eight dimensions: purchase price, running costs, other ownership costs (e.g. motor tax), maintenance, driving comfort, driving range, charging convenience and reliability. Compatibility items focused on disruptions associated with charging and home-charger installation. Simplicity items captured understanding of EV operation, charging practices, charging duration, battery longevity, maintenance arrangements, total cost of ownership and environmental impact. Trialability indicated whether participants had ever driven a BEV or PHEV. Visibility was measured using two items capturing how often participants notice EVs in use locally and how often they observe charging infrastructure.

Communication exposure measures mirrored those for heat pumps.

2.2.3 Individual Characteristics

Individual characteristics were measured at the end of the survey to minimise priming effects. These included personal innovativeness (adapted from Agarwal & Prasad, 1998), opinion leadership (Childers, 1986), environmental concern (Andersson et al., 2023), concern with social status (Anderson et al., 2015), and risk aversion measured using an incentivised lottery task (Eckel & Grossman, 2008). Standard socio-demographic variables were also collected.

2.3 Analytic Approach

The primary analyses were pre-registered prior to data collection (https://osf.io/qyb8c?view_only=522b47f23418452793ab6a253116b302). Following Diffusion of Innovations theory and prior empirical work (e.g. Peters & Dütschke, 2014), respondents were classified as early adopters (already adopted or intending to adopt at next replacement or purchase), early majority (open to adoption), late majority (cautious and inclined to adopt only once adoption is widespread), and laggards (no intention to adopt). Observed distributions were compared with the theoretical distribution proposed by Rogers (2003), adjusted to four categories, using chi-square goodness-of-fit tests.

Technology perception measures were combined into composite indices where internal consistency was acceptable (Cronbach's α ≥ .70; Nunnally, 1978). Variables exhibiting strong floor or ceiling effects were recoded prior to analysis to ensure adequate cell sizes. Multicollinearity was assessed to ensure no predictor pairs exceeded correlations of .70 (Dormann et al., 2013). Compatibility items were reverse-scored so that higher values indicate greater perceived compatibility. Trialability was coded as a binary indicator for each technology. Communication exposure variables were recoded to indicate predominantly positive exposure, predominantly negative exposure or no exposure for each source type.

Predictors of adopter category were analysed using generalised partial proportional odds models (Williams, 2006), which permit coefficients to vary across adoption thresholds where the proportional odds assumption is violated (i.e., where diagnostic tests show the effects differ depending on the starting category). Separate models were estimated for technology perceptions, communication exposure and individual characteristics, followed by a combined model. All models controlled for age, gender, education and residential location, as well as home ownership status in the heat-pump models and driving-licence status in the EV models. Participants who reported they would never face a relevant adoption decision (i.e. those who expected never to purchase a home or never to drive) were excluded from the respective analyses. Bonferroni–Holm corrections were applied to p-values in combined models.

Finally, exploratory structural equation models examined whether communication exposure is associated with adoption indirectly through technology perceptions. A latent perceptions construct was specified using relative advantage, compatibility, simplicity, trialability and visibility indicators. Due to limited cell sizes, communication exposure was coded as a three-level variable distinguishing no exposure, predominantly positive exposure and predominantly negative exposure. Individual characteristics independently associated with adopter category were included first as direct predictors and subsequently as interaction terms with communication exposure.

3 Results

In this section, we first compare the observed distribution of adopter categories against those proposed by Diffusion of Innovation theory. We then present the results from statistical models of heat pump adoption followed by models of EV adoption, with a final section presenting the structural equation model.

3.1 Distribution of Adopter Categories

Figure 1 compares the observed distribution of adopter categories for heat pumps and EVs against the theoretical distribution proposed by Diffusion of Innovations Theory. Participants who already own a heat pump (8.2%) or an EV (6.9%) were grouped with those who intend to adopt one (6.9% and 8.4%, respectively) to form the early adopter category.

Chi-Square goodness-of-fit tests show that the observed distributions for both technologies depart significantly from the theoretical distribution (heat pumps: χ^2 (3) = 170.84, $p < .001$; EVs: χ^2 (3) = 182.89, $p < .001$). As shown in Figure 1, these departures are characterised by a smaller-than-expected late majority category and higher-than-expected laggard groups. This pattern is evident for both technologies but is more pronounced for EVs.

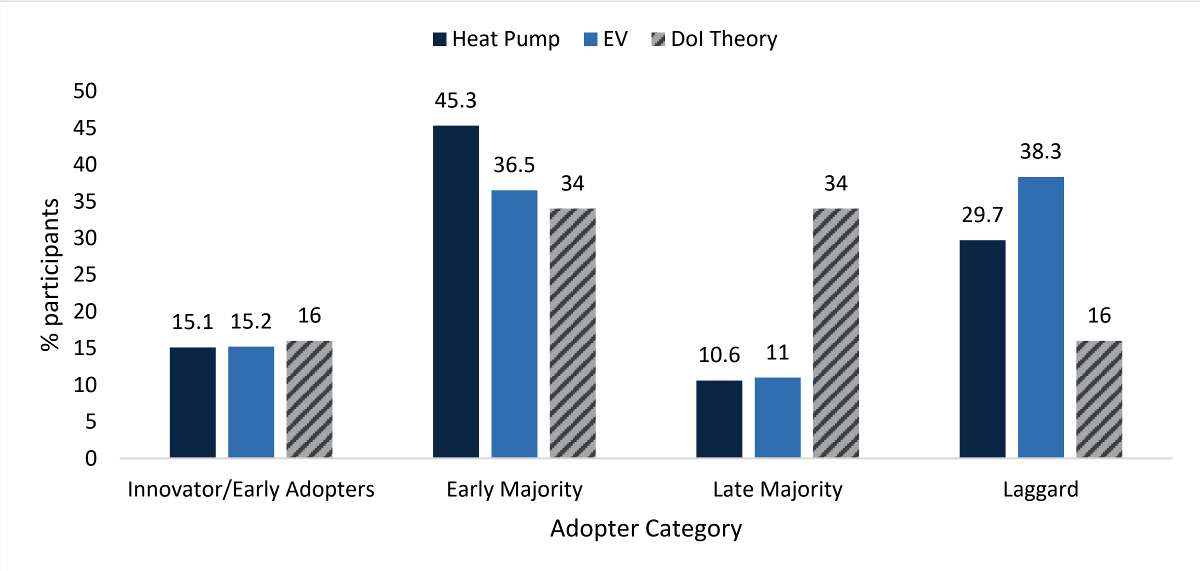

Figure 1. Distribution of adopter categories. Innovators reported having a heat pump or EV; Early Adopters responded "I intend to install/purchase one"; Early Majority responded "I am open to installing/purchasing one"; Late Majority responses "I would

only install/purchase one when most other people have done so"; Laggards responded "I don't see myself every installing/purchasing one".

3.2 Heat Pumps

3.2.1 Technology Perceptions

Distributions of heat-pump perception measures are reported in the Supplementary Materials. The relative-advantage index is approximately normally distributed around the midpoint (M = 4.3, SD = 1.35), indicating mixed assessments relative to existing heating systems. Compatibility scores (M = 3.5, SD = 1.50) suggesting that installation and use are generally perceived as somewhat disruptive. Simplicity scores are more variable but exhibit a pronounced spike at the lowest scale point (M = 3.3, SD = 1.75), indicating a subset of respondents reporting very low perceived understanding. Nearly one-third (29.0%) reported some form of trialability, having previously used a heat pump or visited a dwelling equipped with one. Visibility was low overall (M = 2.5, SD = 1.68), with the modal response indicating that participants rarely notice heat pumps in their local area.

Table 3 presents generalised ordered logistic regression models. Tests of the proportional odds assumption indicate violations for simplicity ($p < .001$) and trialability ($p = .014$), and threshold-specific coefficients are therefore reported. The assumption holds for all other predictors and for the model overall ($\chi^2 = 15.12$, $p = .370$). As shown in Model 1, higher perceived relative advantage, compatibility and visibility are associated with greater openness to adoption across all adopter cateogry thresholds. Simplicity and trialability are significant only at the upper threshold, distinguishing early adopters from all other categories. The model explains approximately 30% of variation in adopter category, indicating moderate-to-strong explanatory power.

3.2.2 Communication Exposure

Most participants reported no exposure to information about heat pumps, with exposure rates ranging from 10.5% for social media to 31.4% for family and friends (Supplementary Materials). Otherwise, communications from all sources tended to be characterised as positive (7.8% on social media to 23.6% from family and friends) rather than negative (1.9% from industry professionals to 7.8% from family and friends). Due to low cell counts, social media and industry professional sources were excluded from the regression models.

Model 2 in Table 3 shows that positive communication from family and friends and mass media is associated with greater openness to adoption, while negative communication is associated with lower intent. This model explains substantially less variance (~12%) than the technology-perceptions model.

Table 3. Generalised ordered regression models predicting heat pump adopter category.

	Model 1 Technology Perceptions			Model 2 Communication Exposure	Model 3 Individual Characteristics			Model 4 Combined		
Technology Perceptions										
Relative Advantage		0.76***							0.66***	
		(0.08)							(0.07)	
Compatibility		0.37***							0.38***	
		(0.05)							(0.06)	
Simplicity	0.00	0.05	0.46***					-0.08	0.07	0.54***
	(0.06)	(0.05)	(0.09)					(0.07)	(0.06)	(0.09)
Trialability	0.29	0.56*	1.31***					0.04	0.51*	1.55***
	(0.24)	(0.23)	(0.27)					(0.26)	(0.24)	(0.28)
Visibility		0.21***							0.19***	
		(0.05)							(0.05)	
Communication Exposure										
Family/Friends (Ref: None)										
Negative				-0.66**					-0.18	
				(0.25)					(0.28)	
Positive				1.09***					-0.07	
				(0.16)					(0.19)	
Mass Media (Ref: None)										
Negative				-0.66					0.09	
				(0.37)					(0.42)	
Positive				1.26***				0.90**	0.78**	-0.44
				(0.26)				(0.30)	(0.25)	(0.31)
Individual Characteristics										
Personal Innovativeness (Ref: Most Open)										
2					-0.29	-0.59*	-0.95**	0.06	-0.37	-1.18**
					(0.31)	(0.29)	(0.27)	(0.35)	(0.34)	(0.35)
3					-0.21	-0.71*	-0.85**	0.03	-0.37	-0.77
					(0.29)	(0.28)	(0.28)	(0.35)	(0.33)	(0.35)

4							-0.74*	-1.37***	-0.95*	-0.11	-0.76	0.47
							(0.36)	(0.35)	(0.43)	(0.41)	(0.40)	(0.52)
Least Open								-0.91**			-0.39	
								(0.34)			(0.39)	
Opinion Leadership								0.04			-0.02	
								(0.05)			(0.06)	
Environmental Concern								0.13*		-0.09	0.10	0.24*
								(0.06)		(0.07)	(0.06)	(0.09)
Status Concern								0.15**		0.11	-0.01	-0.11
								(0.06)		(0.06)	(0.06)	(0.08)
Risk Seeking								0.01*			0.00	
								(0.01)			(0.01)	
Socio-Economic Status												
C1C2	0.48*	0.13	0.02		0.22			0.35			0.52*	
	(0.24)	(0.24)	(0.28)		(0.19)			(0.19)			(0.21)	
DEF		0.13			-0.35			-0.15			0.11	
		(0.24)			(0.22)			(0.23)			(0.25)	
Other Socio-Demographics												
Age (Ref: under 40 years)												
40-59 years		-0.23			-0.33*			-0.31			-0.22	
		(0.18)			(0.16)			(0.17)			(0.19)	
60+ years	-0.66**	-0.50*	-1.98***	-0.90***	-0.84***	-1.76***	-0.83***	-0.85***	-1.86***	-0.77	-0.63	-2.04***
	(0.23)	(0.23)	(0.18)	(0.21)	(0.20)	(0.38)	(0.22)	(0.22)	(0.39)	(0.25)	(0.24)	(0.49)
Man (Ref: Woman)		0.11			0.49			0.09			0.10	
		(0.14)			(0.13)			(0.13)			(0.15)	
Degree (Ref: Below degree)		0.11			0.18			0.21			0.14	
		(0.15)			(0.14)			(0.20)			(0.16)	
Urban (Ref: Rural)		-0.12			(0.09)			0.06			-0.18	
		(0.15)			(0.14)			(0.14)			(0.16)	
Owns Home (Ref: Renter)		-0.49			-1.00***			-0.28			-1.03***	
		(0.26)			(0.18)			0.21			(0.17)	

	Model 1			Model 2			Model 3			Model 4		
Constant	-2.46*** (0.48)	-4.22*** (0.48)	-9.79*** (0.79)	1.91 (0.30)	1.03 (0.27)	-1.83 (0.29)	1.16 (0.50)	0.43 (0.48)	-2.31 (0.54)	-2.69*** (0.61)	-3.73*** (0.61)	-9.01*** (0.81)
Obs.		924			924			924			924	
R^2		0.30			0.12			0.13			0.31	

Note. ****p* < .001; ***p* < .01; **p* < .05. Split cells indicate threshold effects (above Laggard, Late Majority and Early Majority, respectively). Unsplit cells indicate an ordinal effect that is consistent across thresholds. *N* = 924; non-homeowners with no intentions to buy a house and homeowners who report being unlikely to replace their heating system are excluded, as are non-binary/other gender and those with missing socio-economic grade (due to small cell sizes).

Table 4. Generalised ordered regression models predicting EV adopter category.

	Model 1 Technology Perceptions			Model 2 Communication Exposure			Model 3 Individual Characteristics			Model 4 Combined		
Technology Perceptions												
Relative Advantage		0.85*** (0.08)									0.79*** (0.09)	
Compatibility (Refuelling)	0.09 (0.06)	0.17** (0.06)	0.30*** 0.08							0.06 (0.06)	0.13* (0.06)	0.29*** (0.08)
Compatibility (Charger Installation)		0.26*** (0.04)									0.25*** (0.04)	
Simplicity	0.07 (0.06)	-0.07 (0.06)	-0.39*** (0.10)							0.12 (0.07)	-0.05 (0.07)	-0.41*** (0.11)
Trialability	-0.18 (0.21)	-0.13 (0.20)	0.70* (0.28)							-0.21 (0.21)	-0.10 (0.20)	0.78** (0.29)
Visibility (Other Driving)		0.12* (0.05)									0.06 (0.05)	

Visibility (Infrastructure)	0.11*						0.11*	
	(0.05)						(0.05)	
Communication Exposure								
Family/Friends (Ref: None)								
Negative		-0.50**					-0.18	
		(0.21)					(0.24)	
Positive		1.26***					0.43*	
		(0.16)					(0.18)	
Mass Media (Ref: None)								
Negative		-0.16					-0.27	
		(0.25)					(0.27)	
Positive		0.44**					0.01	
		(0.15)					(0.18)	
Individual Characteristics								
Personal Innovativeness (Ref: Most Open)								
2				0.17			0.08	
				(0.23)			(0.27)	
3				-0.16			-0.01	
				(0.23)			(0.27)	
4			-0.19	-0.77*	-0.86	0.17	-0.66	-0.96
			(0.33)	(0.33)	(0.52)	(0.38)	(0.39)	(0.76)
Least Open				-0.96**			-0.67	
				(0.34)			(0.39)	
Opinion Leadership				0.10*		0.17*	-0.00	-0.14
				(0.05)		(0.07)	(0.07)	(0.11)
Environmental Concern				0.32***		0.09	0.23**	0.15
				(0.05)		(0.07)	(0.07)	(0.11)
Status Concern				0.09*			0.06	
				(0.04)			(0.05)	
Risk Seeking				0.00			-0.00	
				(0.01)			(0.01)	
Socio-Economic Status								

C1C2		-0.34			-0.46*			-0.35			-0.19*	
		(0.21)			(0.19)			(0.19)			(0.21)	
DEF		-0.74**			-0.82***			-0.76**			-0.56*	
		(0.25)			(0.22)			(0.22)			(0.26)	
Other Socio-Demographics												
Age (Ref: under 40 years)												
40-59 years		-0.46**			-0.22			-0.08			-0.19	
		(0.18)			(0.16)			(0.16)			(0.22)	
60+ years		-0.88***			-0.63***			-0.56***		-0.89***	-0.56*	-0.89***
		(0.20)			(0.18)			(0.19)		(0.22)	(0.26)	(0.22)
Man (Ref: Woman)	0.39*	0.15	-0.42		0.22			0.17		0.45*	0.21	-0.38
	(0.18)	(0.18)	(0.28)		(0.13)			(0.13)		(0.19)	(0.19)	(0.29)
Degree (Ref: Below degree)		0.06			0.17			0.13			0.02	
		(0.16)			(0.14)			(0.14)			(0.16)	
Urban (Ref: Rural)		-0.16		0.28	0.39*	-0.25	0.18	0.28	-0.29		-0.15	
		(0.16)		(0.15)	(0.16)	(0.21)	(0.16)	(0.16)	(0.21)		(0.16)	
Driver's Licence (Ref: No Licence)		-0.26			-0.37			-0.12			-0.17	
		(0.30)			(0.25)			0.25			(0.31)	
Constant	-3.94***	-4.15***	-6.59***	0.65	0.07	-1.69***	-0.76	-1.30**	-3.01***	-5.01***	-4.84***	-6.39***
	(0.56)	(0.56)	(0.72)	(0.26)	(0.26)	(0.29)	(0.44)	(0.44)	(0.46)	(0.73)	(0.74)	(1.04)
Obs.		823			823			823			823	
R^2		0.27			0.10			0.09			0.29	

Note. ***p < .001; **p < .01; *p < .05. Split cells indicate threshold effects (above Laggard, Late Majority and Early Majority, respectively). Unsplit cells indicate an ordinal effect that is consistent across thresholds. N = 823; non-car owners with no intentions to buy a car are excluded, as are non-binary/other gender and those with missing socio-economic grade (due to small cell sizes).

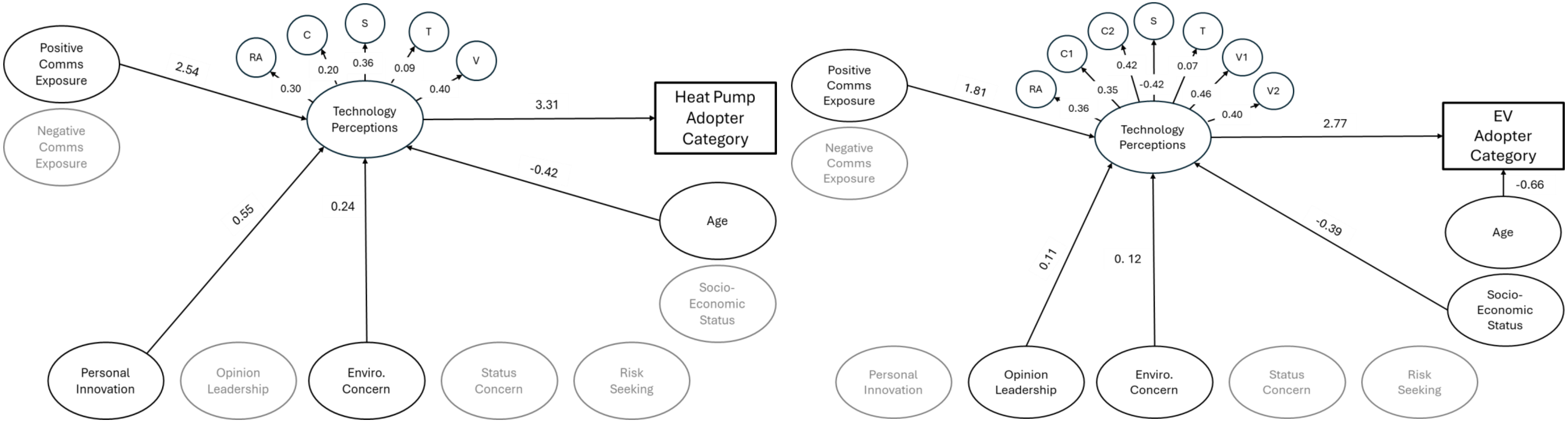

Figure 2. Structural equation models predicting adopter category for heat pumps (left) and EVs (right). For clarity, non-significant associations are omitted. RA = relative advantage; C = compatibility; S = simplicity; T = trialability; V = visibility.

3.2.3 Individual Characteristics

Distributions of individual characteristics are reported in the Supplementary Materials. No pairwise correlations exceeded the pre-registered multicollinearity threshold. Several innovativeness categories violated the proportional odds assumption but the overall pattern indicates that more innovative individuals are more willing to adopt heat pumps (Model 3 in Table 3). Environmental concern, social status concern and lower risk aversion are associated with greater adoption intention, whereas opinion leadership and socio-economic status are not. This model explains approximately 13% of variation in adopter category.

Turning to socio-demographic controls, older respondents are consistently less open to adopting heat pumps, and homeowners are less open than renters. This latter difference may reflect the fact that renters can express favourable attitudes toward heat pumps without facing the practical and financial constraints associated with installation, whereas homeowners, by contrast, may evaluate adoption more realistically because they would ultimately bear responsibility for the investment.

No other demographic patterns emerge reliably.

3.2.4 Combined Model

Model 4 in Table 3 combines technology perceptions, communication exposure and individual characteristics. Technology-perception variables retain robust associations with adopter category, while most communication and individual-characteristic effects attenuate. Perceived relative advantage is the strongest predictor (b = 0.66, SE = 0.07). Simplicity and trialability remain significant only at the upper threshold, distinguishing early adopters. Positive mass-media exposure predicts movement out of lower-intention categories, while environmental concern predicts entry into the early-adopter category. This model explains a similar proportion of variance (31%) to the technology-perceptions model alone, indicating limited incremental explanatory power beyond perceptions.

3.3 Electric Vehicles

3.3.1 Technology Perceptions

For EVs, relative advantage is centred slightly below the midpoint (M = 3.6, SD = 1.22), indicating modest average disadvantage relative to internal combustion engine vehicles. Compatibility perceptions are also negative overall, particularly in relation to refuelling routines (M = 3.1, SD = 1.78), though less so for home-charger installation (M

= 3.6, *SD* = 2.06). Simplicity perceptions are more positive (*M* = 4.3, *SD* = 1.77) and exhibit a small spike at the highest scale point. Approximately 30.2% of respondents reported having driven a non-ICE vehicle. Visibility was higher than for heat pumps, especially with respect to seeing EVs in use locally (*M* = 4.1, *SD* = 1.78), though less so for charging infrastructure (*M* = 3.5, *SD* = 1.82). (H)

Violations of the proportional odds assumption were detected for simplicity, trialability and refuelling compatibility, implying that their effect differed across adoption-stage transitions; the assumption held for all other predictors and for the model overall (χ^2 = 16.95, *p* = .593). As shown in Model 1 (Table 4), relative advantage, installation compatibility and both visibility indicators predict greater adoption intention across thresholds. Refuelling compatibility and trialability are significant primarily at higher thresholds. Notably, lower perceived simplicity is associated with greater intention to adopt at the highest threshold, a counterintuitive result addressed in Section 4.2. The model explains approximately 27% of variation in adopter category.

3.3.2 Communication Exposure

Communication exposure for EVs was more common than for heat pumps, though majorities still report no exposure from each source (ranging from 58.1% from family and friends to 84.0% from industry professionals). Again, communications tended to be more positive (11.0% from industry professionals to 29.2% from family and friends) than negative (5.0% from industry professionals to 12.7% from family and friends). All predictors satisfied the proportional odds assumption, as does the overall model (χ^2 = 10.17, *p* = .896). Model 2 (Table 4) shows similar patterns to heat pumps: communication from family and friends is associated with adoption intention in the expected direction, while positive mass-media communication predicts greater intention across thresholds. The model explains approximately 10% of variation.

3.3.3 Individual Characteristics

The proportional odds assumption holds for all predictors and the overall model (χ^2 = 37.10, *p* = .117) with the exception of one innovativeness category (*p* = .029). Personal Innovativeness showed a limited effect with reduced intention only among those in the lowest innovativeness category (Model 3 in Table 4). Opinion leadership, environmental concern and concern with social status are positively associated with adoption intention, while risk aversion is not. Lower socio-economic status is associated with lower adoption intention. As with heat pumps, older respondents are less open to adoption.

3.3.4 Combined Model

The combined EV model (Model 4 in Table 4) broadly mirrors the heat-pump results. Technology perception variables, particularly relative advantage (b = 0.79, SE = 0.09), remain the strongest predictors. Unlike heat pumps, communication from family and friends remains a significant predictor in the combined model, while mass-media effects attenuate. Socio-economic status emerges as the only consistent individual-characteristic predictor, with environmental concern predicting progression into the early-majority category. The model explains approximately 29% of variance, similar to the perceptions-only model.

3.4 Structural Equation Models

Figure 2 presents exploratory structural equation models, showing the estimated structure of associations between predictor variables and adopter categories. Arrows indicates significant pathways and coefficients indicate effect sizes. Non-significant associated are omitted. The models show similar patterns across both technologies. All perception items load significantly onto a latent technology-perceptions construct. Positive communication exposure is associated with greater openness to adoption indirectly through more favourable technology perceptions, with no significant direct effect on adopter category. Negative communication exposure shows no reliable association with perceptions or adoption, though low cell sizes limit statistical power.

Individual characteristics are also primarily associated with adoption technology perceptions rather than via direct effects. For both technologies, greater environmental concern predicts more positive perceptions. For heat pumps, higher personal innovativeness is associated with more positive perceptions, whereas for EVs this role is played by opinion leadership. Social-status concern and risk aversion are not significantly associated with perceptions or adoption intentions. Lower socio-economic status predicts more negative perceptions of EVs but not heat pumps, while older age is associated with more negative perceptions of heat pumps and lower openness to EV adoption. For clarity, Figure 2 displays only statistically significant pathways; full model estimates are reported in the Supplementary Materials.

4 Discussion

This study tested key propositions of Diffusion of Innovations theory for two priority decarbonisation technologies: heat pumps and electric vehicles (EVs). Across both technologies, technology perceptions emerged as the strongest and most consistent predictors of adoption intentions. In contrast, communication exposure and individual characteristics showed weaker direct associations and appeared to influence adoption largely through their effects on perceptions. Together, the findings strengthen the behavioural foundations of low-carbon technology diffusion research and modelling.

4.1 Distribution of Adoption Intentions

The observed adopter-category distributions for both technologies depart substantially from the S-curve proposed by Rogers (2003), with a markedly smaller late-majority segment and a larger share of respondents classified as laggards (RQ1). This deviation is consistent with evidence that low-carbon technologies often follow diffusion trajectories that differ from those observed for consumer durables or information technologies, and with broader evidence of heterogeneity in technology diffusion (Meade & Islam, 2006; Nemet et al, 2023; Peters & Dütschke, 2014). This deviation is more pronounced for EVs than for heat pumps, potentially reflecting stronger inertia and lock-in for private transport. Alternatively, lower familiarity with heat pumps may leave more consumers open to adoption in principle before practical costs and constraints become salient (Timmons et al., 2026).

Because adopter categories are based primarily on stated intentions rather than realised behaviour, they should be interpreted as indicators of diffusion potential rather than actual adoption stages. Nevertheless, if stated preferences exceed realised uptake (Coffman et al., 2017), our distribution's suggestion of slower diffusion may in fact underestimate the size of the late-majority and laggard segments. This would imply slower diffusion than standard Diffusion of Innovations projections suggest, reinforcing recent calls for empirical validation of diffusion assumptions (Domarchi & Cherchi, 2023).

4.2 Technology Perceptions

Across both technologies, perceptions of the technology itself emerge as the strongest and most consistent predictors of adoption intention (RQ2). Relative advantage, compatibility and visibility are associated with greater openness to adoption across much or all of the diffusion spectrum, while simplicity and trialability primarily distinguish those willing to adopt earliest from all other groups. This pattern closely aligns with Diffusion of Innovation theory's emphasis on perceptions as proximate drivers of adoption decisions (Rogers, 2003).

The relative scale of associations is also noteworthy. Across both models, perceived relative advantage is substantially more strongly associated with adoption intent than other predictors. This finding aligns with evidence on firm adoption of energy efficient technologies, but applied to consumer decisions (e.g., Völlnik et al., 2002). Relative advantage is inherently comparative, meaning these evaluations are likely shaped by prevailing market conditions, such as electricity, transport fuel and home-heating fuel prices. Importantly, our measure captures perceived rather than objectively measured relative advantage. Whether negative evaluations are driven by misperceptions is an important avenue for future research.

Notably, trialability is strongly associated with adoption only at the upper end of the adoption spectrum for both technologies. Direct experience appears to operate as a tipping mechanism that converts openness into action-oriented intent, rather than as a general driver of diffusion. Visibility likewise matters for both technologies, but more strongly for EVs, consistent with their greater everyday observability and social salience (Schuitema et al., 2013) and evidence of limited visibility of charging infrastructure as a barrier among non-EV drivers (Hoogland, Kurani, Hardman & Chakraborty, 2024). For heat pumps, ownership is largely invisible once installed, potentially limiting social contagion effects.

One unexpected finding was that higher perceived simplicity was associated with lower EV adoption intentions. This counterintuitive result may reflect genuine awareness of practical differences between EVs and conventional vehicles, such as charging and range constraints, or alternatively overconfidence among respondents resistant to adoption. Given the self-reported nature of the measure, the relationship between objective knowledge, perceived understanding and adoption intentions warrants further investigation. Future research may also consider whether BEVs and PHEVs may be perceived differently.

4.3 Communication Exposure

Communication exposure shows weaker and less consistent associations with adoption intention than perceptions (RQs 3 and 5). Direct effects of communication are modest, source-dependent and often attenuate after controlling for perceptions. These findings may help reconcile mixed evidence on the effectiveness of information campaigns in promoting technology adoption (Eppstein et al., 2011; Räihä & Ruokamo, 2021).

The exploratory structural equation models suggest that positive communication exposure operates primarily indirectly, through more favourable technology perceptions, rather than through direct effects on intentions. This provides empirical support for a central, but rarely tested, mechanism implied in Diffusion of Innovation theory: communication shapes adoption not by persuasion alone, but by framing how technologies are evaluated. The findings suggest that communication is most likely to be effective when it targets perceptions underpinning adoption decisions, particularly perceptions of relative advantage, compatibility and visibility. The absence of clear effects for negative communication should be interpreted cautiously, given limited statistical power, but also suggests that informational deficits may be more consequential than hostile narratives.

4.4 Individual Characteristics

Individual characteristics are associated with adoption intention when considered in isolation, but their influence diminishes once technology perceptions are included (RQs 4 and 5). Environmental concern is the most consistent predictor across both technologies, though it primarily operates by shaping perceptions rather than directly. Notably, while environmental concern distinguishes early adopters, it does not reliably predict movement into the early- or late-majority categories, suggesting that efforts to increase environmental awareness alone may have limited effects on mass-market uptake if perceived relative advantage, compatibility and other practical considerations remain unchanged.

Other characteristics vary by technology. General openness to innovations matters for heat pumps but not EVs, while opinion leadership plays a stronger role for EVs. Findings on socio-economic status are particularly interesting. Higher socio-economic status is associated with greater EV adoption willingness, but not heat pumps (cf. Wilson et al., 2017). This difference possibly reflects greater familiarity with vehicle purchase costs than heat pump investments, for which consumer knowledge remains comparatively limited (Timmons, Shier & Ó Ceallaigh, 2026).

Risk aversion plays a notably limited role. While lower risk aversion is associated with stronger heat pump adoption intentions in models that exclude perceptual variables, this effect attenuates once perceptions are included, and no robust association emerges for EV adoption. This finding is particularly noteworthy given the prominence of risk aversion in agent-based diffusion models of low-carbon technologies, where it is often assumed to differentiate early adopters from laggards (e.g., McCoy & Lyons, 2014). Importantly, risk aversion was measured using an incentive-compatible lottery task rather than self-reported attitudes, reducing concerns about measurement error or social desirability bias.

These findings suggest that individual characteristics influence adoption primarily by shaping how technologies are perceived and evaluated, rather than by directly determining adoption decisions. This challenges approaches that treat psychological traits as fixed determinants of adopter category and underscores the importance of modelling the perceptual mechanisms through which individual differences exert influence (Chadwick et al., 2022). More broadly, the results support perspectives that view adopter profiles as emerging through interactions between users, technologies and social environments rather than fixed categories (Kanger et al, 2019).

4.5 Implications

The results have several implications for policy and diffusion modelling. For policy, they highlight the limits of interventions targeting stable individual traits, such as risk tolerance or innovativeness. Measures that improve how technologies are experienced and perceived, particularly by reducing perceived performance uncertainty and addressing perceived disadvantages, are likely to be more effective.

The findings also have important implications for how diffusion trajectories are conceptualised. Adoption intentions for both technologies depart markedly from the canonical S-curve, with a more respondents classifying themselves as unwilling ever to adopt. If taken at face value, the theoretical distribution may produce overly optimistic projections of long-term uptake. However, the apparent concentration of laggards should not be interpreted as evidence of fixed resistance. Many respondents appear responsive technology perceptions, visibility and social communication, suggesting that some may behave more like late majority adopters as uncertainty reduces and social norms shift.

For diffusion and agent-based modelling, the findings suggest caution in treating risk aversion as a primary driver of adoption dynamics. Although often modelled as a fixed determinant of adoption thresholds, its effects appear largely indirect and mediated through technology perceptions. Models that endogenise perceptions, for example allowing them to evolve in response to communication, visibility and experience, may therefore provide a more empirically realistic representation of adoption processes than those that rely primarily on static psychological heterogeneity. This has implications for projections of policy effectiveness, particularly where risk aversion is used to justify strong inertia among late adopters.

More broadly, the study contributes to the empirical refinement of Diffusion of Innovations theory. By examining technology perceptions, communication exposure and individual characteristics simultaneously, the analysis clarifies their distinct roles in the diffusion process (Chadwick et al., 2022). The findings suggest that these predictor classes should not be treated as equivalent drivers of adoption, but rather as operating at different levels. Technology perceptions function as proximate determinants of adoption stage, while communication exposure and individual characteristics act more indirectly by shaping how technologies are understood and evaluated.

4.6 Limitations

Several limitations should be acknowledged. First, adoption categories are based on self-reported intention rather than observed behaviour. While stated intentions may not translate directly into future adoption, they may either overstate or understate realised uptake. For example, respondents may underestimate the likelihood of adopting when eventually faced with a heating-system or vehicle replacement decision.

Second, the perception measures subjective perceptions rather than objective technology characteristics. The accuracy of these perceptions is therefore uncertain: individuals who are more willing to adopt may hold overly positive views of the technologies, while those more resistant may exaggerate drawbacks or uncertainties. From a policy perspective, this distinction is important, as interventions may need to address not only information deficits but also misperceptions. Future research that benchmarks public perceptions against independently verified performance, cost and reliability data could provide valuable guidance for targeting policy interventions more effectively.

Finally, although Ireland provides a demanding and policy-relevant test case, the absolute values of some measures reported here may depend on the national and economic context in which data are collected. For example, perceptions of the relative advantage of EVs and heat pumps are likely influenced by prevailing fuel and electricity prices, which varied substantially in the years preceding data collection in April 2025. Consequently, average levels of these perceptions may differ across countries or time periods. However, there is no obvious reason to expect that such contextual differences would fundamentally alter the relationships between the key variables examined in this study, even if they affect their average levels.

4.7 Conclusion

This study provides an empirical test of Diffusion of Innovations theory for two central residential decarbonisation technologies, advancing both theoretical understanding and policy relevance. Across heat pumps and EVs, technology perceptions emerge as the strongest predictors of adoption intention, while communication exposure and individual characteristics exert weaker and largely indirect effects. Adoption intention distributions diverge substantially from canonical S-curve assumptions, highlighting the need for empirically grounded diffusion modelling.

By analysing both technologies within the same nationally representative sample and modelling adoption as a stage-based ordinal process, the study demonstrates both shared and technology-specific diffusion mechanisms. These findings suggest that effective decarbonisation policy requires sustained attention to how technologies are perceived, experienced and made visible within everyday social contexts.

5 References

Adamo, A., Martín, H., de la Hoz, J., Rubio, J., & Valero, J. (2024). Regulatory framework for the promotion of heat pumps in the European Union. *Energy Reports*, *12*, 5909-5930. https://doi.org/10.1016/j.egyr.2024.11.043

Agarwal, R., & Prasad, J. (1998). The antecedents and consequents of user perceptions in information technology adoption. *Decision support systems*, *22*(1), 15-29. https://doi.org/10.1016/S0167-9236(97)00006-7

Anderson, C., Hildreth, J. A. D., & Howland, L. (2015). Is the desire for status a fundamental human motive? A review of the empirical literature. *Psychological bulletin*, *141*(3), 574. http://dx.doi.org/10.1037/a0038781

Anderson, S. T., & Newell, R. G. (2004). Information programs for technology adoption: The case of energy-efficiency audits. *Resource and Energy Economics*, *26*(1), 27–50. https://doi.org/10.1016/j.reseneeco.2003.07.001

Andersson, Y., Timmons, S., Lee, M., & Lunn, P. (2024). Going green in stages: Psychological processes behind intention formation and action for climate mitigation. *ESRI Working Paper No. 785*. https://www.esri.ie/system/files/publications/WP785.pdf

Anwyl-Irvine, A. L., Massonnié, J., Flitton, A., Kirkham, N., & Evershed, J. K. (2020). Gorilla in our midst: An online behavioral experiment builder. *Behavior research methods*, *52*(1), 388-407. https://doi.org/10.3758/s13428-019-01237-x

Axsen, J., Goldberg, S., & Bailey, J. (2016). How might potential future plug-in electric vehicle buyers differ from current “Pioneer” owners?. *Transportation Research Part D: Transport and Environment*, *47*, 357-370. https://doi.org/10.1016/j.trd.2016.05.015

Carthy, P., Farrell, N., Harold, J., & Timmons, S. (2026). Consumer acceptance of Time-of-Use Tariffs: The role of information and price salience. *ESRI Working Paper No. 820*. https://www.esri.ie/system/files/publications/WP820_0.pdf

Chadwick, K., Russell-Bennett, R., & Biddle, N. (2022). The role of human influences on adoption and rejection of energy technology: A systematised critical review of the literature on household energy transitions. *Energy Research & Social Science*, *89*, 102528. https://doi.org/10.1016/j.erss.2022.102528

Childers, T. L. (1986). Assessment of the psychometric properties of an opinion leadership scale. *Journal of marketing research*, *23*(2), 184-188. https://doi.org/10.1177/002224378602300211

Coffman, M., Bernstein, P., & Wee, S. (2017). Electric vehicles revisited: a review of factors that affect adoption. *Transport Reviews*, *37*(1), 79-93. https://doi.org/10.1080/01441647.2016.1217282

Domarchi, C., & Cherchi, E. (2023). Electric vehicle forecasts: a review of models and methods including diffusion and substitution effects. *Transport reviews*, *43*(6), 1118-1143. https://doi.org/10.1080/01441647.2023.2195687

Dormann, C. F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., ... & Lautenbach, S. (2013). Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. *Ecography*, *36*(1), 27-46. https://doi.org/10.1111/j.1600-0587.2012.07348.x

Du, H., Han, Q., & de Vries, B. (2022). Modelling energy-efficient renovation adoption and diffusion process for households: A review and a way forward. *Sustainable Cities and Society*, *77*, 103560. https://doi.org/10.1016/j.scs.2021.103560

Du, H., Liu, D., Sovacool, B. K., Wang, Y., Ma, S., & Li, R. Y. M. (2018). Who buys New Energy Vehicles in China? Assessing social-psychological predictors of purchasing awareness, intention, and policy. *Transportation Research Part F: Traffic Psychology and Behaviour*, *58*, 56-69. https://doi.org/10.1016/j.trf.2018.05.008

Eckel, C. C., & Grossman, P. J. (2008). Men, women and risk aversion: Experimental evidence. *Handbook of experimental economics results*, *1*, 1061-1073. https://doi.org/10.1016/S1574-0722(07)00113-8

Egmond, C., Jonkers, R., & Kok, G. (2006). One size fits all? Policy instruments should fit the segments of target groups. *Energy Policy*, *34*(18), 3464-3474. https://doi.org/10.1016/j.enpol.2005.07.017

Emmann, C. H., Arens, L., & Theuvsen, L. (2013). Individual acceptance of the biogas innovation: A structural equation model. *Energy Policy*, *62*, 372-378. https://doi.org/10.1016/j.enpol.2013.07.083

Eppe, P. S., Niehoff, E., Albers, C., & Bouman, T. (2025). Sustainable energy technology adoption for a low-carbon future: a global meta-analysis of psychological determinants. *Energy Research & Social Science*, *126*, 104152. https://doi.org/10.1016/j.erss.2025.104152

Eppstein, M. J., Grover, D. K., Marshall, J. S., & Rizzo, D. M. (2011). An agent-based model to study market penetration of plug-in hybrid electric vehicles. *Energy policy*, *39*(6), 3789-3802. https://doi.org/10.1016/j.enpol.2011.04.007

Erdem, C., Şentürk, İ., & Şimşek, T. (2010). Identifying the factors affecting the willingness to pay for fuel-efficient vehicles in Turkey: A case of hybrids. *Energy Policy, The Role of Trust in Managing Uncertainties in the Transition to a Sustainable Energy Economy, Special Section with Regular Papers*, *38*(6), 3038–3043. https://doi.org/10.1016/j.enpol.2010.01.043

European Commission (2026, July 17). Electrification action plan (COM(2026) 595 final). EUR-Lex. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52026DC0595&qid=1784715609929

Fleiter, T., Hirzel, S., & Worrell, E. (2012). The characteristics of energy-efficiency measures – a neglected dimension. *Energy Policy, Renewable Energy in China*, *51*, 502–513. https://doi.org/10.1016/j.enpol.2012.08.054

Franceschinis, C., Thiene, M., Scarpa, R., Rose, J., Moretto, M., & Cavalli, R. (2017). Adoption of renewable heating systems: An empirical test of the diffusion of innovation theory. *Energy*, *125*, 313–326. https://doi.org/10.1016/j.energy.2017.02.060

Gnann, T., Speth, D., Seddig, K., Stich, M., Schade, W., & Vilchez, J. G. (2022). How to integrate real-world user behavior into models of the market diffusion of alternative fuels in passenger cars-An in-depth comparison of three models for Germany. *Renewable and Sustainable Energy Reviews*, *158*, 112103. https://doi.org/10.1016/j.rser.2022.112103

Günther, A., Engel, L., Hornsey, M. J., Nielsen, K. S., Roy, J., Steg, L., ... & Hahnel, U. J. (2025). Psychological and contextual determinants of clean energy technology adoption. *Nature Reviews Clean Technology*, *1*(8), 547-565. https://doi.org/10.1038/s44359-025-00075-9

Hardman, S., Shafaeen, M., & Tal, G. (2024). Identifying mass market adoption in the transition to electric vehicles. *Environmental Research Letters*, *19*(11), 111005. https://doi.org/ 10.1088/1748-9326/ad7bd1

Jaiswal, D., Deshmukh, A. K., & Thaichon, P. (2022). Who will adopt electric vehicles? Segmenting and exemplifying potential buyer heterogeneity and forthcoming research. *Journal of Retailing and Consumer Services*, *67*, 102969. https://doi.org/10.1016/j.jretconser.2022.102969

Kanger, L., Geels, F. W., Sovacool, B., & Schot, J. (2019). Technological diffusion as a process of societal embedding: Lessons from historical automobile transitions for future electric mobility. *Transportation Research Part D: Transport and Environment*, *71*, 47-66. https://doi.org/10.1016/j.trd.2018.11.012

Kangur, A., Jager, W., Verbrugge, R., & Bockarjova, M. (2017). An agent-based model for diffusion of electric vehicles. *Journal of Environmental Psychology*, *52*, 166-182. https://doi.org/10.1016/j.jenvp.2017.01.002

Kangur, A., Jager, W., Verbrugge, R., & Bockarjova, M. (2017). An agent-based model for diffusion of electric vehicles. *Journal of Environmental Psychology*, *52*, 166-182. https://doi.org/10.1016/j.jenvp.2017.01.002

Knobloch, F., Hanssen, S. V., Lam, A., Pollitt, H., Salas, P., Chewpreecha, U., ... & Mercure, J. F. (2020). Net emission reductions from electric cars and heat pumps in 59 world regions over time. *Nature sustainability*, *3*(6), 437-447. https://doi.org/10.1038/s41893-020-0488-7

Kumar, R. R., Guha, P., & Chakraborty, A. (2022). Comparative assessment and selection of electric vehicle diffusion models: A global outlook. *Energy*, *238*, 121932. https://doi.org/10.1016/j.energy.2021.121932

Lee, J. H., Hardman, S. J., & Tal, G. (2019). Who is buying electric vehicles in California? Characterising early adopter heterogeneity and forecasting market diffusion. *Energy Research & Social Science*, *55*, 218-226. https://doi.org/10.1016/j.erss.2019.05.011

Mac Uidhir, T., Rogan, F., Collins, M., Curtis, J., & Gallachóir, B. P. Ó. (2020). Improving energy savings from a residential retrofit policy: A new model to inform better retrofit decisions. *Energy and Buildings*, *209*, 109656. https://doi.org/10.1016/j.enbuild.2019.109656

Mahajan, V., Muller, E., & Bass, F. M. (1995). Diffusion of new products: Empirical generalizations and managerial uses. *Marketing science*, *14*(3_supplement), G79-G88. https://doi.org/10.1287/mksc.14.3.G79

McCoy, D., & Lyons, S. (2014). Consumer preferences and the influence of networks in electric vehicle diffusion: An agent-based microsimulation in Ireland. *Energy Research & Social Science*, *3*, 89-101. https://doi.org/10.1016/j.erss.2014.07.008

Meade, N., & Islam, T. (2006). Modelling and forecasting the diffusion of innovation–A 25-year review. *International Journal of forecasting*, *22*(3), 519-545. https://doi.org/10.1016/j.ijforecast.2006.01.005

Meles, T. H., & Ryan, L. (2022). Adoption of renewable home heating systems: An agent-based model of heat pumps in Ireland. *Renewable and Sustainable Energy Reviews*, *169*, 112853. https://doi.org/10.1016/j.rser.2022.112853

Nemet, G., Greene, J., Müller-Hansen, F., & Minx, J. C. (2023). Dataset on the adoption of historical technologies informs the scale-up of emerging carbon dioxide removal measures. *Communications Earth & Environment*, *4*(1), 397. https://doi.org/10.1038/s43247-023-01056-1

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

Nunnally, J. C. (1978). An overview of psychological measurement. *Clinical diagnosis of mental disorders: A handbook*, 97-146.

Peres, R., Muller, E., & Mahajan, V. (2010). Innovation diffusion and new product growth models: A critical review and research directions. *International journal of research in marketing*, *27*(2), 91-106. https://doi.org/10.1016/j.ijresmar.2009.12.012

Peters, A., & Dütschke, E. (2014). How do consumers perceive electric vehicles? A comparison of German consumer groups. *Journal of Environmental Policy & Planning*, *16*(3), 359-377.

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*, 247-261. https://doi.org/10.1016/j.jtrangeo.2017.06.009

Räihä, J., & Ruokamo, E. (2021). Determinants of supplementary heating system choices and adoption consideration in Finland. *Energy and Buildings*, *251*, 111366. https://doi.org/10.1016/j.enbuild.2021.111366

Ramadoss, T. V., Lee, J. H., Davis, A. W., Hardman, S., & Tal, G. (2025). Classifying electric vehicle adopters and forecasting progress to full adoption. *npj Sustainable Mobility and Transport*, *2*(1), 32. https://doi.org/10.1038/s44333-025-00049-1

Rietkerk-van der Wijngaart, M., de Jager, L., Scholz, G., Chappin, E., & De Vries, G. (2025). Bridging behavioral theory and household energy decisions: enhancing agent-based models with behavioral analysis. *Frontiers in Psychology*, *16*, 1568730. https://doi.org/10.3389/fpsyg.2025.1568730

Roberts, C., Geels, F. W., Lockwood, M., Newell, P., Schmitz, H., Turnheim, B., & Jordan, A. (2018). The politics of accelerating low-carbon transitions: Towards a new research agenda. *Energy research & social science*, *44*, 304-311. https://doi.org/10.1016/j.erss.2018.06.001

Rogers, E. M., (2003), Diffusion of Innovations, Fifth edition, New York: Free Press

Schuitema, G., Anable, J., Skippon, S., & Kinnear, N. (2013). The role of instrumental, hedonic and symbolic attributes in the intention to adopt electric vehicles. *Transportation Research Part A: Policy and Practice*, *48*, 39-49. https://doi.org/10.1016/j.tra.2012.10.004

Seebauer, S. (2015). Why early adopters engage in interpersonal diffusion of technological innovations: An empirical study on electric bicycles and electric scooters. *Transportation Research Part A: Policy and Practice*, *78*, 146–160. https://doi.org/10.1016/j.tra.2015.04.017

Sharp, B. E., & Miller, S. A. (2016). Potential for integrating diffusion of innovation principles into life cycle assessment of emerging technologies. *Environmental science & technology*, *50*(6), 2771-2781. https://doi.org/10.1021/acs.est.5b03239

Smith, B., Olaru, D., Jabeen, F., & Greaves, S. (2017). Electric vehicles adoption: Environmental enthusiast bias in discrete choice models. *Transportation Research Part D: Transport and Environment*, *51*, 290–303. https://doi.org/10.1016/j.trd.2017.01.008

Sopha, B. M., Klöckner, C. A., & Hertwich, E. G. (2013). Adoption and diffusion of heating systems in Norway: Coupling agent-based modeling with empirical research. *Environmental Innovation and Societal Transitions*, *8*, 42-61. https://doi.org/10.1016/j.eist.2013.06.001

Strazzera, E., Meleddu, D., Contu, D., & Fornara, F. (2024). Willingness to pay for innovative heating/cooling systems: A comprehensive appraisal of drivers and barriers to adoption in Ireland and Italy. *Renewable and Sustainable Energy Reviews*, *192*, 114192. https://doi.org/10.1016/j.rser.2023.114192

Timmons, S., Shier, A. J. & Ó Ceallaigh, D. (2026). Effects of building fabric requirements on willingness to adopt a heat pump. *ESRI Working Paper No. 835*.

Völlink, T., Meertens, R., & Midden, C. J. H. (2002). Innovating 'Diffusion of Innovation' theory: Innovation characteristics and the intention of utility companies to adopt energy conservation interventions. *Journal of Environmental Psychology*, *22*(4), 333–344. https://doi.org/10.1006/jevp.2001.0237

Williams, R. (2006). Generalized ordered logit/partial proportional odds models for ordinal dependent variables. *The stata journal*, *6*(1), 58-82. https://doi.org/10.1177/1536867X0600600104

Wilson, C., & Dowlatabadi, H. (2007). Models of decision making and residential energy use. *Annu. Rev. Environ. Resour.*, *32*(1), 169-203. https://doi.org/10.1146/annurev.energy.32.053006.141137

Wilson, C., Hargreaves, T., & Hauxwell-Baldwin, R. (2017). Benefits and risks of smart home technologies. *Energy policy*, *103*, 72-83. https://doi.org/10.1016/j.enpol.2016.12.047

Wolf, I., Schroeder, T., Neumann, J., & de Haan, G. (2015). Changing minds about electric cars: An empirically grounded agent-based modeling approach. *Technological forecasting and social change*, *94*, 269-285. https://doi.org/10.1016/j.techfore.2014.10.010

Zhang, H., & Vorobeychik, Y. (2019). Empirically grounded agent-based models of innovation diffusion: a critical review. *Artificial Intelligence Review*, *52*(1), 707-741. https://doi.org/10.1007/s10462-017-9577-z