Consumer Uptake of Digital Low-Carbon Innovations

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Abstract— **Digitalisation is transforming the consumer landscape. Digitally-enabled mobility, food provision, domestic living, and energy supply can help reduce carbon emissions. We use stated preference data from a nationally-representative sample in the UK (n=3014) to understand consumer adoption of 13 digital low-carbon innovations across mobility, food, homes and energy domains. Using diffusion of innovations as our analytical framework, we test three main adoption drivers: adopter characteristics, social influence, and innovation attributes. We use blocks of variables measuring each adoption driver as predictors in logit models that distinguish adopters from non-adopters. We focus our analysis on adoption drivers that are significant and consistent predictors of digital innovation adoption across different contexts.**

Compared to non-adopters, we find that early adopters of digital low-carbon innovations are more likely to be younger, in employment, living in multi-person households, digitally skilful, environmentally active, and technologically active. We also find that early adopters are more exposed to inter-personal information flows (i.e., social influence), use social media more intensively, and perceive the innovations to offer higher relative advantage over current practices, be easy to use, be more compatible both with their values and their lifestyles. These drivers of adoption hold across mobility, food, homes and energy-related innovations, so can be translated into generalisable strategies, policies, and interventions for stimulating consumer uptake of digital low-carbon innovations. Although our data collection specifically characterises adopters and non-adopters in the UK, the innovations in our sample are increasingly available in markets worldwide so our findings have broad applicability.

Keywords—digital, innovation, adoption, consumer, diffusion, low-carbon, climate change mitigation, technology

I. Introduction

Daily life has become digitalised. McKinsey define digitalisation as "the nearly instant, free, and flawless ability to connect people, devices, and physical objects anywhere" [1]. Digitalisation is transforming the consumer landscape, shaping how we socialize, travel, shop, live at home, and relax. A wide range of digital innovations - both software and hardware - are available to individuals and households as consumers of services ranging from heating homes and ordering food to moving around cities and generating energy. Providing these services requires infrastructures, networks of actors, rules and regulations. Ordering food using a smartphone app is the consumer-facing element of a provisioning system comprising farmers, distribution centres, supermarkets, delivery services, and route optimisation algorithms. Digital consumer innovations are the interface between end-users and these provisioning systems.

A. *Digital low-carbon innovations*

The digital consumer innovations analysed in this study are shown in Fig. 1 for mobility (blue), food (green), homes and energy (red/orange). These offer alternatives to resource-intensive consumption practices that include driving single-occupancy private vehicles, doing big food shops in large out-of-town supermarkets, or using energy at home however and whenever needed [2].

The digital innovations shown in Fig. 1 were selected for two reasons. First, evidence shows they can all contribute to carbon emission reductions [3]. Consequently we refer to 'digital low-carbon innovations' throughout, although we recognise that being 'low-carbon' is contingent on how the innovations are designed, used, and regulated, as well as the energy and carbon footprint of associated digital infrastructure. As an example, using a shared ride-hailing app like UberPool instead of driving a single occupancy car can reduce emissions per trip, but can also rebound into more emissions if the number of trips increases [4]. Uncertainties about the direct, indirect and systemic impacts of digitalisation are reflected in how many studies have characterised divergent digital-climate futures using metaphors like 'Heaven vs. Hell', 'Utopia vs. Dystopia', 'Fire Retardant vs. Fire Accelerant' [5-7].

Second, the innovations in Fig. 1 vary in terms of application, emission-reduction mechanism, and adoption context. This matches the study purpose of identifying generalisable drivers of digital innovation adoption. The digital low-carbon innovations in Fig. 1 are variously used for travelling, driving, ordering or exchanging food, managing heat, light and appliances in the domestic environment, and providing storage or flexibility services to power grids. These innovations can help reduce carbon emissions in five main ways (Fig. 1):

(1) by substituting for physical movement - e.g., digital food hubs, meal kits (as well as teleworking and videoconferencing);

(2) by accessing services instead of owning physical goods - e.g., car clubs, ride-sharing, shared ride-hailing;

(3) by exchanging physical goods and reducing waste - e.g., peer-to-peer (P2P) car-sharing, 11th hour food apps, peer-to-peer (P2P) electricity trading;

(4) by controlling & managing energy demand - e.g., smart heating systems, smart lighting, (also electric vehicles and e-bikes);

(5) by integrating consumption activity into supply networks to support efficient system functioning - e.g., smart home appliances, solar generation and storage systems, electric vehicle-to-grid.

This research was supported by European Research Council (ERC) grants #678799 (SILCI project) and #101003083 (iDODDLE project).

Domain	Digital Low-Carbon Innovation		Market Share *	Product or Service	Mechanism for Reducing Emissions **	UK Coverage
Mobility (n=6)	Car clubs (carsharing in US)		<1%	service	accessing	national
	Peer-to-peer (P2P) carsharing		<1%	service	exchanging	national
	Liftsharing (ridesharing in US)		<1%	service	accessing	national
	Shared ride-hailing (or taxi-buses)		<0.1%	service	accessing	some cities
	Electric vehicles		<1%	product	integrating	national
	E-bikes		~2%	product	integrating	national
Food (n=3)	Online food hubs		<0.1%	service	substituting	some areas
	Meal kits (or recipe boxes)		<0.1%	service	substituting	national
	11th hour food apps		<1%	service	exchanging	national
Homes (n=4)	Smart heating		~6%	product	controlling	national
	Smart lighting		~5%	product	controlling	national
	Smart appliances		<1%	product	integrating	national
	Services provided to power grids	Electricity generation with storage	<0.1%	product	integrating	national
		Peer-to-peer electricity trading	<0.1%	service	exchanging	some city trials
		Electric vehicle-to-grid	<0.1%	service	integrating	some areas

* estimated from available data   ** see text for details

Fig. 1. Digital low-carbon innovations analysed in this study. Upper panel shows key market and innovation characteristics; lower panel shows illustrative app icons.

As shown in the market share estimates in Fig. 1, many digital low-carbon innovations are at the edges of mainstream markets (notwithstanding the now widespread use of e-commerce and videoconferencing services). Consequently, any major impact on carbon emissions from digital low-carbon innovations first depends on widespread consumer uptake or adoption.

B. *Frameworks for studying innovation adoption*

There are many different theories, frameworks, and approaches for studying innovation adoption. They can be roughly grouped according to their main unit of analysis and scope.

First, behavioural, cognitive, and economic approaches measure personal and contextual determinants of adoption, and the conditions under which adoption is enabled or constrained. Individual adopters are the unit of analysis. Examples include models from behavioural psychology like the theory of planned behaviour [8] or the technology acceptance model [9, 10]. Diffusion of innovations similarly uses an innovation decision model of individual adopters, but contextualises this in the social networks through which inter-personal information flows as part of the innovation diffusion process [11]. Microeconomic models frame innovation adoption as the outcome of a utility-maximising decision based on an individual adopter's known preferences [12].

Second, sociological approaches are interested in collective or structured patterns of innovation adoption and use, and the social and material contexts in which they are embedded. Shared or contextualised practices are the unit of analysis. Two examples are social practice theory [13] and domestication theory [14]. Social practices are constituted by materials, competences, and meanings; innovation adoption is framed as a dynamic reconfiguration of these elements of practice and their interrelationships [15]. Domestication theory is concerned with how technologies and users co-evolve in a process of 'normalisation' as users learn, adapt, innovate new usages, establish new routines or identities, and give particular functions and meanings to how technologies fit into daily life [16].

Third, systems approaches are interested in the socio-technical systems within which innovations appear, compete, succeed or fail. Multi-scale and dynamic systems are the unit of analysis. Examples include the multi-level perspective [17], technological diffusion and systems theories [18, 19], and innovation systems theories [20, 21]. The multi-level perspective frames innovation diffusion as a dynamic between micro (niche), meso (regime), and macro (landscape) scales. Emerging initially in protected niches, innovations compete to destabilise incumbent technologies, actors, and institutions that make up the prevailing socio-technical regime [22, 23]. Exogenous landscape-level forces can open up windows of opportunity for regime change. Technological systems approaches share an interest in the institutional and infrastructural context in which innovations are developed, tested, adopted, and deployed [18]. Market diffusion is characteristically described by logistic or S-shaped growth curves as new technology substitutes for old [19]. Innovation systems frameworks focus on the structures and functions that enable innovations to emerge through research, development, demonstration and market formation stages, prior to their commercial maturity [24].

Each of these broad research approaches has distinctive emphases, applications, and methods. For example, individual approaches often use quantitative data measuring adoption dynamics underway, sociological approaches use qualitative, longitudinal data from case studies, and systems approaches generally use secondary data from documented historical transitions.

For our study, we selected diffusion of innovations as our research framework for three reasons. First, we were interested in comparatively analysing multiple innovations using standardised data (not feasible using sociological theories). Second, we were interested specifically in consumer preferences, behaviours, and interactions (not feasible using systems theories). Third, we were interested in digital interpersonal information flows ('electronic word-of-mouth') in diffusion processes. Diffusion of innovations and related adoption models have been widely used to investigate digital technologies and services used in daily life [25].

C. Diffusion of innovations (DoI)

'Diffusion of innovations' (DoI) by Everett Rogers synthesises insights from hundreds of such studies across fields as diverse as public health, marketing, rural development and agriculture, international development, and workplace information and communication technologies (ICTs) [11]. This gives rise to a generalisable analytical framework that characterises the process of innovation adoption and the drivers of diffusion. In the DoI framework, innovations spread through a population of heterogeneous adopters who vary in their propensity towards trying out new ideas. Novelty-seeking early adopters communicate their experiences through social networks, helping to reduce the perceived risks of innovation adoption among later adopters. Diffusion is therefore a fundamentally social process [26-28].

DoI studies of digital consumer innovations include smartphone use [29], chat bots [30], mobile banking apps [31], Facebook apps [32], and smart home technologies [33]. As these examples show, adoption and diffusion studies tend to focus on specific innovations, dating back to the foundational 1940s study of hybrid-seed corn adoption among Iowa farmers [34]. Studies comparatively assessing multiple innovations are less common [35]. One recent example generalises insights on diffusion characteristics and timescales for 100 environmental innovations including organic food, renewable energy, energy-efficient appliances, and sustainable mobility [36]. The speed and extent of diffusion for each innovation is explained a function of its product, adopter, market and sectoral characteristics. The most influential explanation of adoption was "compatibility with routines". A follow-up study with a larger set of 130 environmental innovations similarly found that the "need for behaviour modification" as well as "uncertainties on the part of adopters" are inhibitors of diffusion, while a high degree of "compatibility" as well as strong "self-reinforcing effects" through word of mouth in social networks are enablers of diffusion [37]. No generalisable effects of policy-related factors on adoption and diffusion were found in either study.

While impressive in scope and generalisability, an important limitation of these studies is that all the explanatory variables measuring adoption and diffusion drivers were subjectively scored or coded by the authors, so their methodology is not replicable (see also [35]).

Online surveys (stated preferences) are the most common method used to understand adopters' experiences and decision processes, and non-adopters' intentions or propensities to adopt. Standard batteries of multi-item Likert scale questions measure specific adoption predictors, including opinion leadership [38], values [39], or ease of use [10]. Statistical methods including logit models [12, 40] or structural equation models [30, 41] are then used to test hypotheses on adoption drivers or develop models that predict individuals' adoption propensities towards specific innovations.

D. Research question and design

Our study uses the diffusion of innovations (DoI) framework to empirically test whether there are generalisable explanations of early adoption that hold across a diverse sample of digital low-carbon innovations and adoption contexts (Fig. 1). Our research question is: What drives initial consumer uptake of digital low-carbon innovations?

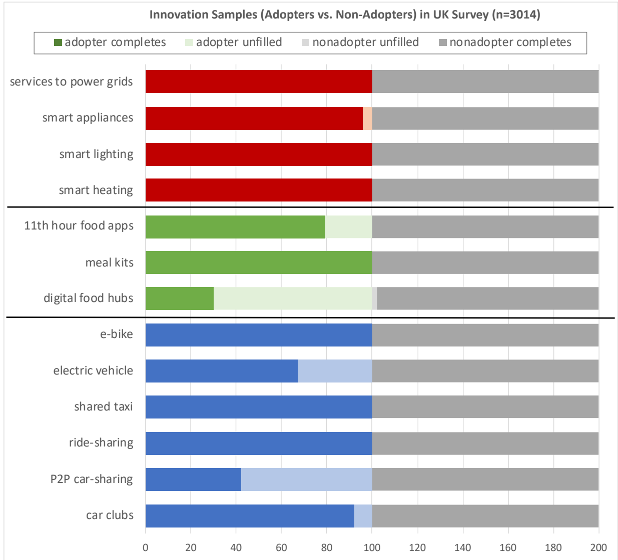

Fig. 2. Samples sizes of adopters (coloured bars) and non-adopters (grey bars) for each innovation. Each sample had a target of 100 such that completed surveys (dark shading) + unfilled quotas (light shading) = 100.

Applying the DoI framework to understand consumer uptake of digital low-carbon innovations means: (1) identifying and comparing heterogeneous groups of adopters (e.g., early adopters vs. non-adopters); (2) measuring the strength of social influence or interpersonal information flows between early adopters and non-adopters; (3) controlling for the strength of appeal of specific innovation attributes.

The novelty of our study is threefold. First, we comparatively assess a range of digital low-carbon innovations using a standardised methodology and data. Second, we focus on identifying generalisable insights on early adoption drivers that hold across innovations and contexts. Third, we translate these insights into policies and intervention strategies for harnessing digitalisation to support less energy-intensive forms of consumer behaviour.

II. METHOD AND DATA

We use diffusion of innovations (DoI) as our analytical framework, and so focus on three main drivers of adoption:

(1) Adopter characteristics and heterogeneity (e.g., income, age, skills, values). For example, DoI predicts that - in general - early adopters who take practical and social risks trying out innovations tend to be more skilled, cosmopolite, wealthy, young, and innovative.

(2) Social networks and social influence (e.g., strong ties, homophily, electronic word-of-mouth). For example, DoI predicts that - in general - flows of information in social networks between trusted others are a driver of adoption as they help reduce perceived risks with innovation adoption.

(3) Innovation attributes (e.g., compatibility, relative advantage). For example, DoI predicts that - in general - innovations that are more compatible with potential users' values and lifestyles will be adopted faster.

All three drivers of adoption have been widely tested for specific innovations and hold in broad terms across adoption contexts [11]. However, they have not been systematically tested for digital low-carbon innovations.

Although DoI places adopters, innovations, and information flows through social networks as the central units of analysis, it is not blind to the influence of external context such as prices, regulations, and physical infrastructures. These important influences on innovation adoption are captured indirectly though potential adopters' perceptions of an innovation's attributes. For example, if a given low-carbon innovation is competitive on cost (due to purchase incentives), and is readily available and accessible (due to infrastructure investments), it will perform more strongly on perceived attributes of relative advantage, compatibility, and ease of use, which in turn will be associated with faster adoption. We discuss this further below.

We use large-scale stated preference data from a nationally-representative sample in the UK (n=3014) to understand consumer adoption of digital low-carbon innovations across mobility, food, homes and energy domains (Fig. 1). Our diverse set of innovations ranges from car clubs and shared ride-hailing to online food hubs and smart thermostats. We refer to these as 'innovations' as they are relatively or very recently introduced into consumer markets in the UK, and currently have low market shares. DoI stylises the first 2.5% of adopters as 'innovators' and the next 12.5% as 'early adopters' [11]. All our innovations are firmly in these market segments.

We refer to our set of innovations as 'low-carbon' given available evidence showing clear emission reduction potentials if rebound and intensification risks can be managed [3]. We refer to our set of innovations as 'digital' as a key part of their functionality or value proposition is provided through apps, cloud-based services, platforms, real-time data analytics, learning algorithms, or other forms of data-dependent service-provision. Two of the innovations - electric vehicles and e-bikes - appear anomalous. We include these electric mobility innovations under the 'digital' umbrella because: (1) how they integrate into energy and transport networks is digitally mediated (e.g., managing re-charging loads on power networks, traffic flows); (2) electric vehicles are increasingly controlled by software that can be updated and patched (e.g., Teslas have been described as 'iPads-on-wheels' [42]); (3) electric and shared mobility are entwined drivers of change in the transportation system, and shared systems rely on apps and platforms [43].

We collected data from both early adopters and non-adopters of each innovation so we could isolate the distinctive characteristics of adopters. According to DoI, early adopters' are more comfortable with the technological and social risks of trialling new consumption practices, and play a critical role in communicating their experiences of innovation adoption through social networks. We therefore expect early adopters to have distinctive characteristics and social influence behaviours.

We implemented our questionnaire survey in Sep-Dec 2019 (pre-Covid-19) using respondent panels of the market research company, Dynata, ensuring age, sex, and income representativeness of the adult UK population. We used a quota sampling design to target n=100 adopters and n=100 non-adopters of each innovation, identified in an initial

Blocks of Independent Variables	CAR CLUBS	ONLINE FOOD HUBS	SMART HEATING
SOCIODEMOGRAPHICS CHARACTERISTICS			
Gender (Female)	-	-	-
Age (Over 45)	0.40	0.12	-
Education (Degree)	3.00	-	-
Employment	4.01	-	2.22
Household Income (Low)	-	0.12	0.51
Household Finances (OK)	-	-	-
Household Size (Single)	-	-	0.38
Household Lifecycle (Schoolkids)	-	-	-
OTHER ADOPTER CHARACTERISTICS			
Values: Openness To Change (3 items)	2.08	-	-
Values: Self Transcendence (3 items)	-	-	-
Values: Self Enhancement (3 items)	-	-	-
Values: Traditional (3 items)	-	-	-
Digital Skills: Apps (4 items)	44.96	-	17.42
Environmental Lifestyle Activities (5 items)	-	-	1.50
Technological Lifestyle Activities (5 items)	1.71	2.49	-
Personality: Neuroticism (3 items)	-	-	-
Personality: Openness (3 items)	-	-	-
Personality: Extroversion (3 items)	-	-	-
Personality: Agreeableness (3 items)	-	-	-
Personality: Conscientiousness (3 items)	0.48	-	1.73
INNOVATION ATTRIBUTES			
Relative Advantage	2.07	-	1.93
Complexity (= inverse of Ease of Use)	0.62	-	0.65
Compatibility	2.04	-	2.43
Observability	-	2.28	-
Trialability	-	-	-
Protects Environment	-	-	-
Tackles Climate Change	-	-	-
INFORMATION FLOWS			
Domain Innovativeness (3 items)	2.63	3.99	2.81
Social Influence (8 items)	4.51	-	2.13
Info Sources Inter-Personal (4 types)	-	-	0.40
Info Sources General Media (2 types)	-	-	2.12
SOCIAL NETWORK STRUCTURE			
Social Media Intensity (# types * hrs online)	1.15	1.13	1.17
Social Media Usage (hrs online)	-	-	-
Strong Ties (#)	-	-	-
Strong Ties Transitivity (Strong)	-	-	-
Strong Ties Homophily (Age)	-	-	-
Strong Ties Homophily (Income)	-	-	-
Strong Ties Homophily (Local)	-	-	-
Strong Ties Homophily (Family)	-	-	-
Weak Ties (#)	-	-	-
CONTEXTUAL FACTORS			
Owns (ICE) Car			
Use Car If Owned >1/Month	-		
Use Car (Single Occupancy) >1/Week	0.23		
Use Bike/eBike >1/Week	-		
Commute by Car (Single Occupancy)	2.23		
Commute by Walk/Bike/eBike	3.52		
Commute Time	-		
Main Decisionmaker on Travel/Food/Home	-	-	-
Expenditure on Travel/Food/Home	-	-	0.37
Home Type (house)	-	-	3.43
Home Tenure (owner)	-	-	-
Home Duration (>=4 years)	0.44	-	0.43
Home Location (urban)	0.32	-	-
MODEL FIT (Integrated across all variables)			
total n (n adopters)	176 (74)	99 (11)	136 (73)
pseudo R2	**0.56**	**0.31**	**0.41**

Fig. 3. Logit models predicting adoption for three digital low-carbon innovations (car clubs, online food hubs, smart heating). Explanatory variables were tested sequentially in blocks (socio-demographics, other adopter characteristics, etc.). Only significant coefficients are reported for variables in each block. Coefficients are expressed as odds ratios, with green shading denoting odds ratios > 1 (i.e., more likely in adopters) and orange shading denoting odds ratios < 1 (i.e., less likely in adopters). Darker shading indicates significance at a smaller p-value (.05, .01, .001). Model fit statistics at the bottom are for the final integrated model with significant variables across all blocks. Coefficients are not shown for this integrated model.

screening set of questions. Only non-adopters who had heard of an innovation were subsequently asked questions specific to that innovation (to avoid hypothetical biases).

Although we were unable to reach target quotas for innovations with very low market shares (e.g., peer-to-peer (P2P) car-sharing, online food hubs), samples sizes were sufficient for our analysis (Fig. 2). However, low numbers of responses for three domestic energy innovations were addressed by combining them into a single innovation category describing how digitalisation enables domestic energy producers to integrate into electricity networks through storing, trading, or (re)charging their vehicles (see bottom rows in Fig. 1, and upper row in Fig. 2).

The main survey comprised blocks of innovation-specific questions (e.g., on perceived attributes), blocks of domain-specific questions (e.g., on transport behaviours), and blocks of adopter-specific questions (e.g., on social networks). Each of these blocks is based on the DoI analytical framework. Overall the full survey had nine blocks of questions as follows:

1. Adoption - on respondents' awareness and use of each innovation;
2. Domain Activity - on respondents' current behaviour in one particular domain (transport, food, homes, energy);
3. Domain Innovativeness - on respondents' propensity to adopt innovations in one particular domain;
4. Innovation Familiarity - on respondents' familiarity with one particular innovation;
5. Innovation Attributes - on respondents' perceptions of the attributes of one particular innovation;
6. Innovation Information - on respondents' information-seeking and social influence related to one particular innovation;
7. Social Network - on respondents' social network position and role;
8. Personal Characteristics - on respondents' personality, lifestyle and values;
9. Personal and Contextual Situation - on respondents' circumstances, living conditions, and socio-economics.

The full survey instrument containing all questions and response wordings, as well as the data collected from UK respondents, is publicly available in the ReShare open data repository [https://reshare.ukdataservice.ac.uk/854723/].

Each question block comprised multiple single-item questions (e.g., on socioeconomics, social network structure) and/or multi-item questions (e.g., on social influence, values, personality). Multi-item questions or scales were used to estimate latent or underlying factors using standard data reduction techniques (principal component analysis). For example, a standard 12 item scale measuring values from [39] was reduced to four underlying factors representing distinct value types: traditional, self-enhancement, self-transcendence, openness to change (Fig. 5).

We used blocks of variable measuring each driver of adoption as predictors in statistical models that distinguish adopters from non-adopters of each innovation. We started by sequentially introducing blocks of explanatory variable into logit models explaining adoption. Fig. 3 gives examples of these innovation-specific logit models for three of the innovations in our sample. Only significant coefficients are reported for variables in each block. Coefficients are expressed as odds ratios, with green shading denoting odds ratios > 1 (i.e., more likely in adopters) and orange shading denoting odds ratios < 1 (i.e., less likely in adopters). Darker shading indicates significance at a smaller p-value (.05, .01, .001). Taking the car clubs model as an example, the odds ratio of 0.4 for the variable 'age (over 45)' and the odds ratio of 3.0 for the variable 'education (degree)' mean that early adopters of car clubs are less than half as likely to be older than non-adopters of car clubs, but three times as likely to be educated to degree level.

The final 'integrative' model for each innovation combines the significant variables from each block model to provide a parsimonious overall explanation of adoption for each innovation with good explanatory power (pseudo R^2).

Although each innovation-specific model can be analysed and interpreted separately, our study emphasis is on generalisable insights across adoption contexts. Consequently we focus our analysis here on predictors of adoption that are significant and consistent across multiple logit models for digital low-carbon innovations in mobility, homes, food and energy domains.

III. RESULTS

We first present generalisable results for each driver of adoption (in the different blocks of explanatory variable). In all cases, we only show variables that are significant predictors for at least 3 of the 13 innovations analysed.

A. *Adopter characteristics and heterogeneity*

We find that early consumer adopters of digital low-carbon innovations are more likely to be younger, in employment, higher income, living in multi-person households, digitally skilful, environmentally active, and technologically active (Fig. 4 & 5).

We used cluster analysis to identify groups of similar early adopters on the personal characteristics shown in Fig. 5 [44]. We identified three distinct clusters of early adopters which we labelled 'techies' (38% of the sample), 'greens' (20%), and 'pioneers' (41%). Techies have strong egoistic values, more technological lifestyles, and higher digital skills. Greens have strong biospheric values, and more environmental lifestyles. Pioneers combine the characteristics of both techies and greens, and are also strong opinion leaders.

B. *Social influence, information flows, and social networks*

We find that early adopters of digital low-carbon innovations have high 'domain innovativeness' in the consumption domain corresponding to the innovation (e.g., the transport domain for respondents asked questions on car clubs, or the homes domain for those asked questions on smart heating). Domain innovativeness measures an individual's predisposition towards a product class, reflecting a tendency to learn about and adopt new products within a specific domain of interest [45, 46].

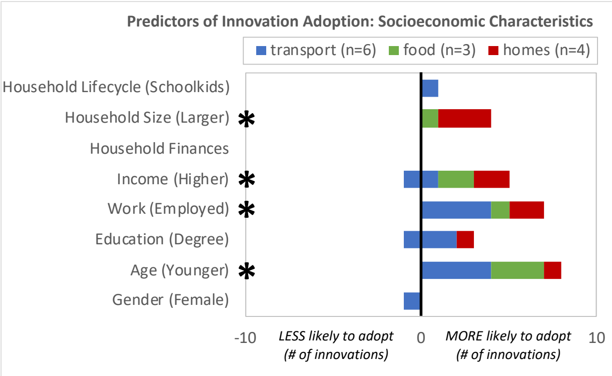

Fig. 4. Socioeconomic characteristics tested as predictors of innovation adoption. Variables marked by * are significant and consistent predictors of adoption for at least 3 of 13 digital low-carbon innovations.

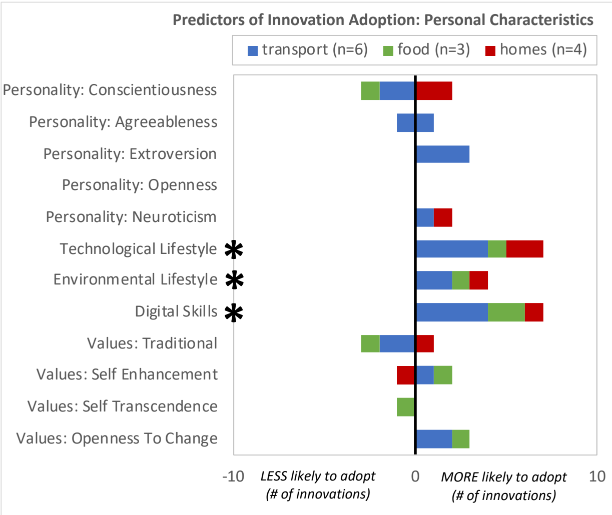

Fig. 5. Personal characteristics tested as predictors of innovation adoption. Variables marked by * are significant and consistent predictors of adoption for at least 3 of 13 digital low-carbon innovations.

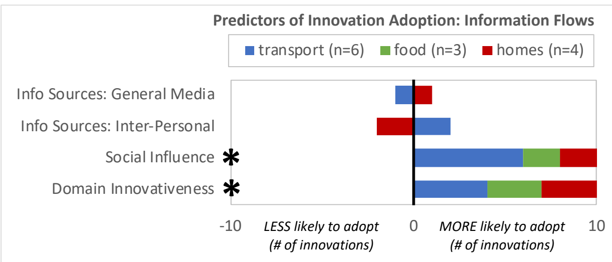

Fig. 6. Social influence tested as predictors of innovation adoption. Variables marked by * are significant and consistent predictors of adoption for at least 3 of 13 digital low-carbon innovations.

Adopters also receive more information about the innovation through social influence mechanisms (Fig. 6). The composite 'social influence' variable measures the combined effect of word-of-mouth, electronic word-of-mouth, peer effects, and social norms [47]. Further analysis shows that three of the four mechanisms are strong and consistent predictors of adoption (peer effects are the exception). Electronic word-of-mouth has the strongest effect size.

We also find early adopters have more diverse online networks and use social media more intensively so are

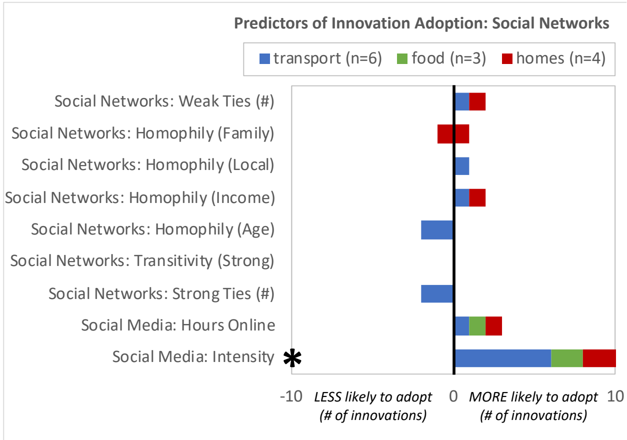

Fig. 7. Social network factors tested as predictors of innovation adoption. Variables marked by * are significant and consistent predictors of adoption for at least 3 of 13 digital low-carbon innovations.

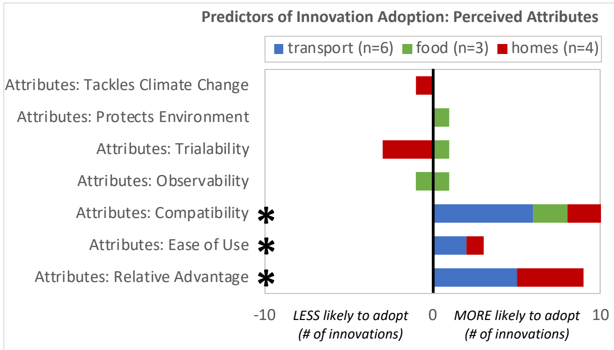

Fig. 8. Innovation attributes tested as predictors of innovation adoption. Variables marked by * are significant and consistent predictors of adoption for at least 3 of 13 digital low-carbon innovations.

exposed to more electronic word-of-mouth as a digitally-mediated form of social influence (Fig. 7). In line with expectations from diffusion of innovations, the communication of information and sharing of experiences about innovations is a powerful driver of adoption.

However we do not find any consistent effects of social network structure such as homophily (having social contacts similar to oneself), transitivity (cliquey-ness), and density (number of strong and weak ties) (Fig. 7). Social network structures are person-specific rather than innovation-specific, so we reason that information flows about specific innovations are not constrained by homophilous, cliquey, or less extensive social networks.

C. *Innovation attributes.*

We find that early adopters of digital low-carbon innovations perceive the innovations to offer higher relative advantage over current practices, to be easy to use, and to be more compatible both with their values and their lifestyles (Fig. 8). However we do not find adopters perceive the innovations to be beneficial for climate change or the environment. Digital alternatives to energy-intensive consumption practices have to have strong functional appeal beyond being low carbon, particularly as the environmentally-oriented adopter segment is a minority [48].

D. Integrated model with all adoption drivers.

Including all blocks of variable controls for covariance or overlapping associations between different drivers (independent variables) and innovation adoption (dependent variable) (Fig. 9). At the most general level, we find that compared to non-adopters, early adopters of digital low-carbon innovations tend to: (1) be domain innovators who are also more exposed to social influence and have a more diverse online presence across multiple platforms; (2) perceive innovations to have higher relative advantage and compatibility with their values and lifestyles; (3) have higher digital skills and technologically-oriented lifestyles, or are more environmentally-minded. Conversely, we find no consistent differences between adopters and non-adopters in terms of socioeconomic characteristics, social network structures, or personal situation including living and working contexts.

IV. GENERALISABLE INSIGHTS ACROSS MULTIPLE DIGITAL LOW-CARBON INNOVATIONS

There are strong and consistent drivers of adoption across digital low-carbon innovations and adoption contexts (Figs. 4-9). Our findings for each of the three main drivers of early adoption were broadly in line with expectations from the DoI framework. However, the consistency of these findings across three or more digital low-carbon innovations was surprising given strong variations in adoption context in mobility, food, homes and energy domains. This shows both that there are generalisable drivers of consumer uptake of digital innovations. It also suggests that DoI effectively internalises variation in adoption contexts through its independent variables.

A. Social influence through digital media

Observability and trialability are generally important attributes for product innovations to reduce social and functional risks perceived by potential adopters. Our findings show that consumer uptake of digital low-carbon innovations relies less on these innovation attributes, and more on interpersonal interaction through digital media. First, electronic word-of-mouth is the strongest mechanism of social influence (relative to word-of-mouth, social norms, and peer effects). Second, use of digital innovations is only weakly 'visible' particularly in domestic contexts so observability as an innovation attribute is not a consistent predictor of adoption. Third, many digital innovations are subscription or use-based services rather than products with sunk costs, so trialability is also not a consistent predictor of adoption.

Taken together these findings emphasise how digital information flows through inter-personal and social media channels are an important means for early adopters to communicate the relative advantage and compatibility of innovations and so reduce perceived risks and uncertainties among would-be adopters to stimulate further uptake.

B. Market positioning and appeal

Digital low-carbon innovations must strengthen their appeal on basic attributes. Despite the emission-reduction benefits of our sample of digital low-carbon innovations, appealing to green consumer values or aspirations is insufficient. Environmentally-minded and technologically-oriented adopters form distinct consumer segments which means a broader market appeal for low-carbon digital innovations. The larger early adopter segments are

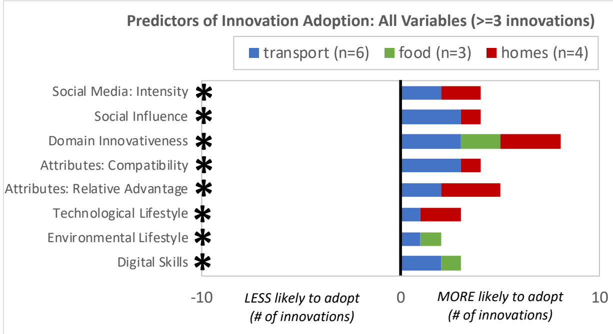

Fig. 9. Integrated models of innovation adoption, taking into account socioeconomic, adopter, social influence and innovation attribute variables. Variables marked by * are significant and consistent predictors of adoption for at least 3 of 13 digital low-carbon innovations.

characterised by technophilia, innovativeness, and egoistic values consistent with the need for innovations to offer compelling functionality. Digital low-carbon innovations have to deliver on 'core' attributes (e.g., convenient, compatible, cost-saving, easy to use) while differentiating on 'non-core' attributes that offer an advantage over mainstream consumption practices (e.g., flexibility, controllability, social connections, local embeddedness) [49].

C. Supportive adoption contexts & innovation attributes

DoI emphasises adopters and innovations, in contrast to other sociological or systems theories discussed earlier that emphasise external context such as policies, infrastructures, and social patterns of behaviour as influences on adoption. For low-carbon innovations in particular, policy or market incentives (e.g., purchase subsidies for electric vehicles) or market rules (e.g., efficiency standards or grid-integration rules for new low-carbon technologies) are critical enablers of widespread diffusion.

DoI captures these external incentives or constraints indirectly though adopters' perceptions of innovation attributes. So, for example, availability of recharging infrastructure for potential adopters of electric vehicles is not measured *per se*, but it is captured indirectly through the perceived relative advantage or ease of use of an electric vehicle. Potential adopters living in areas with limited or no recharging infrastructure would report weakly appealing attributes (e.g., low relative advantage) and would be less likely to adopt. This is consistent with our statistical models (Fig. 8 & 9). Consequently policy strategies that strengthen supportive adoption contexts remain important, even if DoI does not measure them directly, as they improve the perceived appeal of innovations among potential adopters.

D. From early adopters to would-be adopters

Taken together, these generalisable insights consistent across multiple digital low-carbon innovations show the building blocks of more widespread uptake are in place. Early adopters with distinctive personal and socioeconomic characteristics are communicating socially about their experiences. These inter-personal information flows through social networks (including electronic word-of-mouth on social media) should reduce potential adopters' uncertainties and strengthen their perceptions of innovations' usefulness, compatibility with routines, and relative advantage. If user-feedback helps service providers' improve on innovation performance, enabled by supportive policy contexts and infrastructures, this in turn should stimulate further adoption, inter-personal communication, and risk reduction. This self-reinforcing dynamic of adoption and diffusion that characterises innovation success stories can be supported and stimulated by a range of intervention strategies that target the main adoption drivers identified by DoI.

V. Strategies to accelerate consumer uptake

Diffusion of innovations (DoI) has generated a wealth of evidence on diffusion strategies that act on one or more of these drivers of adoption [11]. These apply to, or can be readily adapted to, the digital low-carbon innovations in this study, with examples as follows.

Strategies that increase inter-personal exchange of information and experiences include neighbourhood schemes, open houses, recruitment of opinion leaders including social influencers (opinion leaders spreading information through electronic word-of-mouth) [47]. Related strategies can also seek to strengthen and diversify social networks of interaction including through cross-national knowledge exchange collaborations and other initiatives to share adoption experiences more widely.

Strategies that make new ideas and experiences more appealing and salient include product positioning and differentiation, product development to improve performance on core attributes, institutional norms (e.g., workplace schemes) [49]. Note that 'conventional' market or regulatory strategies that act on adoption contexts would also be captured here, such as market rules enabling households to provide services to power grids [50].

Strategies that incentivise early adopters include targeting early adopters (e.g., purchase subsidies), target places with high propensity adopters (e.g., pioneer cities or neighbourhoods), providing adopters with incentives to recruit others (e.g., recommend-a-friend) [27].

Including social networks and social influence effects as potential targets for policies and interventions broadens out the conventional emphasis on prices, infrastructures, and regulations for stimulating adoption. This is particularly important in the climate change field in which there is a tendency to rely heavily on public policy and government actors to effect change. Collectively these strategies represent a dynamic of 'social learning' about digital low-carbon innovations with potentially reinforcing dynamics or positive feedbacks as positive experiences are communicated through ever larger networks of potential adopters. Social learning can therefore interact synergistically with technological learning processes that see costs fall and performance improve as innovations gain market share [51].

VI. Inter-dependencies between innovations

Inter-dependencies and spillover effects in the adoption of digital low-carbon innovations are potential accelerators of consumer uptake. 'Adoption spillovers' describe how positive experiences with innovation A are communicated socially and stimulate faster adoption of innovation B that has a similar value proposition (e.g., A and B are both digital platform-based or networked forms of consumption). 'Functional spillovers' describe how the distinctive appeal of innovation C is also shared by innovation D that has similar attributes (e.g., both C and D are a shift from owning physical goods to accessing services). 'Adopter spillovers' describe how the cognitive, behavioural, and sociodemographic characteristics of adopters of innovation E are similar to those of adopters of innovation F (e.g., digitally-skilful urban professionals). These interdependencies frame diffusion of digital low-carbon innovations as a concurrent and synergistic process [2].

However, inter-dependencies between adopters, innovations, and social networks can lead to negative as well as positive feedbacks. Negative experiences with digital low-carbon innovations may result from: (i) poor access to infrastructure, e.g., fast broadband; (ii) functional complexity, particularly for those without strong digital skills or capabilities; (iii) adverse impacts on energy or carbon emissions, e.g., through rebound or intensification effects; (iv) exploitative commercial practices, e.g., monetisation of personal data; (v) antagonistic public policy, e.g., if digital innovations compete with public services so are restricted or over-regulated. Negative experiences among early adopters of an innovation - if communicated socially - can also stifle experimentation with similar innovations in different domains, if the negative experiences are relevant to digital low-carbon innovations more generally. These negative feedbacks are in addition to the adverse effects on the innovation itself (e.g., this particular car club had insufficient vehicles to meet my driving needs).

Our cross-sectional study does find evidence consistent with at least three of these hypothesised spillover effects: a common emphasis on social influence mechanisms through inter-personal networks including social media ('adoption spillovers'); a shared set of basic (core) and differentiating (non-core) innovation attributes ('functional spillovers'); and a common set of socioeconomic, identity, and cognitive characteristics for adopters across domains ('adopter spillovers'). However, study designs to isolate and measure these spillover effects would need to be dynamic over time. This is an important area for further research.

VII. Implications for just transitions

Stimulating early adoption is effective but tends to be regressive. Climate change mitigation and social justice objectives are increasingly intertwined. A just transition towards net-zero emphasises skills and training for employment diversification, support for 'stranded' communities dependent on fossil fuel industries, a more even geographic distribution of costs and benefits, progressive policies biasing transition costs towards socioeconomic groups with more resources and capabilities while also supporting lower-income households [52]. In contrast, the consumer uptake of digital low-carbon innovations depends on risk-taking early adopters to communicate the benefits of innovation adoption and reduce perceived risks and uncertainties. Early adopter incentives and policies tend to be regressive in that they target and benefit people with more capabilities (e.g., income, education, skills) in geographic areas with more supportive adoption contexts, evidenced in the higher relative advantage and compatibility of innovations [53]. This raises interesting policy tensions between effectiveness and equity in the diffusion of digital low-carbon innovations [54].

VIII. Liimitations

There are important limitations of our study design, related both to our use of DoI as the analytical framework, and to our data collection in a single country (the UK) and pre-pandemic (late 2019).

DoI focuses on adopters, innovations, and communication flows. As noted earlier, this means adoption contexts (with the exception of social networks) are measured only implicitly through perceived innovation attributes. Other approaches including the sociological and systems theories discussed earlier privilege understanding of adoption contexts over individual adoption decisions. Further research using these approaches would provide a different, but complementary lens on the adoption insights provided by this study. This is particularly important for innovations whose widespread adoption is strongly dependent on available infrastructure (e.g.,. electric vehicle charging), or on new social practices or cultures of consumption (e.g., shared mobility).

Although the UK was our study context, the innovations in our sample are widely available in consumer markets in Europe, North America, Asia and beyond, albeit with regional variation. As examples, smart home technology markets are global [55]; so too are electric vehicles [56]. The US and Canada have long histories with shared mobility innovations including liftsharing (or ridesharing), and more recently shared ridehailing (or taxi-buses) [57]. Many European countries are experimenting with innovative utility business models allowing end-users to provide services to grids [50]. As a result we consider our results to be broadly applicable to non-UK adoption contexts, although testing the replicability of our findings elsewhere is an important area for further research.

The enduring effect of Covid-19 on consumer uptake of digital innovations is harder to predict. The digitalisation of daily life was sharply accelerated by Covid-19 lockdowns that - almost overnight - shifted working, schooling, shopping, socialising, and recreating online [58]. This in turn forced rapid adaptation and adjustment to digitally-mediated daily routines [59]. Experiences were markedly different. Households with flexible living spaces, good access to devices and infrastructure, and requisite digital skills found benefits in avoided commutes, flexibility, and less stressful work environments. Households without found themselves stressed, marginalised, or excluded from newly emergent digital activities [60]. How Covid-19 will impact longer-term patterns of working (e.g., white collar teleworking), mobility (e.g., daily commutes), living (de-urbanisation), and shopping (e.g., e- commerce) are still playing out. Resulting implications for land use, urban densities, lifestyles, as well as carbon emissions are still uncertain [61]. Testing and replicating our findings in the post-Covid-19 consumer context is another important area for further research.

IX. Conclusions

Our study used consistent stated-preference data and standardised data-processing and analysis methodologies to analyse 13 digital low-carbon innovations across mobility, food, homes and energy domains. Few studies analyse multiple innovations using comparable data and methodologies that enable cross-context generalisation.

We find that social influence, innovation attributes, and certain adopter characteristics are all consistent predictors of consumer uptake across adoption contexts, in line with expectations from diffusion of innovations [11]. Interpersonal communication and diffusion mechanisms are relevant, important, and underexploited means of accelerating consumer uptake of digital low-carbon innovations as part of efforts to tackle climate change.

These generalisable results show how digitalisation is opening up new service possibilities for consumers to transition to appealing and less resource-intensive modes of mobility, food purchasing, domestic living, and energy 'pro-sumerism' [62]. This in turn broadens out the portfolio of emission-reduction strategies and interventions beyond conventional price and regulatory instruments.

However, emission-reduction benefits of digital innovations are not deterministic, and risks need careful management. A recent review clearly showed the emission-reduction potential of the digital innovations in our sample [3]. However digital forms of service provision also risk increasing energy demand and carbon emissions through mechanisms of rebound and intensification. Rebound describes how improvements in a product or service, particularly in terms of cost, leads to an increase in use. Intensification describes how new products or services can intensify dependence on energy networks. More broadly, digital innovations can also deepen inequalities of access and undermine civic trust if personal data is harvested and use inappropriately. These risks need careful management as part of a wider strategy for harnessing digitalisation for public purpose.

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