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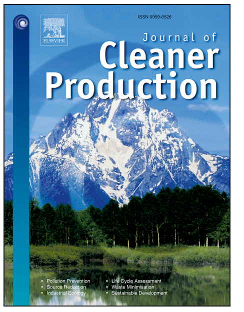

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Disentangling the carbon emissions impact of digital consumer innovations

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Abstract

Digital consumer innovations provide functionality to consumers through different impact mechanisms. These act indirectly on carbon emissions by shaping behaviour. Outcomes include energy/emissions mitigation or, growth through rebound effects, where energy savings are offset by increasing demand for energy.

In this study we use meta-regression techniques to quantify the relative strength of different impact mechanisms on emissions for a diverse set of digital innovations. We use data from two key synthesis studies, providing 135 estimates of impact across 22 different digital consumer innovations. We measure impacts using different metrics including activity, energy use, or carbon emissions (CO^2/CO^2 eq). We refer to these as “emissions-related outcomes”.

We find strong evidence that impact mechanisms explain differences in emissions-related outcomes between digital consumer innovations. Digital consumer innovations that influence behaviour by technology ‘substitution’ e.g., food gamification apps, have a significantly larger impact (44% reduction) than those that ‘coordinate’ e.g., food pairing apps (17% reduction) or those that that improve ‘control’ e.g., smart home appliances (20% reduction).

Estimates of impact included in energy studies are highly sensitive to boundary decisions and assumptions made by researchers, introducing further uncertainties into their magnitude and direction. When we control for variation in study design such as whether emissions-related outcomes data were collected using field experiments, or simulations we find that differences between impact mechanisms are amplified. A further key finding is that impact mechanisms explain more of the difference between-innovations than deployment context.

Our novel approach of classifying innovations by the underlying causal mechanism through which they change user behaviour and so energy emissions adds a new dimension to methodological work on indirect impacts for which system boundary and variable definition are not fixed. Identifying causal mechanisms with the largest benefits for emissions reduction also guides policy, innovators, service providers, and digital users concerned with carbon footprint.

Keywords: impact mechanism; consumer actions; digital infrastructure; rebound effects; energy use, emissions.

Highlights:

- Meta-analysis of the emissions-related impact of 22 digital consumer innovations across transport, food and homes
- Measurement of the emissions reduction potential of six digital impact mechanisms
- Contrast with reduction potential of other confounding factors, including type of action (Avoid-Shift-Improve)
- Statistical approach controls for the impact of study design

1.0 Introduction

Digital consumer innovations (DCIs) are novel goods or services available to consumers. They are digital or digitally enabled, accessed or controlled through smartphones or other information communication technologies. They offer alternatives to mainstream consumption practices. Their use can help reduce carbon emissions in line with the Paris Agreement on climate change [1, 2].

The impact of digitalisation on energy and emissions is direct, indirect and systemic [3]. Direct impacts include the energy and emissions footprint in the production, operation and disposal of information communications technologies, including devices, and supporting infrastructure (information communication networks, and data centres). The direct impacts of digitalisation are estimated in the range of 1.5-4% of global greenhouse gas (GHG) emissions [4, 5]. Indirect impacts relate to changes in processes, systems and user behaviour, are more uncertain and vary widely across DCIs. Systemic impacts relate to economic activity more generally (e.g., jobs, skills), society and governance systems and are even more uncertain as impact pathways are diffuse [6]. Hilty, Köhler [7] describe an alternative taxonomy distinguishing the ordering of these effects from 1st-order (direct), 2nd-order (indirect - user) and 3rd-order (indirect - society wide).

Impact mechanisms characterise the underlying processes through which DCIs can help reduce energy use and emissions [3, 8-11]. They describe the behaviour-driven application of DCIs, emphasising the user-function that technical improvements provide. They link specific DCIs to potential emissions reduction benefits that result from changes in how energy services are provided or consumed [12]. They are described in the literature as ‘higher order’ (second order, or indirect) effects that result from the services that information communications technology provide to users [13, 14].

Understanding the mechanisms through which digitalisation impacts energy helps guide innovation activity towards functionality linked to energy savings, and emphasises the need to tackle rebound outcomes for certain types of DCI.

On the one hand, DCIs help optimise, control, substitute, and coordinate the efficiency with which energy is used for a wide range of activities. But on the other hand, by saving time, and reducing the cost, and friction of these activities, digitalisation can lead to growth in demand – the ‘rebound’ or induced demand effect. This basic trade-off between efficiency and growth determines the net indirect impact of digitalisation on energy use and GHG emissions [15, 16].

In this study we build on existing typologies [3, 10, 17] to characterise six impact mechanisms through which DCIs can help reduce energy use and emissions (see Table 1).

Table 1. Taxonomy of impact mechanisms used in this study

Mechanism	Definition	Examples
Access	Access a service instead of owning a good	Ride sharing matches drivers with riders, verifying trustworthiness
Coordinate	Coordinate real-time demand with available supply	Mobility-as-a-Service incorporates up-to-date booking and payment for services
Optimise	Optimise how a system functions to reduce its energy needs	Autonomous Vehicles incorporate smart charging schedules responsive to electricity network information
Substitute	Substitute with a less energy-intensive technology or form of service provision	Digital hubs connect users with local sources of food
Virtualisation	Virtualise from physical-to-digital forms of service provision	Videoconferencing & virtual interaction replace physical travel.
Control	Control or manage how a user-service is provided, including for resource efficiency	Smart lighting (including motion sensors) adaptively responds to external conditions and users' needs

The ‘access’ mechanism enables opportunity for using services with high utilisation rates of physical technologies or assets. Mobility services such as car clubs or Mobility-as-a-Service (MaaS), for example, present alternatives to owning or using single-occupancy private cars. Radical societal shifts such as a widespread adoption of electrified modes of transportation or shared mobility services as alternatives to car ownership has high potential for energy use reduction [18, 19]. Replacement of incumbent technologies or activities with digital applications takes a shorter lead time than the creation of completely new systems [20].

‘Coordinate’ and ‘optimise’ are system orientated mechanisms that rationalise the use of energy resulting in increased efficiency or reduced waste [3]. DCIs using a ‘coordinate’ mechanism, facilitate the exchange of goods and services e.g., ridesharing, ride hailing, and peer-to-peer exchange of goods matching real-time demand with available resources. They are heavily dependent on accessible digital infrastructure (including networks, platforms, and applications). The digital platform is a way for highly distributed and granular (small-scale) distributed surplus supply e.g., a spare seat in a car, a spare meal from a restaurant, an unused kitchen appliance or book to be ‘matched’ with demand spatially and in close to real-time. ‘Optimise’ defines how a system operates to enhance performance, increase efficiency and curb energy needs [3, 13]. Fully connected and automated vehicles enhance travel convenience, dynamically optimise routes, and reduce journey times when linked to other information communications technologies [3, 9, 11]. Smart charging/discharging optimisation (e.g., in shared fleets of AVs) is made possible through sensors and software that are responsive to real-time electricity network information [21].

‘Substitute’ is the replacement of conventional goods and services with digital goods and services e.g., digital hubs for local food displace large-scale food production and retail distribution with food delivered directly to consumers from multiple local producers. Digital platforms match users with providers. ‘Virtualise’ involves the complete/partial digitalisation of existing goods or services by facilitating physical-to-physical replacement (e.g., substitution of goods of higher for lower carbon intensity) or physical-to-digital replacement of goods for services (e.g., videoconferences deploying virtualisation instead of physical interaction).

‘Control’ is a user-oriented mechanism that enables greater energy efficiency e.g., in residential buildings, through smart heating systems, smart lighting, or home energy management systems

(HEMS). These DCIs 'control' or manage how energy is used to provide a service in residential settings. For example, smart heating can be user-controlled to provide thermal comfort only in occupied rooms. We use a simple definition of efficiency that relates to the minimum input of resources to meet user's needs - providing sufficiency with less. Expanded definitions consider interactions between social, economic, and environmental factors [22].

The relative influence of different impact mechanisms across DCIs has not been well established in literature. By framing and measuring the relative strength of these six mechanisms across a diverse sample of DCIs we contribute both to the methodological strengthening of research focussed on indirect impacts and the substantiation of impact mechanisms as underlying causal instruments of change in demand-based carbon emissions.

Many studies have estimated the impact of DCIs on activity, energy consumption, or greenhouse gas (GHG) emissions. We refer to these different metrics as "emissions-related outcomes". Differences in measures and outcomes between these studies brings uncertainties in the assessment of DCIs impact [3, 14]. Although synthesis studies characterise these uncertainties across different innovations, they do not explain them. Horner, Shehabi [3] collectively refer to these as 'known unknowns'. In this study we are concerned with disentangling these uncertainties by characterising and measuring the impact of mechanisms not previously observed. We focus on 22 different DCIs which have all been introduced into the market within the last 10 years and/or have a least 15% market share. For these DCIs there is also clear, empirical evidence of potential emissions-reduction benefit.

Table 2. Definitions for Selected DCIs included in this study

Domain of Application	**DCI**	**Description**	**General digital infrastructure requirements**
Transport	Car clubs (car-sharing in US)	A membership-based service offering short-term rental of vehicles e.g., Zipcar	platform for booking & locating available vehicles
	Ride-sharing (carpooling in US, lift sharing in UK)	Networks connecting passengers and drivers for shared car journeys or commutes e.g., Liftshare	platform for matching drivers with riders & verifying trustworthiness
	Shared taxis (shared ride hailing, taxi-buses)	Cars or minivans with multiple passengers on similar schedules, booked at short notice via apps e.g., UberPool	platform for real-time scheduling of passengers via app
	Mobility-as-a-Service (MaaS)	App-based integrated scheduling, booking, and payment platform for multimodal mobility services e.g., Whim	platform for multi-modal integrated scheduling, booking & payment
	E-bikes*	Bicycles with an electric motor and battery for pedal assistance up to limited speeds e.g., Gocycle G3	control app, charging schedule, pricing & payment schedule
	Fully autonomous vehicles	Vehicles that can be autonomously driven without active human intervention e.g., Waymo	operating system - sensors, information storage & communications, control software
	Neighbourhood Electric Vehicles (NEVs)*	Light-weight, low-speed, battery-driven vehicles allowed on roads e.g., Waev	control app - charging scheduling, pricing & payment
	Bike-sharing	Fleets of bicycles available for short-term rental from fixed points	platform - match users with available resources & locations (pricing & payment)

		(docked) or free-floating (dockless), e.g., Mobike.	
	Telecommuting	Remote working enabled by information and communication technology (ICT) e.g., Slack.	ICT-enabled home working, communications software
	Videoconferencing and virtual meetings	Virtual interactions between people in different physical locations, enabled by ICTs e.g., Cisco TelePresence.	communications software, display monitor, microphone, camera, internet
	Digital hubs for local food	Buy food for delivery directly from multiple local producers e.g., Open Food Network	platform - match users with providers (pricing & payment)
Food	Meal kits (or meal boxes)	Home deliveries of fresh produce pre-portioned for cooking specific recipes e.g., Hello Fresh	app based ordering, scheduling systems
	11th hour apps	Food outlets advertise surplus fresh food at reduced prices e.g., Too Good to Go	app-based, real-time sourcing of surplus food from multiple providers
	Food pairing apps	Design food recipes using surplus ingredients e.g., Plant Jammer	platform for matching surplus home ingredients to recipes
	Food gamification apps (e.g., for waste reduction)	Elements of gameplay used to support efforts to reduce food waste or meat consumption e.g., Quit Meat	info app & algorithm
	Smart heating systems	Monitoring, automation, adaptive learning, and control (via app) of heating e.g., Nest	internet-connectivity supporting adaptive learning on heating preferences
Homes	Smart lighting	Customisation and control (via app) of lighting e.g., Philips Hue	app based control, scheduling of lighting
	Home energy management systems (HEMS)	Monitoring, control, and management system for multiple home functions including heating, cooling, lighting, appliances, and solar photovoltaics (PV) e.g., GreenWave Reality	management system: software, sensors, info storage & communications
	Heat pumps*	Heating (or cooling) technologies that extract available heat from the air or ground to thermally condition homes e.g., Worcester Bosch	demand responsive heating or cooling system
	Pre-fabricated whole home retrofits*	Custom-fitted high-performance building shells combined with solar PV and heat pump units fabricated off-site and retrofitted externally e.g., Energiesprong	digital scanning, 3D printing and 3D design modelling in off-site fabrication
	P2P (peer-to-peer) exchange of goods	Networks of individuals for exchanging products, tools, and other material items, e.g., SnapGoods	app / network to match users with providers
	Disaggregated real-time energy feedback	Activity- or appliance-level electricity or gas consumption data available to households e.g., Neurio	information app and algorithm

*E-bikes are included as digital innovations as they can include apps for charging, scheduling, sharing, pricing & payment. NEVs can be controlled using a digital signal processor. The NEV market is undergoing a rapid digital transformation, the adoption of digital technologies such as artificial intelligence (AI), internet of things (IoT), and blockchain are further enhancing operational efficiency. Heat pumps are included as digital as they can be used in flexible scheduling mode in response to price signals from electricity networks. Pre-fab retrofits incorporate digitalisation through scanning, 3D printing, and 3D design modelling techniques used in off-site fabrication processes.

1.1 Deployment context

Deployment context describes characteristic differences, not inherent to the DCI itself but likely to have a confounding influence on the strength of different impact mechanisms e.g., policy, infrastructure, markets [3]. We identify and quantify four of these for comparison purposes: domain of application, type of action, dependence on digital accessibility and skills, and dependence on physical infrastructure. In Table 3 we further characterise each DCI in terms of the impact mechanism through which they influence emissions-related-outcomes, and their corresponding deployment context.

Table 3 - Mapping of DCIs across Influences on Emissions-Related Outcomes

Digital consumer innovation	Impact mechanism	Deployment Context			
		Domain of application	Type of action	Dependence on digital accessibility and skills	Dependence on physical infrastructure
Car clubs (car-sharing in US)	Access	Transport	Shift	High	Low
Ride-sharing (carpooling in US, lift sharing in UK)	Coordinate		Shift	Medium	Low
Shared taxis (shared ride hailing, taxi-buses)	Coordinate		Shift	High	Low
Mobility-as-a-Service (MaaS)	Access		Shift	High	Medium
E-bikes	Substitute		Shift	Low	Low
Fully autonomous vehicles	Optimise		Improve	High	High
Neighbourhood Electric Vehicles (NEVs)	Substitute		Improve	Low	Medium
Bike-sharing	Access		Shift	High	Medium
Telecommuting	Virtualise		Avoid	High	Low
Videoconferencing and virtual meetings	Virtualise		Avoid	High	Low
Digital hubs for local food	Substitute	Food	Shift	High	Medium
Meal kits (or meal boxes)	Coordinate		Shift	High	Medium
11th hour apps	Coordinate		Avoid	High	Low
Food pairing apps	Coordinate		Avoid	Medium	Low
Food gamification apps (e.g., for waste reduction)	Substitute		Avoid	Medium	Low
Smart heating systems	Control	Homes	Improve	High	High
Smart lighting	Control		Improve	Medium	High
Home energy management systems	Control		Improve	High	Medium
Heat pumps	Control		Improve	Low	High
Pre-fabricated whole home retrofits	Substitute		Improve	Medium	High

P2P (peer-to-peer) exchange of goods	Coordinate		Avoid	Medium	Low
Disaggregated real-time energy feedback	Control		Improve	Medium	Medium

Domain of application characterises the settings that influence consumption behaviour. It is defined as a classification of provision by site of practice or use [23]. DCIs tend to be grouped within three domains: transport, food, and homes (household energy) [24-27]. In general there is a lack of comparative research into the influence of different domains on the impact of DCIs, with transport historically prioritised in studies [18, 28].

Type of action is captured in the Avoid-Shift-Improve (A-S-I) framework. This is an established framework used by the transportation research community but increasingly being applied in other research fields [25, 28, 29]. It describes three distinct actions associated with the use and ownership of a DCI. 'Avoid' relates to consuming less of a good or service, e.g., telecommuting avoids work-related travel by working partially or entirely at home or locations close to home. 'Shift' relates to consuming more resource-efficient forms of good or service, e.g., Maas replaces single occupancy vehicle journeys with multimodal shared mobility. 'Improve' relates to a technological shift which upgrades the resource efficiency of an existing good or service, e.g., smart heating systems improve efficiency for heating, ventilation, air conditioning, cooking and electrical appliances.

DCIs variously depend on availability and access to Information Communications Technology (ICT) infrastructure and services (e.g., digital platforms, networks, and connectivity). DCIs offer services via physical goods and infrastructure, necessitating an additional layer of dependence. DCIs that incorporate deeper digitalisation mechanisms have the potential for greater savings in emissions [30]. However, DCIs requiring high levels of digital skills may be less accessible so limiting the impact of their use [31]. Many DCIs also rely on dedicated physical infrastructure in order to provide a useful service, such as docking stations for bike sharing, and building energy infrastructure (PV panels, batteries, grid connection) in the case of Home Energy Management Systems (HEMS) [32-34]. As digital technology continues to develop, there are additional requirements for new infrastructure and reconfiguration of existing infrastructure [32]. Van der Vooren [35] emphasises the relevance of this transition in transport systems. In this study we distinguish two types of structural dependency (digital and physical).

Digital skills and accessibility enable impact mechanisms to influence emissions-related outcomes. They relate to user skills and competencies required to interact with digital infrastructure and supporting services such as digital platforms, applications, and software [36, 37]. Individualised services rather than goods form an increasing share of consumption met through widespread digitalisation and service automation that require access and capabilities e.g., booking a shared taxi via a smart phone application [38, 39]. Digitally-enabled services may rely on physical infrastructures such as transportation networks. The extent of this dependence enables or constrains the potential of different digital impact mechanisms (e.g., access to shared car fleets depends on availability of dedicated parking spaces). The interplay between digital capabilities and physical infrastructure has strategic relevance for providers and users [40]. Within these two types of structural dependency we further define different levels of dependency (see Appendix A Table A1. Structural dependencies influencing the effectiveness of impact mechanisms).

1.2 Controlling Influences on Emissions-Related Outcomes

The field of impact estimation is concerned with study design robustness and standardisation. It is important therefore to contribute to explanations of underlying causal mechanisms to try and account for some of the uncertainty [3, 41]. We define and account for four key sources of methodological uncertainly. These are internal validity and robustness; external validity and generalisability; type of emissions related outcome; and analytical method. Internal validity and robustness compares strength of study design for making robust inferences about the magnitude of emissions-related outcomes. It is a known 'effect modifier' and cause of heterogeneity in outcomes, particularly observable across studies in the homes domain [27]. Meta-analysis performed on low quality primary studies also have a tendency to overestimate an intervention [42]. External validity and generalisability compares the wider applicability of the results. This measure considers self-selection bias, sample size, heterogeneity, and whether field trials or natural experiments have been conducted. Ivanova, Barrett [27] consider internal and external validity to be a cause of heterogeneity in mitigation potential. Sample size is also negatively correlated with effect size [43].

Studies also vary in the type of emissions-related outcome. Changes in activity levels (behaviour) measure the amount of activity or useful service/energy service consumed by a DCI, e.g., annual vehicle miles travelled, kilograms of avoided food. Changes in energy measure the amount of energy or resources needed to provide a useful service e.g., well-to-wheel energy consumption. Changes in carbon measure the amount of greenhouse gas emissions (CO_2 or CO_2-equivalent greenhouse gases) e.g., lifecycle CO_2 emissions per passenger-kilometre. Analytical method relates to key design decisions made by the researcher distinguishing between for example, empirical approaches (collection of observed data through field trials or natural experiments) and simulation approaches (a digital parameterised model of a real-world system) (see Appendix A Table A2. Taxonomy of study design characteristics influencing the measurement of energy consumption and emissions).

1.3 The Aim of this Study

The impact of DCIs on emissions is likely to vary based on characteristic differences and subject to wide ranging influences currently not captured in synthesis studies. The main aim of this study is to disentangle these influences to enable generalisation of the magnitude of impacts. We do this by focussing on the underlying causal mechanism of the impact unique to digitalisation. Our findings will help explain uncertainties previously attributed to study design variation.

2.0 Materials and Methods

2.1 The Data

We use data taken from two key publications. Both are synthesis studies containing multiple estimates of the emissions-related outcomes of DCIs. These are:

- *Potential Climate Benefits of Digital Consumer Innovations* <u>(N=120 estimates)</u> [14]
- *Demand, Services and Social Aspects of Mitigation*, the contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) (<u>N=15 estimates</u>)

Study 1, Wilson, Kerr [14] is a directed review of 215 studies assessing the potential emissions benefit of DCIs across transport, food and homes. The studies included measure one of three outcomes: activity levels, energy use, CO_2 emissions (or CO_2equivalent). At least six papers for every DCI were included in the study.

Study 2, Creutzig, Devine-Wright [1] is a review of 90 studies assessing the digital service opportunities for transport, nutrition, shelter, and education and entertainment. Studies measure the same three outcomes (activity levels, energy use, CO_2 emissions (or CO_2equivalent). Findings are incorporated in the Sixth Assessment Report of the IPCC, and subject to a rigorous two-stage review process.

Across these studies we extract 135 impact estimates for 22 different DCIs (see Table 4).

Table 4. Number of studies and number of estimates of emissions-related outcomes for each DCI

Domain of Application	Digital Consumer Innovation	Impact mechanism	(n) Estimates (n studies)
Transport	Car clubs (car-sharing in US)	Access	11 (7)
	Ride-sharing (carpooling in US, lift sharing in UK)	Coordinate	5 (5)
	Shared taxis (shared ride hailing, taxi-buses)	Coordinate	8 (8)
	Mobility-as-a-Service (MaaS)	Access	1 (1)
	E-bikes	Substitute	4 (4)
	Fully autonomous vehicles	Optimise	9 (6)
	Neighbourhood Electric Vehicles (NEVs)	Substitute	2 (2)
	Bike-sharing	Access	4 (4)
	Telecommuting	Virtualise	13 (7)
	Videoconferencing and virtual meetings	Virtualise	10 (8)
Food	Digital hubs for local food	Substitute	5 (3)
	Meal kits (or meal boxes)	Control	10 (4)
	11th hour apps	Coordinate	2 (2)
	Food pairing apps	Coordinate	1 (1)
	Food gamification apps (e.g., for waste reduction)	Substitute	5 (5)
Homes	Smart heating systems	Control	5 (3)
	Smart lighting	Control	5 (3)
	Home energy management systems	Control	17 (11)
	Heat pumps	Control	5 (3)
	Pre-fabricated whole home retrofits	Substitute	2 (2)
	P2P (peer-to-peer) exchange of goods	Coordinate	1 (1)
	Disaggregated real-time energy feedback	Control	10 (7)
	Total		135 (96)

2.2 Data Preparation

From each study we extract quantitative estimates of the emissions-related outcomes of DCIs. All estimates measure percent change (%Δ) from the adoption or use of a DCI compared to a baseline measurement or reference point of no adoption/use. The outcome estimate relates to one of three types: (i) change in activity (%Δ activity (n=24)); (ii) change in energy (%Δ energy (n=54)); (iii) change in CO_2 emissions (or CO_2equivalent) (%Δ emissions (n=57)), collectively referred to as "emissions-related outcomes".

Where studies include multiple point estimates across a range of values, we calculate the midpoint as a representation of the mean [44]. Around a third of studies contain multiple estimates due to different outcome metrics (energy; emissions), differing assumptions (e.g., 1 worker household, 2 or more worker household), or a variant on the innovation type (e.g., ride sharing in a conventional vehicle or an electric vehicle). For completeness we include multiple estimates from these studies and treat them as independent. Although there is some risk of covariance (due to methodological similarity), it is not possible to treat the data as multi-level, because not all studies provide multiple estimates [45].

To operationalise study design characteristics, each study included in the meta-analysis is reviewed by two coders independently and subjectively. Relevant information is extracted according to a pre-

prepared coding framework, and the four study design characteristics coded according to these criteria. This is then re-appraised by a second independent coder. For methodological approach we initially identified seven categories with empirical methods subdivided according to natural experiment, field trial or demonstration project. These are subsequently aggregated due to small sample sizes. (see Appendix A Table A3. Estimates of (n) of emissions-related-outcomes across impact mechanisms and deployment context).

2.3 Data Analysis

Data analysis is based on meta-analysis techniques [41]. Meta-analysis is an established framework for synthesis approaches. By combining results of comparable studies we increase the range of DCIs observed, the statistical power, and generalisability of findings, compared to individual studies [46]. The 96 individual studies we use are representative of North America, Asia, Australasia, and Africa. They vary in generalisability, from studies based on a single household [47] to those based on several million households [48]. By using meta-analysis techniques we combine these strengths, to critically evaluate and build on findings, and importantly address questions that are not posed by individual studies.

All statistical tests are based on meta-regression methods and include directional tests of association. Following sensitivity testing we rejected the use of formal meta-analysis software. This requires methodological details, not consistently reported in studies, e.g., measures of variability such as standard deviation and standard error. Using Stata Release 16 [49] we apply three tests:

Test 1 – We test separate bivariate associations between magnitude of impact (emissions-related outcomes) and (1) impact mechanism (2) deployment context (3) study design. We use descriptive statistics. To account for 'spread' and 'outliers' we use both parametric and non-parametric tests.

Test 2 - As Test 1 but testing directional associations. We use bivariate regression methods, and post-estimation to predict the magnitude of impact of each predictor variable. For each model we also predict explained variance (R^2/pseudo R^2).

Test 3 – As Test 2 but with the inclusion of controls for study design. We use multivariate regression methods.

3.0 Results

We find only non-parametric tests are significant, suggesting synthesised approaches that rely on mean values of the emissions-related outcome will not provide reliable estimates. Subsequently we base all three tests on non-parametric meta-regression. Test 1 is a Kruskal-Wallace test [50]. This test uses a Chi^2 distribution to compare differences between two or more groups. It is non-specific in this respect, and any significant result confirms only that there are differences between at least two categories of the predictor variable. Test 2 is a bivariate quantile regression [51]. This is a non-parametric linear regression approach which predicts median impact values as a linear function of the distribution of the predictor variable. The bivariate quantile regression model takes the following form:

$$y_i = \beta_0^{(p)} + \beta_1^{(p)} x_i + \varepsilon_i^{(p)}$$

Where y= outcome (emissions-related outcomes), β_0=constant, β_i=slope on predictor variable x_i, (p) = p^{th} quantile regression model percentile

Test 3 is a multivariate quantile regression [51]. The multivariate quantile regression model takes the following form:

$$y_i = \beta_0^{(p)} + \beta_1^{(p)} x_i + \beta_2^{(p)} z_i + \varepsilon_i^{(p)}$$

Where y= outcome (emissions-related outcomes), β_0=constant, x_i = , β_i =slope on predictor variable x_i, β_2=slope on vector of control variables z_i, (p) = p^{th} quantile regression model percentile

We present results in a series of tables. All tables report % reduction (-) or increase (+) in emissions-related outcomes, highlighting significant differences.

3.1 Results: Impact Mechanisms and Deployment Context

Table 5 – Results for Test 1 (Chi^2 statistic) and Test 2 (bivariate quantile regression), comparing the magnitude of emissions-related outcomes across impact mechanisms, and deployment context.

Influence on emissions-related outcomes			**Results for Test 1** **Metric = Chi^2 Statistic**	**Results for Test 2** **Metric = % reduction (or increase) in emissions-related outcomes**
Impact mechanism		Access	Chi^2(6) = 16.134 Prob>chi^2 = 0.007*	-15.5
		Coordinate		-22.0
		Substitute		-34**
		Optimise		-9.0
		Virtualise		-0.6
		Control		-20
Deployment Context	Domain of Application	Transport	Chi^2(2) = 5.369 Prob>chi2= 0.068	-11
		Food		-23.1
		Homes		-16.6
	Type of action	Avoid	Chi^2(2) = 5.628 Prob>chi^2 = 0.060	-6.1**
		Shift		-20.0
		Improve		-18
	Dependence on digital skills and accessibility	High	Chi^2 (2) = 5.145 Prob>chi^2 = 0.076	-14.5
		Medium		-13.8
		Low		-70.0**
	Dependence on physical infrastructure	High	Chi^2 (2) = 2.66 Prob>chi$^{2=}$ 0.875	-18
		Medium		-15.0
		Low		-17.0

** denotes difference is significant to 99% CI, * denotes significant to 95% CI

DCIs that mitigate GHG emissions through the substitution mechanism have significantly larger impact (estimated reduction of 34%) compared to all other mechanisms (access (15.5%), coordinate (22%), optimise (9%), virtualise (0.6%), and control (20%)).

Although food-based DCIs have the largest impact (estimated reduction in emissions-related outcomes of 23.1%), this is not significantly different from homes (16.6%) or transport (11%).

DCIs that enable 'avoid' actions have a significantly lower impact (estimated reduction in emissions-related outcomes of 6.1%), compared to those that enable 'shift' (estimated reduction of 20%) and 'improve' actions (18%). Our findings contradict studies suggesting 'improve' actions have the greatest emissions potential [52-54].

We also find significant differences between high, medium, and low dependencies on digital skills and accessibility. Innovations that require high levels of digital skills and accessibility e.g., digital hubs for local food have a significantly lower impact (estimated reduction of 14.5%) than those with low dependence e.g., e-bikes (estimated reduction of 70%).

We find no significant differences between DCIs that have high dependence on physical infrastructure e.g., AVs and HEMs (estimated reduction of 18%), those that have medium dependence e.g., meal kits (15%), or low dependence e.g., videoconferencing and virtual meetings (17%) .

3.2 Results: Study Design Characteristics as a Secondary Influence on Emissions-Related Outcomes

Table 6 – Results for Test 1 (Chi² statistic) and Test 2 (bivariate quantile regression), comparing the magnitude of emissions-related outcomes across study design categories

Study design characteristic	**Study design category**	**Results for Test 1**	**Results for Test 2**
		Metric = Chi² Statistic	**Metric = % reduction (or increase) in emissions-related outcomes**
Internal validity / robustness	High/Medium	$Chi^2(2) = 3.974$ $Prob>chi^2 = 0.046$*	-11.4
	Low		-20.5*
External validity / generalisability	High	$Chi^2 (2) = 7.372$ $Prob>chi^2 = 0.025$*	-8.5*
	Medium		-11.4
	Low		-21.9
Emissions-related outcomes	%Δ activity	$Chi^2 (2) = 8.834$ $Prob>chi^2 = 0.659$	-20.0
	%Δ energy		-13.1
	%Δ carbon		-16.7
Analytical method	Accounting	$Chi^2 (3) = 1.406$ $Prob>chi^2 = 0.704$	-13.1
	Empirical		-13.5
	Simple Estimation		-20.0
	Simulation		-20.0

** denotes difference is significant to 99% CI, * denotes significant to 95% CI

Comparing the results across study design characteristics (Table 6), these suggest there are significant differences between studies based on variations in the strength of internal validity/robustness and external validity/generalisability. Studies with low internal validity/robustness estimate higher reductions (20.5%) compared to studies with high/medium internal validity/robustness (11.4%). Similarly, studies with low external validity/generalisability estimate higher reductions (21.9%), compared to studies with high external validity/generalisability (8.5%). These findings are consistent with Ivanova, Barrett [27].

We find no significant differences between type of emissions-related outcomes. Studies that estimate impact as %Δ activities are more likely to estimate higher reductions (20%), compared to those that estimate impact as energy (13.1%) or emissions (16.7%). We find no significant differences between studies based on different analytical methods. Modelling studies (accounting models 13.1% simple estimation models 20%, simulation models 20%) do not estimate higher reductions compared to empirical methods (13.5%).

Our findings in general reflect the difficulty in observing the direct relationship between emissions-related-outcomes and study design which is unlikely to be independent of DCI characteristics. Our data shows for example there is a significant association between type of emissions-related-outcome and domain of application (Chi2 = 73.63, p<0.000) (see Appendix A, Table A4. Association between type of emissions-related outcomes and domain of application).

3.3 Results: Impact Mechanisms as a Primary Influence on Emissions-Related Outcomes, Controlling for Secondary Influences of Study Design

In this final section of results, we examine the impact of DCIs on emissions-related outcomes when we account for the secondary influence of study design. Results are reported in a comparative table, comparing Test 2 (bivariate quantile regression) and Test 3 (multivariate quantile regression controlling for study design characteristics) (Table 7).

Table 7 – Results for Test 3 (multivariate quantile regression), comparing the magnitude of emissions-related outcomes across impact mechanisms, and deployment context controlling for study design characteristics

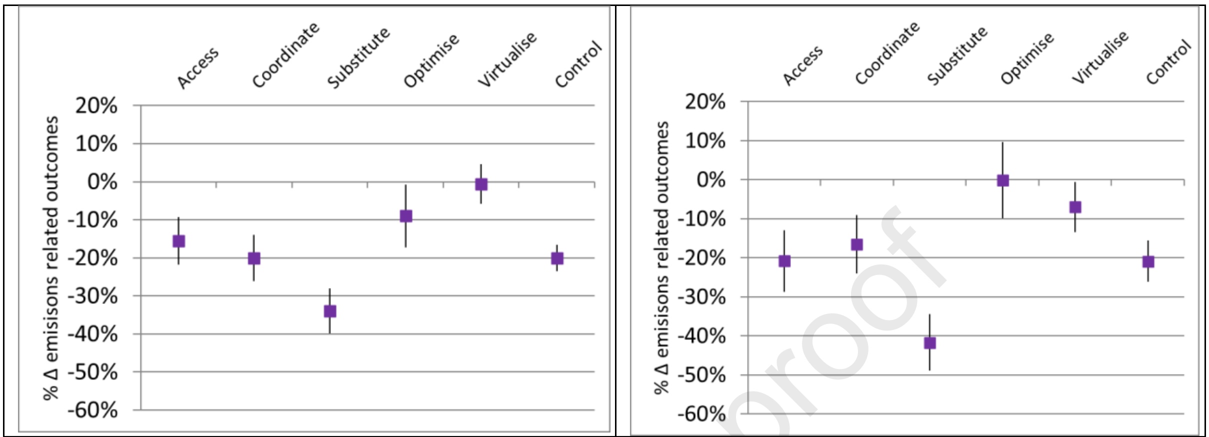
Influence on emissions-related outcomes			Results for Test 2	Results for Test 3	Absolute (%) change magnitude |test3-test2|
			Estimated % change in impact (emissions-related outcomes)		
			no controls	*controls*	*change*
Impact mechanism		Access	-15.5	-20.4	4.9
		Coordinate	-20.0	-17.8	2.2
		Substitute	-34**	-44.1**	10.1
		Optimise	-9.0	0.5	9.5
		Virtualise	-0.6	-6.2	5.6
		Control	-21.34	-20.9	0.5
Explained variance pseudo R^2 (%)			*5.6*	*8.1*	*2.5*
Deployment Context	Domain of Application	Transport	*-11.0*	-9.0	2.0
		Food	*-23.1*	-37.1**	14.0
		Homes	*-16.7*	-14.3	2.4
	Explained variance pseudo R^2 (%)		*1.2*	*5.2*	*4.0*
	Type of action	Avoid	*-6.1***	-9.7**	3.6
		Shift	*-20.0*	-20.8	0.8
		Improve	*-18.0*	-14.6	3.4
	Explained variance pseudo R^2 (%)		*1.7*	*4.2*	*2.5*
	Dependence on digital skills and accessibility	High	*-14.5*	-14.0	.51
		Medium	*-13.8*	-18.5	4.7
		Low	*-70.0***	-60.8**	9.2
	Explained variance pseudo R^2 (%)		*0.5*	*4.1*	*3.7*
	Dependence on access to physical infrastructure	High	*-18.0*	-14.0	4.0
		Medium	*-15.0*	-18.8	3.8
		Low	*-17.0*	-15.5	1.5
	Explained variance pseudo R^2 (%)		0.01	3.1	*3.1*

** denotes significant to 99% CI, * denotes significant to 95% C.I.

Study design characteristics have a secondary influence on the magnitude and direction of emissions-related outcomes across different impact mechanisms, domain of application, and dependence on digital skills and accessibility. This finding is supported by a general increase in explained variance (pseudo R^2) between Test 2 and Test 3 for all influencing characteristics.

An important finding is that impact mechanisms account for the highest explained variance in emissions-related-outcomes (5.6%) compared to deployment context. Explained variance also increases with the addition of study design controls (8.1%) (see Table 7). This is still modest but does suggest that impact mechanisms are a higher order main effect compared to the four variables measured within deployment context and compared to study design.

Across impact mechanisms evidence remains in support of our overall findings. We find a significant difference in the magnitude of emissions-related outcomes for DCIs that provide functionality thorough 'substitution' compared to all other impact mechanisms. When we control for secondary influences, we capture potential rebound effects (+0.5%)in the measurement of DCIs which 'optimise' (see Figure 1, Graph 1(a) and 1(b)). We see a decrease in the magnitude of emissions-related outcomes of 9.5%.



Graph 1(a) Estimated change in emissions-related outcomes across impact mechanisms, no controls	Graph 1(b) Estimated change in emissions-related outcomes across impact mechanisms, with controls

Figure 1 – Change in emissions-related outcomes across impact mechanisms, comparing between study estimates without additional controls for differences in study design (Graph 1(a)) and with additional controls for differences in study design (Graph 1(b)). Graphs depict median impact (bullet) with standard error bars.

Our findings show that we can generalise the magnitude of impacts across applications and contexts by focusing on the underlying causal mechanism of the impact unique to DCIs. This helps explain uncertainty which was previously attributed to study design variation for different applications. Controlling for study design variation further strengthens the explanatory power of impact mechanisms.

4.0 Discussion

Key Finding 1 - DCIs that provide functionality through substitution have high emissions reduction potential. Our findings suggest that DCIs that impact consumption behaviour via 'substitution' could contribute on average a 44.1% reduction in emissions-related outcomes (compared to a baseline of zero). Whilst DCIs that provide functionality through 'optimisation' have attributes which possess substantial consumer appeal, there remains uncertainty regarding the impact of optimisation technologies in the transport domain where efficiencies e.g., in vehicle automation, potentially create induced demand [55-57]. When we control for study design, DCIs that 'optimise' have a slightly negative impact (0.5% increase in emissions-related outcomes compared to a baseline of zero).

Key Finding 2 – DCIs that avoid high emissions activity have the lowest mitigation potential. This finding (avoid -9.7%, shift -21%, improve -14.9%) aligns with Creutzig, Niamir [29] who find 'avoid' has the lowest mitigation potential across buildings, transport, and food end-use sectors. Grubler, Wilson [58] propose that while 'improve' actions have historically been given prominence, avoidance and modal shift actions advance the feasibility of a 'low-carbon supply-side transformation'. The IPCC (2014) presented the A-S-I framework as a hierarchy of actions in which 'avoid' is the first course of action, followed by 'shift' and 'improve' [59]. Pye, Broad [60]suggest that an approach which focuses on 'avoid' and 'shift' is well-aligned with policy goals. In reality, a diversity of strategies is required to achieve ambitious climate targets [61].

Key Finding 3 – Characteristic differences between application contexts influence the impact of digital consumer innovations. There is substantial GHG emissions mitigation potential across each of the domains of transport, food, and homes (energy) [24-27]. Historically, impact-related studies have tended to focus on a single domain, with transport often given higher priority [18, 23]. A smaller number of studies consider impacts across multiple domains [62]. We find that food-related DCIs have potentially the largest impact on emissions-related outcomes (Transport -9.0%, Food -37.0%, Homes -14.3%). In drawing conclusions, we note that the selected food domain DCIs within our study use either the 'coordination' mechanism (exchanging with others to minimise food waste e.g., through digital apps) or 'substitution' (local foods substituted for imported foods via digital hubs) impact mechanisms, which we find have higher emissions reduction potential (Key Finding 1).

Key Finding 4 - **Ensuring good access to digitalisation and physical infrastructure is an enabler of impact but is not a critical determinant of the magnitude of impact**. Global digitalisation is steering progress towards increased dependence on digital access and skills, physical infrastructure and complex interdependence across sectors [30]. Our study has not been able to disentangle these effects. We find very modest differences across high and medium dependence on digital accessibility and skills, with a large, estimated reduction in emissions with low dependence. We note however, that DCIs classified as having lower dependence on digital access and skills tend to be the same DCIs operating through a 'substitution' impact mechanism which demonstrates a larger emissions-related outcome (Key Finding 1). As digital technology continues to evolve the requirements for additional enabling physical infrastructure, and future reconfigurations to existing infrastructure is widely recognised [32]. Van der Vooren [35] emphasises the importance of this transition in transport systems. The diffusion of radically new vehicle technologies, for example could be impeded by charging infrastructure deficiencies [63].

Key Finding 5: Study design characteristics exert a secondary influence on the magnitude of impact across different studies. In this key finding we concur with Horner, Shehabi [3]. Differences in impact are highly likely to reflect the subjectivity of decisions made by researchers in the study design process. There are of course inherent challenges to improving consistency in approaches to measuring the indirect effects of different impact mechanisms, which largely rely on the availability and validity of established empirical work. We suggest future work could be improved by encouraging standardised methodological approaches that enhance consistency in the framing and reporting of methodologies and results. Standardisation of reporting within studies would enable methodological differences across study design to be characterised and measured. Related reporting of uncertainties and errors would enable more advanced meta-analysis software to be reliably employed in future synthesis work. Bremer, Kamiya [64] allude to a critical need to develop and employ robust and consistent methodologies to assess, review and evaluate the energy and climate effects of digitalisation. In this they concur with the International Telecommunications Union [2] whose aim is to improve the consistency, transparency and comprehensiveness of how the use of ICT solutions impacts GHG emissions over time.

Limitations

We are unable to clearly distinguish between studies that account for rebound effects [65, 66] within their estimates of digital impact. This is an important consideration as it has a potentially large influence [67, 68]. For example, in a recent study Meshulam, Font-Vivanco [69] estimate that 50-94% of the expected GHG emission reductions from a free peer-to-peer food sharing platform, is offset by rebound effects. However, across the selected impact studies only a few account for these effects;

most studies do not. Rebound effects due to digitalisation are therefore not included as a variable in the study design controls. To understand the relationship between DCIs and energy and resource use more fully, these effects should be integrated into future impact studies.

5.0 Conclusion

There is a pressing need for intensified engagement and participatory dialogue between industry, companies in the ICT sector, ICT users and other stakeholders, and research communities. These collaborative processes could integrate deeper understanding of the use of innovative digital applications and the potential for climate change mitigation. In this study we contribute to this debate by disentangling the relative importance of different drivers of change in emissions-related outcomes for DCIs. We take a novel approach to test the relative magnitude of different impact mechanisms. Uniquely, we separate and concurrently control for uncertainties across impact estimates related to different study design characteristics. Our analytical framework combined with quantitative findings offer a more diverse perspective than previous studies and allows more granular consideration of the disparate influence of DCIs on energy use and emissions.

Our work can help to deliver well-defined strategies for decision/policymakers. It can provide clearer focus on which impact mechanisms, mitigation actions, and application domains, offer the greatest reduction potential. Policy can shape digitalisation pathways with consequential influence on energy demand, and GHG emissions [70-72]. Decision makers can build integrated approaches between the dematerialisation strategies of the circular economy and digitalisation to meet the needs of different user groups [71, 73, 74]. Policy can direct digitalisation strategies towards meeting wider sustainability goals, promoting clean energy sources, investment in digital infrastructure, and the provision of state-of-the-art sustainable systems [73, 75]. To minimise the inherent risks of climate overshoot, there is also a need for policy development to counter the potential for rebound/demand induction associated with certain impact mechanisms.

Bibliography

1. Creutzig, F., et al., *Demand, services and social aspects of mitigation*, in *Climate Change 2022: Mitigation of Climate Change. Working Group III contribution to Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC)*, J. Skea and P.R. Shukla, Editors. 2022, Intergovernmental Panel on Climate Change (IPCC): Geneva, Switzerland.
2. International Telecommunication Union. *Digital Skills Insights*. 2020 4 Jan 2022]; Available from: https://academy.itu.int/sites/default/files/media2/file/Digital%20Skills%20Insights%202020.pdf.
3. Horner, N.C., A. Shehabi, and I.L. Azevedo, *Known unknowns: indirect energy effects of information and communication technology.* Environmental Research Letters, 2016. **11**(10): p. 103001.
4. Freitag, C., et al., *The real climate and transformative impact of ICT: A critique of estimates, trends, and regulations.* Patterns, 2021. **2**(9).
5. Bieser, J.C., et al., *A review of assessments of the greenhouse gas footprint and abatement potential of information and communication technology.* Environmental Impact Assessment Review, 2023. **99**: p. 107033.
6. Creutzig, F., et al., *Designing a virtuous cycle: Quality of governance, effective climate change mitigation, and just outcomes support each other.* Global Environmental Change, 2023. **82**: p. 102726.
7. Hilty, L.M., et al., *Rebound effects of progress in information technology.* Poiesis & Praxis, 2006. **4**(1): p. 19-38.
8. Court, V. and S. Sorrell, *Digitalisation of goods: a systematic review of the determinants and magnitude of the impacts on energy consumption.* Environmental Research Letters, 2020. **15**(4): p. 043001.
9. Gawron, J.H., et al., *Life cycle assessment of connected and automated vehicles: sensing and computing subsystem and vehicle level effects.* Environmental science & technology, 2018. **52**(5): p. 3249-3256.
10. Rattle, R., *Computing Our Way to Paradise?: The Role of Internet and Communication Technologies in Sustainable Consumption and Globalization*. 2010: Rowman & Littlefield.
11. Taiebat, M., et al., *A review on energy, environmental, and sustainability implications of connected and automated vehicles.* Environmental science & technology, 2018. **52**(20): p. 11449-11465.
12. Wilson, C., et al., *The potential contribution of disruptive low-carbon innovations to 1.5 C climate mitigation.* Energy Efficiency, 2019. **12**(2): p. 423-440.
13. Pohl, J., L.M. Hilty, and M. Finkbeiner, *How LCA contributes to the environmental assessment of higher order effects of ICT application: A review of different approaches.* Journal of cleaner production, 2019. **219**: p. 698-712.
14. Wilson, C., et al., *Potential climate benefits of digital consumer innovations.* Annual Review of Environment and Resources, 2020. **45**: p. 113-144.
15. Lange, S., J. Pohl, and T. Santarius, *Digitalization and energy consumption. Does ICT reduce energy demand?* Ecological Economics, 2020. **176**: p. 106760.
16. Briglauer, W., et al., *The impact of ICT on electricity and energy consumption and resulting CO2 emissions: A literature review.* International Review of Environmental and Resource Economics, 2023. **17**(2-3): p. 319-361.
17. Berkhout, F. and J. Hertin, *De-materialising and re-materialising: digital technologies and the environment.* Futures, 2004. **36**(8): p. 903-920.
18. Perdana, S., et al., *Expert perceptions of game-changing innovations towards net zero.* Energy Strategy Reviews, 2023. **45**: p. 101022.

19. Sorrell, S., *Digitalisation of goods: a systematic review of the determinants and magnitude of the impacts on energy consumption.* Environmental Research Letters, 2020. **15**(4): p. 043001.
20. Grübler, A., N. Nakićenović, and D.G. Victor, *Dynamics of energy technologies and global change.* Energy policy, 1999. **27**(5): p. 247-280.
21. Iacobucci, R., R. Bruno, and J.-D. Schmöcker, *An integrated optimisation-simulation framework for scalable smart charging and relocation of shared autonomous electric vehicles.* Energies, 2021. **14**(12): p. 3633.
22. Li, S., et al., *Measuring the efficiency of energy and carbon emissions: A review of definitions, models, and input-output variables.* Energies, 2022. **15**(3): p. 962.
23. Butler, L., T. Yigitcanlar, and A. Paz, *Smart Urban Mobility Innovations: A Comprehensive Review and Evaluation.* IEEE Access, 2020. **8**: p. 196034-196049.
24. Aall, C. and J. Hille, *Consumption–a missing dimension in climate policy.* Interdisciplinarity and Climate Change, 2010: p. 85.
25. Creutzig, F., et al., *Towards demand-side solutions for mitigating climate change.* Nature Climate Change, 2018. **8**(4): p. 260-263.
26. Moberg, K.R., et al., *Mobility, food and housing: responsibility, individual consumption and demand-side policies in European deep decarbonisation pathways.* Energy Efficiency, 2019. **12**: p. 497-519.
27. Ivanova, D., et al., *Quantifying the potential for climate change mitigation of consumption options.* Environmental Research Letters, 2020. **15**(9): p. 093001.
28. Creutzig, F., et al., *Transport: A roadblock to climate change mitigation?* Science, 2015. **350**(6263): p. 911-912.
29. Creutzig, F., et al., *Demand-side solutions to climate change mitigation consistent with high levels of well-being.* Nature Climate Change, 2022. **12**(1): p. 36-46.
30. Thacker, S., et al., *Infrastructure for sustainable development.* Nature Sustainability, 2019. **2**(4): p. 324-331.
31. Zhang, J., et al., *Digital consumption innovation, socio-economic factors and low-carbon consumption: Empirical analysis based on China.* Technology in Society, 2021. **67**(May): p. 101730-101730.
32. Gnann, T., et al., *Fast charging infrastructure for electric vehicles: Today's situation and future needs.* Transportation Research Part D: Transport and Environment, 2018. **62**: p. 314-329.
33. Jones, E.C. and B.D. Leibowicz, *Contributions of shared autonomous vehicles to climate change mitigation.* Transportation Research Part D: Transport and Environment, 2019. **72**: p. 279-298.
34. Sochor, J., I.M. Karlsson, and H. Strömberg, *Trying out mobility as a service: Experiences from a field trial and implications for understanding demand.* Transportation Research Record, 2016. **2542**(1): p. 57-64.
35. Van der Vooren, A., *Accelerating technological change. Towards a more sustainable transport system*. 2014, Utrecht University.
36. Bygstad, B. and O. Hanseth. *Transforming digital infrastructures through platformization*. 2019. Association for Information Systems.
37. Hanseth, O. and K. Lyytinen, *Design theory for dynamic complexity in information infrastructures: the case of building internet.* Journal of information technology, 2010. **25**: p. 1-19.
38. Hustad, E. and D.H. Olsen, *Creating a sustainable digital infrastructure: The role of service-oriented architecture.* Procedia Computer Science, 2021. **181**: p. 597-604.
39. Sørensen, C., *Digital platform and-infrastructure innovation.* Mobile Strategy Challenges (In Japanese). H. Higashikuni (ed). Nikkan Kogyo Shimbun Ltd. Tokyo, 2013.

40. Joglekar, N., et al., *Configuration of digital and physical infrastructure platforms: Private and public perspectives.* Production and Operations Management, 2022. **31**(12): p. 4515-4528.
41. Borenstein, M.J., et al., *Introduction to meta-analysis*. 2009, Chichester: J Wiley & Sons Ltd.
42. Moher, D., et al., *Does quality of reports of randomised trials affect estimates of intervention efficacy reported in meta-analyses?* The Lancet, 1998. **352**(9128): p. 609-613.
43. Composto, J.W. and E.U. Weber, *Effectiveness of behavioural interventions to reduce household energy demand: a scoping review.* Environmental Research Letters, 2022. **17**(6): p. 063005.
44. Walter, S. and X. Yao, *Effect sizes can be calculated for studies reporting ranges for outcome variables in systematic reviews.* Journal of clinical epidemiology, 2007. **60**(8): p. 849-852.
45. Rabe-Hesketh, S. and A. Skrondal, *Multilevel and longitudinal modeling using Stata*. 2008: STATA press.
46. Higgins, J. and S. Green, *Cochrane handbook for systematic reviews of interventions version 5.1.0*. 2011: The Cochrane Collaboration.
47. Khajenasiri, I., et al., *A review on Internet of Things solutions for intelligent energy control in buildings for smart city applications.* Energy Procedia, 2017. **111**: p. 770-779.
48. Cai, H., et al., *Environmental benefits of taxi ride sharing in Beijing.* Energy, 2019. **174**: p. 503-508.
49. StataCorp. *Stata Statistical Software: Release 16.* 2019.
50. Field, A., *Discovering statistics using IBM SPSS statistics*. 2013: sage.
51. Gould, W., *Quantile regression with bootstrapped standard errors.* Stata Technical Bulletin, 1993. **2**(9).
52. Maduekwe, M., U. Akpan, and S. Isihak, *Road transport energy consumption and vehicular emissions in Lagos, Nigeria: An application of the LEAP model.* Transportation Research Interdisciplinary Perspectives, 2020. **6**: p. 100172.
53. Zhang, R. and T. Hanaoka, *Cross-cutting scenarios and strategies for designing decarbonization pathways in the transport sector toward carbon neutrality.* Nature communications, 2022. **13**(1): p. 3629.
54. Arioli, M.S., et al., *The evolution of city-scale GHG emissions inventory methods: A systematic review.* Environmental Impact Assessment Review, 2020. **80**: p. 106316.
55. Rubin, J., *Connected autonomous vehicles: Travel behavior and energy use.* Road Vehicle Automation 3, 2016: p. 151-162.
56. Moeckel, R., *Working from home: Modeling the impact of telework on transportation and land use.* Transportation Research Procedia, 2017. **26**: p. 207-214.
57. Wadud, Z., D. MacKenzie, and P. Leiby, *Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles.* Transportation Research Part A: Policy and Practice, 2016. **86**: p. 1-18.
58. Grubler, A., et al., *A low energy demand scenario for meeting the 1.5 C target and sustainable development goals without negative emission technologies.* Nature energy, 2018. **3**(6): p. 515-527.
59. O'Riordan, V., et al., *How and why we travel–mobility demand and emissions from passenger transport.* Transportation Research Part D: Transport and Environment, 2022. **104**: p. 103195.
60. Pye, S., et al., *Modelling net-zero emissions energy systems requires a change in approach.* Climate Policy, 2021. **21**(2): p. 222-231.
61. Milovanoff, A., et al., *Greenhouse gas emission mitigation pathways for urban passenger land transport under ambitious climate targets.* Environmental Science & Technology, 2021. **55**(12): p. 8236-8246.
62. Erdmann, L. and L.M. Hilty, *Scenario analysis: exploring the macroeconomic impacts of information and communication technologies on greenhouse gas emissions.* Journal of Industrial Ecology, 2010. **14**(5): p. 826-843.

63. Bokolo, A.J., *Examining the Adoption of Sustainable eMobility-Sharing in Smart Communities: Diffusion of Innovation Theory Perspective.* Smart Cities, 2023. **6**(4): p. 2057-2080.
64. Bremer, C., et al., *Assessing energy and climate effects of digitalization: Methodological challenges and key recommendations.* nDEE Framing Paper Series, 2023.
65. Coroama, V.C., L.M. Hilty, and M. Birtel, *Effects of Internet-based multiple-site conferences on greenhouse gas emissions.* Telematics and Informatics, 2012. **29**(4): p. 362-374.
66. Kunkel, S. and D. Tyfield, *Digitalisation, sustainable industrialisation and digital rebound–Asking the right questions for a strategic research agenda.* Energy Research & Social Science, 2021. **82**: p. 102295.
67. Coroamă, V.C. and F. Mattern. *Digital rebound–why digitalization will not redeem us our environmental sins*. in *Proceedings 6th international conference on ICT for sustainability. Lappeenranta. http://ceur-ws. org*. 2019.
68. Lange, S., et al., *The induction effect: why the rebound effect is only half the story of technology's failure to achieve sustainability.* Frontiers in Sustainability, 2023. **4**: p. 1178089.
69. Meshulam, T., et al., *Sharing economy rebound: The case of peer-to-peer sharing of food waste.* Journal of Industrial Ecology, 2023. **27**(3): p. 882-895.
70. Bergman, N. and T.J. Foxon, *Drivers and effects of digitalization on energy demand in low-carbon scenarios.* Climate Policy, 2023. **23**(3): p. 329-342.
71. Dzwigol, H., et al., *Digitalization and Energy in Attaining Sustainable Development: Impact on Energy Consumption, Energy Structure, and Energy Intensity.* Energies, 2024. **17**(5): p. 1213.
72. Niamir, L., et al., *Cities Transformation.* 2024.
73. Bento, N., *The potential of digital convergence and sharing of consumer goods to improve living conditions and reduce emissions.* Environmental Research Letters, 2023. **18**(12): p. 124014.
74. Creutzig, F., et al., *Towards a public policy of cities and human settlements in the 21st century.* npj Urban Sustainability, 2024. **4**(1): p. 29.
75. Falchetta, G., et al., *Shared pooled mobility: expert review from nine disciplines and implications for an emerging transdisciplinary research agenda.*

Appendix A – Additional Tables

Table A1. Structural dependencies influencing the effectiveness of impact mechanisms

Structural dependency	Strength	Definition	Examples
Digital skills and accessibility	High	Use necessitates skills and access to digital infrastructure e.g., a platform with real-time matching of users and providers.	Shared taxis
	Medium	Use requires some skills and access to digital infrastructure, e.g., control apps and scheduling	Smart lighting
	Low	Use is possible without skills and access to digital infrastructure, e.g., an app to allow scheduled charging.	E-bikes
Physical Infrastructure	High	Use requires dedicated physical infrastructure e.g., thermostat and in-home wireless network	Smart heating system
	Medium	Use may require dedicated physical infrastructure e.g., distribution warehouse and delivery vehicles.	Digital hubs for local food
	Low	Use does not require dedicated physical infrastructure (additional to publicly available)	P2P exchange of goods

Table A2. Taxonomy of study design characteristics influencing the measurement of energy consumption and emissions

Characteristic	Metric	Measurement criteria	**N (studies)**
Internal validity / robustness	High/Medium	Use of randomised control trial or clearly delineated control groups / pre-test baseline, clear system boundaries, and assumptions, hypothesis testing, testing of alternative explanations includes field trials or demonstration project, which may use controls/pre-test baseline but lacks some clarity in approach.	72
	Low	Single model and scenario, or self-reported behaviour / preferences, absence of methodological detail, coarse assumptions, e.g., 100% household uptake of DCI, or anecdotal evidence	63
External validity / generalisability	High	Large heterogenous sample or synthesis of large-sample field trials, testing performed in different conditions, long-time frame	25
	Medium	Real-world conditions, field trial results, but involve small-medium homogenous samples or the potential for opt-in bias. Large heterogenous sample but account for single condition	35
	Low	Simulation, small sample size e.g., a single-house simulation or single journey type with no time-of-day variation, test performed in controlled conditions, potential opt-in bias	75

Emissions-related outcomes	percent change (%Δ) in activity *	The amount of activity or useful service consumed, e.g., annual vehicle miles travelled (VMT)	25
	percent change (%Δ) in energy *	The amount of energy or resources needed to provide a useful service, e.g., well-to-wheel energy consumption (in GJ)	35
	percent change (%Δ) in carbon *	The amount of greenhouse gas emissions (CO_2 or CO_2-equivalent) e.g., lifecycle CO_2 emissions per passenger-kilometre	75
Analytical method	Accounting	A linear combination of disaggregated variables in a mathematical model (e.g., lifecycle analysis)	28
	Empirical	The collection of observed data through field trials, natural experiments, and demonstration projects	33
	Simple Estimation	Based on empirical or anecdotal evidence with broad assumptions and uncomplicated accounting	20
	Simulation	A digital parameterised model of a real-world system.	54

* relative to a without-digitalisation reference case or baseline

Table A3. Estimates (n) of emissions-related outcomes across impact mechanisms and deployment context

Classification	**Mechanism**	**Estimates (n)**
Impact mechanism	Optimise	9
	Control	52
	Substitute	18
	Virtualise	23
	Access	16
	Coordinate	17
Domain of application	Transport	67
	Food	23
	Homes	45
Type of action	Avoid	32
	Shift	57
	Improve	46
Dependence on digital access and skills	High	100
	Medium	27
	Low	8
Dependence on access to physical infrastructure	High	40
	Medium	35
	Low	60

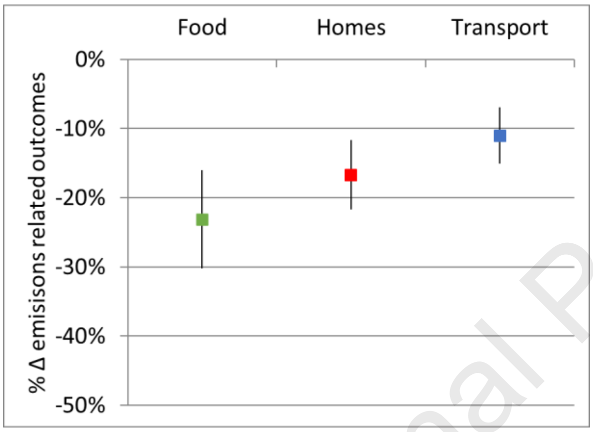
Table A4 – Association between type of emissions-related outcomes and domain of application

Domain		%Δ Activity	%Δ Carbon	%Δ Energy	Total
Food	n	9	9	5	23
	%	39.13%	39.13%	21.74%	100%
Homes	n	1	4	40	45
	%	2.22%	8.89%	88.89%	100%

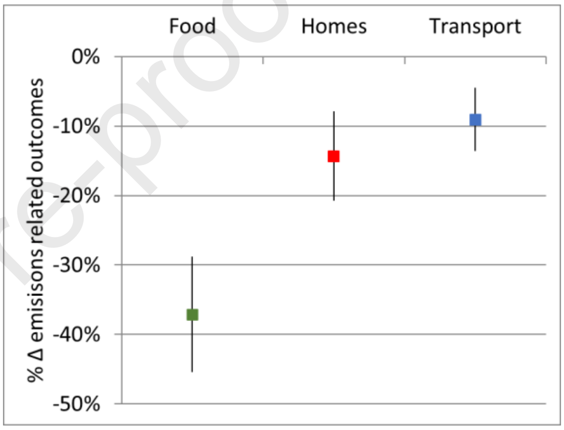
Transport	n	14	44	9	67
	%	20.9	65.67	13.43	100
All Domains	N	24	57	54	135
	%	17.78	42.22	40	100

There are underlying similarities between the choice of emissions-related outcomes by researchers in specific domains. Eighty nine percent of the 45 studies measuring the impact of DCIs in the homes domain were estimated as %Δ energy. In transport, 66% of the 67 studies were estimated as %Δ carbon. Studies in the food domain are more balanced across the three different outcome measures.

Appendix B – Additional Graphs



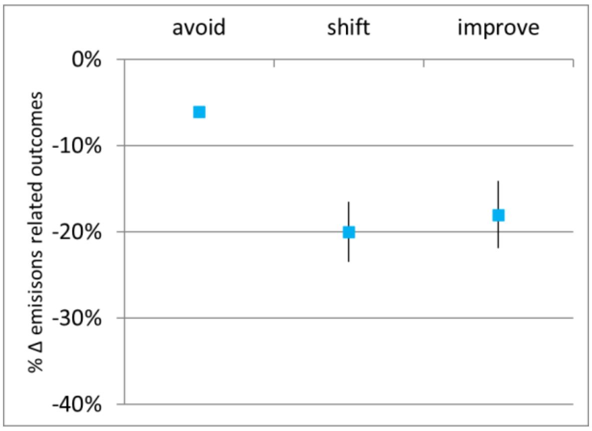
Graph B1(a) Estimated change in outcomes across application domains, with no controls



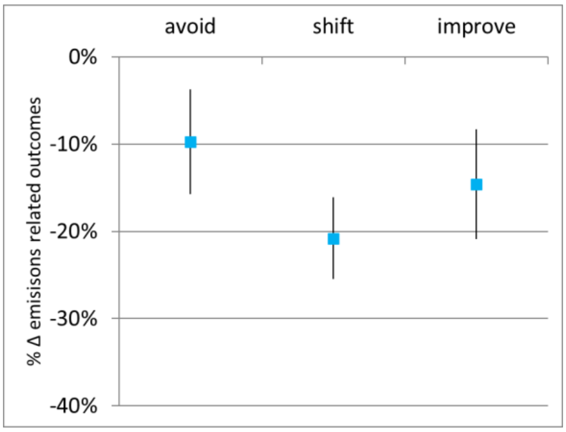
Graph B1(b) Estimated change in outcomes across application domains, with controls

Figure B1 – Change in emissions-related outcomes across domains of provision, comparing between study estimates without additional controls for differences in study design (Graph B1(a)) and with additional controls for differences in study design (Graph B1(b)). Graphs depict median impact (bullet) with standard error bars.

DCIs in the food domain have a significantly larger influence on emissions-related outcomes (compared to homes and transport) when we control for the secondary influences of study design. The impact of food-related DCIs increases from a 23% reduction in emissions-related outcomes (see Graph B1(a)) to over 37% reduction (see Graph B1(b)). The overall effect is that there are significant differences between food and transport related innovations (Graph B1(b) error bars do not overlap).



Graph B2(a) Estimated change in outcomes for type of action, no controls



Graph B2(b) Estimated change in outcomes for type of action, with controls

Figure B2 – Change in emissions-related outcomes across type of action, comparing between study estimates without additional controls for differences in study design (Graph B2(a)) and with additional controls for differences in study design (Graph B2(b)). Graphs depict median impact (bullet) with standard error bars.

We find no significant change in emissions-related outcomes across A-S-I actions. When we control for differences in study design the magnitude of studies measuring digital innovations that 'avoid actions increase by 3.6%. DCIs that 'improve' energy and emission efficiency reduce by 3.4%.

We find very modest change in outcomes across high, medium, and low dependence on digital skills and accessibility when we control for study design, but change remains insignificant. This implies that while ensuring good access to skills is an enabler it is not a critical determinant of the magnitude of impact. Changes in outcomes across high, medium, and low dependence on physical infrastructure are also not statistically significant.

Declaration of interests

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

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: