Evidence Synthesis of Indirect Impacts of Digitalisation on Energy and Emissions

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***Abstract*—The indirect impacts of digitalisation on energy use and carbon emissions are large but uncertain. In this study, we provide quantitative estimates of digitalisation impacts focusing on both energy-saving and energy-increasing potentials.**

We draw on studies of specific digital use cases in transport and consumer goods sectors, and normalise impact estimates as percent changes relative to reference cases without digitalisation. For the industry sector, we draw on statistical models using panel data that estimate how energy demand changes with increased digitalisation. In each case we present the maximum uncertainty ranges of impact estimates, and explore the conditions explaining both lower and upper bounds.

We find strong evidence of both large reductions in energy use through substitution or efficiency improvements (e.g., shared ridehailing: -55% to -18%) and large increases in energy use through rebound or induced demand effects (e.g., ridehailing: +41% to +90%). In some cases, we find evidence of both negative and positive impacts depending on deployment conditions or use context (e.g., e-retail: -94% to +140%; mobility-as-a-service: -50% to +20%). Study design also affects the uncertainty of digitalisation impacts.

Common features of the lower and upper bounds of estimated impact ranges point to generic strategies for aligning digitalisation with climate mitigation goals. These include limiting potential rebound through pricing or other constraints on increased activity, and incentivising business models that integrate digitally-enabled activities into wider systems of provision for mobility or electricity.

***Index Terms*—digital applications, activity, carbon, climate**

I. Introduction

The impacts of digitalisation on energy use and emissions are direct, indirect and systemic [1]. Direct impacts from the energy footprint of information and communication technologies (ICTs) and infrastructure (data centres, networks) are estimated in the range 1.5 - 4% of global greenhouse gas (GHG) emissions [2], [3]. Indirect impacts resulting from changes in processes, systems, and user behaviour are more uncertain, and vary widely across digital applications and sectors. Systemic impacts on economic activity more generally (e.g., jobs, skills) and on society and governance systems are more uncertain still as impact pathways are diffuse [4].

Quantifying the magnitude and uncertainty of indirect impacts is the focus of this paper. Digital applications can improve process efficiency, optimise system performance, and substitute for energy-intensive activities; but reducing cost and friction can also increase service demand (rebound), and expand or intensify energy-using activities (induced demand) resulting in overall growth (scale effect). Indirect impacts are also called enabling or exacerbating effects [5] in relation to GHG abatement mechanisms or potentials [3]. All these terms refer to the energy or GHG impacts resulting from the use of digital applications for certain purposes in specific contexts: i.e., digital 'use cases'.

A landmark 2017 assessment of 'Digitalization and Energy' [6] by the International Energy Agency (IEA) scaled up quantitative estimates of indirect impacts by sector (buildings, transport, industry, energy supply), emphasising energy-saving opportunities that varied by sector and typically ranged in the order of 5-15%.

The Group of Experts on Energy Efficiency (G-EEE) similarly estimate sectoral potentials, drawing on IEA and other data. For example, they find that optimization of industrial processes enabled by digital applications such as internet of things (IoT), automation, and advanced analytics could result in 10-20% energy savings [7].

Industry-led studies including those by the Global e-Sustainability Initiative [5] or GSMA [8] estimate net energy-saving or emission-reducing impacts of digitalisation over similar ranges but with little transparency on assumptions used. Their emphasis is on demonstrating a positive 'enablement factor' meaning that digital applications save more energy than the ICT infrastructure uses in its operation (i.e., the ratio of indirect impacts to direct impacts > 1).

There are two main approaches for estimating indirect impacts: use cases and statistical modelling. The first approach analyses specific applications using empirical data from use cases or case studies in specific deployment contexts [3], or from modelling simulations for emerging or prospective applications for which sufficient observational data are not yet available [9]. The IEA, GEEE and GeSI assessments fall in this tradition. Bieser, Hintemann [3] synthesise indirect impact estimates from multiple use cases across sectors, with

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GHG abatement potentials generally falling in the 10-20% range, but with a lower range of 1.3-8.9% estimated from the most recent global study by GeSI [5]. This GeSI study is based on evidence from seven broad digital technologies (digital access, fast internet, cloud computing, internet of things (IoT), machine learning and artificial intelligence (AI), augmented and virtual reality, and blockchain). All the indirect impacts are expressed as net energy-saving (i.e., demonstrating GHG abatement potentials). This one-sided emphasis is a common bias in industry-led studies [3], exacerbated by the methodological difficulty in use-case studies of accounting for induced demand and scale effects which tend to lie outside study system boundaries.

The second approach for estimating indirect impacts uses statistical modelling of economy-wide or industry sector panel data on ICT or internet penetration across countries over time regressed against energy demand or greenhouse gas emissions [10], [11]. This approach aggregates across all digital applications so does not identify specific causal mechanisms or deployment contexts [12]. Depending on the system boundaries and energy demand data used, this statistical approach may also implicitly include the direct and systemic impacts of digitalisation as well as the indirect impacts. Economy-wide studies in this tradition generally find digitalisation impacts are net energy saving and vary as either a linear or U-shaped function of economic development stage [13], although this evidence is ambiguous in some studies [14].

II. Method & Data

Our study draws on both these traditions to estimate the indirect impacts of digitalisation on energy and emissions in three energy-using sectors (transport, consumer goods, industry). We are not concerned with the direct impacts on energy use of ICT infrastructure itself; for recent reviews of direct impacts, see: [2], [3].

For digital applications in transport and consumer goods sectors, we draw on use-case based studies. These vary in system boundaries and impact metric. Unlike the studies reviewed in [3], we focus not just on use cases with demonstrated energy-saving or GHG abatement potentials, but also on applications that may result in net increases in energy use through rebound, induced demand, or other effects.

For digital applications in industry, we draw on whole-sector statistical modelling studies. Bieser, Hintemann [3] note that use case-based data for industrial applications are less systematically explored than in other sectors. Coarse assumptions of up to 50% energy savings are generalised but without supporting evidence [15].

Our method has four main steps: (1) identification of high impact digital applications or use cases; (2) search & selection of relevant studies; (3) extraction of quantitative impact estimates; (4) synthesis of impact ranges and characterisation of conditions explaining lower and upper bounds. Overall, our method is comprehensive but not systematic, aiming to synthesise data per digital application on at least 3-5 impact estimates based on robust study designs.

First, we identify the main types of digital application with significant potential impacts on energy use in each sector (transport, consumer goods, industry). For this we draw on five recent cross-sectoral synthesis studies including two international assessments by the IEA [6], [16], the sixth assessment report of the Intergovernmental Panel on Climate Change [17] as well as two other reviews [3], [18]. All five studies estimate the relative magnitude of impact on energy use or GHG abatement potential across multiple applications, and so help distinguish a hierarchy of importance. Each application we select is cited in at least one of these synthesis studies; most of them are cited in two or more. This yields seven applications in the transport sector and three in consumer goods, and an interrelated cluster of four applications in the industry sector (automation, AI, internet of things, digital twins) that combine in enabling process efficiency and optimisation. Details of the applications and data sources are provided in corresponding results sections below.

Second, for each selected application we search for recent literature providing quantitative estimates of indirect impacts on energy use. For each application, we use search terms on Web of Science, Scopus, and Google Scholar (convenience sampling) together with mining of bibliographies (snowball sampling) to identify relevant studies. As an example for vehicle-grid integration as a digital application in the transport sector, we use the search terms [("Vehicle to grid" OR "V2G" OR "V2X" OR "smart charging") AND ("energy" OR "fuel" OR "carbon emission*" OR "CO2")].

In our search we prioritise systematic reviews, meta-analyses, or other review studies if available (marked by * in the data source tables below). We also seek to identify studies from diverse geographies or application contexts if available. For each application we target a sample of at least 3-5 studies from which we can extract quantitative impact estimates.

For studies identified through search, our inclusion criteria are: (1) relevance to a specific digitalisation use case or digital application; (2) quantitative impact estimate of digitalisation use case relative to reported or calculable without-digitalisation reference case; (3) definition of use case system boundary and impact estimation methodology.

Criterion (2) on data availability is restrictive as relatively few studies report clearly defined quantitative impact estimates relative to a without-digitalisation reference case. We use criterion (3) on study design as a screen to exclude studies with unclear, incomplete, or otherwise insufficient information on the estimation methodology used such that the impact estimates cannot be interpreted. For example, a study reporting a quantitative impact estimate but without explaining how the reference case was measured nor whether the system boundary included rebound effects would be excluded.

Third, we extract and synthesise quantitative impact estimates. We supplement data extracted from reviews with impact estimates from more recent studies if not already included in the review.

For the use-case based studies in transport and consumer goods, we normalise impact estimates as percent changes

(%Δ) relative to without-digitalisation reference cases. These reference cases are defined differently in each of the underlying studies but in all cases represent an actual or a hypothetical situation in which the digital application is not implemented or present. Examples of reference cases include control contexts in natural experiments, control groups in lab or field experiments, counterfactual scenarios in modelling simulations, or baseline measures that precede the digital application being implemented.

Normalisation of impact estimates into percent change estimates allows direct comparison of relative effect sizes between digital applications. However, the magnitude of impact in absolute energy (GJ) or emission (tCO2) terms depends on the size of the activity affected.

For the statistical modelling studies in the industry sector, we use regression coefficients to express impact estimates as percent changes per 1% increase in ICT penetration (i.e., these data are already normalised, although not relative to a without-digitalisation reference case).

For all the quantitative impact estimates, we distinguish activity, energy intensity, energy, and emission metrics. We focus on activity and energy metrics if available as these are the most direct measures of impact without confounding factors such as the emission intensity of electricity. This method follows the precedent set in the recent IPCC Sixth Assessment Report (see Fig 5.12 in [17]) and also Wilson, Kerr [18] who synthesised evidence on a wide range of consumer-oriented digital applications.

Fourth, we present the maximum uncertainty ranges of indirect impact estimates from lower to upper bounds for each digital application. We also summarise the conditions explaining both lower and upper bounds of the range. In particular we note differences in the scope of deployment (e.g., application or sector), study method (e.g., empirical or simulation), and study system boundaries (e.g., whether rebound and scale effects are included). Despite efforts to standardise indirect impact assessment methodologies [19], studies vary widely in design [20].

Our method is designed to provide a first order synthesis of the indirect impacts of digitalisation on energy use across transport, consumer goods, and industry sectors, identifying both energy-saving opportunities and energy-increasing risks.

III. Results

A. Impact Estimates from Use Cases of Digital Applications in the Transport Sector

1) Selected digital applications: Table I summarises mobility-related digital applications with high potential impact, based on [3], [6], [16], [17], [18] (see Methods). Digitalisation can impact activity, energy or emissions by enabling substitution of private vehicle use (teleworking, ride-hailing, e-retail), increasing vehicle occupancy (shared ride-hailing, autonomous vehicles (AVs)), shifting travel to flexible mode or multi-modal journeys (mobility-as-a-service (MaaS)), facilitating electrification of vehicles (smart charging, vehicle-grid integration (VGI)), and optimising travel patterns (freight logistics, e-retail).

Transport applications intersect with other sectors particularly consumer goods (e-retail) and energy supply (VGI). Vehicle-grid integration (VGI) uses scheduling algorithms and network signals to control smart or bidirectional charging of electric vehicles. This increases demand flexibility and facilitates renewables integration in low-carbon electricity networks.

TABLE I
Digital applications in the transport sector.

digital application	definition
teleworking	ICT-enabled remote working and interaction
ride-hailing	on-demand ride-hailing platforms (e.g. Uber)
shared ride-hailing	multi-occupancy flexible route ride-hailing platforms (e.g., Uber Pool)
mobility-as-a-service (MaaS)	multiple transportation services including public and shared modes integrated into a convenient package accessed through a digital platform, provider, or cloud service
freight logistics optimisation	data-driven optimisation of freight logistics including distribution, routing, and vehicle capacity
vehicle-grid integration (VGI)	electric vehicle charging and discharging to support integration in low-carbon electricity networks
autonomous vehicles (AVs)	vehicles that sense, collect and process large amounts of real-time data on surroundings to enable operation without human involvement or oversight

2) Studies reviewed with quantitative impact estimates: Table II summarises the studies from which quantitative estimates were extracted for the evidence synthesis, and the main study design issues arising per digital application. Overall, the evidence base is limited outside US, Europe, and China. Recent reviews or synthesis studies provide useful impact ranges for some applications including teleworking [21] and VGI [22].

For teleworking, Hook, Court [21] systematically reviewed impact estimates from 39 studies accounting for study design and scope. Travel restrictions during the pandemic increased uptake of teleworking with persistent effects but stronger evidence of non-work travel rebound [23].

Ride-hailing and shared ride-hailing are separated as business models with very different impact. Ride-hailing platforms dominate digital mobility services [24]. In contrast, shared ride-hailing has very low market share so impacts are assessed using urban-scale simulations [25].

User-centric MaaS has the potential to suppress car use, and ownership of second family cars (car-shedding) [26]. Uptake is dependent on access to public transport and mobility services, so is mainly in cities. Evidence on impacts is limited to a few pilots, otherwise evidence is drawn from simulation models [27].

In freight logistics, digitalisation impacts are via route optimisation, increased vehicle capacity utilisation, shared-fleet carrier collaboration, and potential vehicle automation

[28], [29]. Impacts are typically analysed using simulation models [30], [31].

For both VGI and AVs, recent evidence syntheses have drawn mainly on simulation modelling given low market uptake to date. For VGI, Anwar, Muratori [22] synthesised impact estimates from 11 studies on the value of managed EV charging. For AVs, Silva, Cordera [32] and Kopelias, Demiridi [33] reviewed environmental impacts from over 20 studies. Net emission impacts depended on study system boundaries.

TABLE II
STUDIES PER DIGITAL APPLICATION IN THE TRANSPORT SECTOR WITH QUANTITATIVE IMPACT ESTIMATES.

digital application	**n studies**	**main study design**[1]	**geography**	**refs***†
teleworking	n=5 inc. 1 systematic review (n>30)	empirical	mainly US, Europe (3 Global South)	[21]*†, [17]*, [18]*, [1], [23]
ride-hailing	n=5	empirical	mainly US cities	[24]*†, [34], [35], [36], [37]
shared ride-hailing	n=4 inc. 1 synthesis (n=7)	simulation	US, Europe, NZ cities	[38]†, [39], [25], [18]*
MaaS	n=6	empirical, simulation	Europe, 1 Australia	[26], [40], [41], [27], [42], [9]
freight logistics optimisation	n=6	simulation	Global (+ regions), China, Greece	[43], [30], [31], [44], [29], [28]
vehicle-grid integration (VGI)	n=6 inc. 1 systematic review (n=11)	simulation	North America, Europe, China	[22]*†, [45]†, [46], [47], [48], [49]
autonomous vehicles (AVs)	n=7 inc. 2 systematic reviews (each n>20)	simulation	North America, Europe, China, New Zealand	[32]*†, [33]*, [50], [51], [52], [53], [54]

[1]empirical = based on observations, trials, real-world applications; simulation = based on modelling, scenario assumptions
*denotes review or synthesis studies
†denotes the main studies used in the evidence synthesis

3) Quantitative impacts: uncertainty ranges: Table III summarises the maximum uncertainty range of impact estimates per digital application from lower to upper bound of all estimates found in the studies reviewed. Digitalisation impacts are expressed as percent changes (%Δ) relative to without-digitalisation reference cases or counterfactuals (see Methods). Impact estimates use different but related metrics: activity (p.km or v.km), energy (GJ, fuel, or equivalent), greenhouse emissions (CO_2 or CO_2e). Although different metrics cannot be aggregated, the direction and magnitude of change between metrics have similar interpretations.

For teleworking, the main impact is reduction in activity or energy from reduced commuting travel. A larger number of studies use activity metrics, expressed as changes in passenger.kilometres (p.km) or vehicle.kilometres (v.km), both of which are proportional to changes in energy for single occupancy private cars. (One passenger travelling one kilometre equals one passenger.kilometre of activity. These combinatorial activity metrics are commonly used in transport studies).

For ride-hailing and shared ride-hailing, the main impacts are increased activity from deadheading (relocation of passenger-less vehicles) and substitution of alternative modes (private vehicles, public transport). Some studies capture impacts on vehicle ownership and induced demand.

The main impacts for MaaS are a shift in activity to alternative modes (public transport and carsharing services) and car-shedding [26]. Most studies simulate impacts on CO_2 emissions for a range of scenarios combining uptake and modal share assumptions based on stated preference data (e.g., passenger surveys).

For freight logistics, the long-term outlook is for significant growth in overall activity (measured as tonne.kilometres) but this is a secular trend and not specifically the result of induced demand due to digitalisation. Against this backdrop, digitalisation improves operational energy efficiency through improved routing and vehicle capacity utilisation that combine to reduce total vehicle distances travelled (vehicle.kilometres). This is also captured in a few studies through changes in energy consumption. All studies also estimate GHG reduction potentials using emission factors or lifecycle analysis.

For vehicle-grid integration (VGI), the main impacts are reductions in CO2 emissions from the electricity system attributable to lower peak demand with managed smart charging and advanced capabilities of EVs to provide grid-enhancing ancillary services that help displace thermal power plants. In addition, VGI contributes to lowering the curtailment rate (CR) of variable renewable energy (VRE) generation, i.e., intermittent wind and solar. This further reduces CO_2 emissions. Most studies report metrics in terms of changes in CO_2 and curtailment rates at an aggregate electricity system level, or in terms of changes in the emission intensity of a kilometre driven ($\Delta gCO_2/km$) at the level of vehicle activity [46].

For autonomous vehicles (AVs), the main impacts relate to increased efficiency through higher vehicle occupancy in shared autonomous vehicles and rebound effects through induced demand for travel. Study system boundaries typically include direct effects (e.g., on driving speed and performance) and indirect effects (e.g., travel cost reduction, new user groups, less congestion) [50].

4) Conditions explaining lower and upper bounds of uncertainty ranges: The main factors explaining both lower and upper bound impact estimates (min-max ranges) include variations in application characteristics, deployment contexts, study methodologies, and study system boundaries.

For teleworking, min-max ranges are explained mainly by variation in system boundaries including time rebound (e.g., non-work travel) and cross-sectoral effects (e.g. energy use in offices or homes). The lower bound is from large reductions in commuting travel (assumed to be in private cars) and some

TABLE III
SUMMARY OF IMPACT ESTIMATES (LOWER – UPPER BOUND RANGES) IN THE TRANSPORT SECTOR.

digital application	impact ranges (ΔA)	impact ranges (ΔI) or (ΔE)	impact ranges (ΔC) or (ΔCR-VRE)
teleworking	ΔA (v.km) -20% to +3.9% [21] ΔA (p.km) -67% to +18% [17]	ΔE -15% to -0.01% [21]	
ride-hailing	ΔA (v.km) +81.5% to +90% [all]	ΔE +41% to +90% [all]	
shared ride-hailing	ΔA (v.km) -55% to -18% [all]		ΔC -62% to -12.6% [all]
MaaS	ΔA (v.km) -50% to +23% [all]	ΔE -50% to +20% [all]	ΔC -50% to +20% [all]
freight logistics optimisation	ΔA (v.km) -29% to -10% [all]	ΔE -95% to +47% [all]	ΔC -14% to +41% [44]
vehicle-grid integration (VGI)			ΔCR-VRE -37.9% to -15.4% [22] ΔC -14.5% to +0.58% [22]
autonomous vehicles (AVs)		ΔE -45% to +60% [50]	ΔC -94% to +48% [all]

Note: ΔA = % change in activity measured either in passenger.kilometres (p.km) or vehicle kilometres (v.km); ΔI = % change in intensity; ΔE = % change in energy use; ΔC = % change in CO_2 or CO_2e; ΔCR-VRE = % change in curtailment rate (CR) of variable renewable energy (VRE) generation
[] denotes the main studies used for the impact estimate ranges

office energy use. The upper bound is from inclusion of non-work travel (leisure, retail) and home energy use and/or increases in commute distances from home re-location (de-urbanisation). The net impact is generally beneficial but overall economy-wide savings are modest in those studies with more comprehensive system boundaries.

For ride-hailing, the lower bound includes mode replacement (fewer bus & taxi journeys). The upper bound includes deadheading ($\approx$ 69% of total vehicle.kilometres).

For shared ride-hailing, the lower bound is from integration of shared modes into urban public transport systems, reducing congestion and displacing private vehicle use. The upper bound is from limited uptake during peak hours, rebound from empty pick up trips increasing vehicle.kilometres, and the 'cannibalisation' of public transport modes as passengers defect to the more flexible shared vehicles. The upper bound is therefore associated with profit-oriented service providers and the lower bound from social planner type system-optimising service provision.

For MaaS, the impact range is explained by differing assumptions about uptake rate, car-shedding propensity, urban transport planning, and vehicle ownership costs. Lower bound estimates assume maximised uptake and modal shares that includes active (cycling, walking) and public modes within integrated transport systems. Upper bound estimates assume lower uptake and lower shares of public modes in less supportive policy frameworks with only partial sharing of mobility services information, and higher car dependence for non-MaaS users.

For freight logistics, the lower bound represents rapid systemic advances including automation, as well as stringent policies to decarbonise freight. Some studies include fleet renewal with electrification. Upper bound estimates assume current policies, moderate improvement of logistics and vehicle efficiency, low uptake of low-carbon transport technologies.

For VGI, ranges are estimated using varying assumptions about power grid conditions, the extent to which ancillary services are provided by electric vehicles (EVs), and the controlled proportion of EV charging loads. Lower bound estimates assume power systems with limited diversity of VRE supply and conventional grid flexibility (so more potential for VGI to reduce curtailment). Upper bound estimates assume VRE diversity and enhanced grid flexibility. Potential rebound effects due to lower net operating costs of EVs are not considered.

For AVs, impact estimates vary widely based on scenario assumptions with lower bounds given by optimised AV system designs for speed control and congestion reduction, and upper bounds if lower money and time costs of travel induce travel demand.

B. Impact Estimates from Use Cases of Digital Applications in the Consumer Goods Sector

1) Selected digital applications: Table IV summarises digital applications related to consumer goods with high potential impact based on [3], [6], [16], [17], [18] (see Methods). Two of these impact ownership and use of physical goods or products: exchanging or trading via digital platforms; and accessing services ('usership') displacing ownership. A third application, e-retail, impacts shopping behaviour and related travel.

TABLE IV
DIGITAL APPLICATIONS IN THE CONSUMER GOODS SECTOR.

digital application	definition
P2P trading (goods)	peer-to-peer exchange of privately-owned goods through networks of individuals using a digital platform to create closed loop supply chains
usership	access to services (instead of owning goods) enabled by functional convergence onto multi-purpose digital devices. Also 'e-materialisation'
e-retail	online shopping for products or goods delivered to homes

2) Studies reviewed with quantitative impact estimates: Table V summarises the studies from which quantitative estimates were extracted for the evidence synthesis, and the main study design issues arising per digital application. The evidence base extends beyond the Global North to include East Asia and South America. Recent meta-analysis provide useful impact ranges for some applications.

Digital platforms facilitate P2P trading or exchange of goods and product-service system (PSS) business models [55], [56] that can extend the lifetime of goods and reduce waste [57].

On-demand services enabled by digitalisation are part of a general shift from owning to accessing (or 'usership'). This also includes substitution of physical products (books, newspapers, DVDs) for digital alternatives on purchase or subscription models ('e-materialisation') [58]. Multi-functional digital devices can displace single-purpose appliances [59], [60]. Simulation studies estimate resulting changes in materials and embodied energy [61].

For e-retail, Rai, Touami [62] conducted a systematic quantitative review of impact assessments from 21 studies comparing online and in-store purchase of various product types. Most reviewed studies omitted changes in consumer behaviour and variation due to newer business models (i.e., click-and-collect, cross-border e-commerce, or quick commerce). This is an important omission as the online value share of fast-moving consumer goods is expected to rise to around 15% in China, 12% in UK, and 8% in the US by 2025 [63].

TABLE V
STUDIES PER DIGITAL APPLICATION IN THE CONSUMER GOODS SECTOR WITH QUANTITATIVE IMPACT ESTIMATES.

digital application	**n studies**	**main study design**[1]	**geography**	**refs**[*†]
P2P trading (goods)	n=5 inc. 1 meta-analysis (n=21)	empirical	mainly Global North, China, Japan, Latin America	[57], [64], [55], [65], [56]
usership	n=3 inc. 1 review	empirical, simulation	global (11 regions)	[17], [58], [61]
e-retail	n=4 inc. 1 systematic review (n=21)	simulation	mainly Europe, US, China	[62][*†], [66], [67], [68]

[1]empirical = based on observations, trials, real-world applications; simulation = based on modelling, scenario assumptions
[*]denotes review or synthesis studies
[†]denotes the main studies used in the evidence synthesis

3) Quantitative impacts: uncertainty ranges: Table VI summarises the maximum uncertainty range per digital application from lower to upper bound of all impact estimates found in the studies reviewed. Digitalisation impacts are expressed as percent changes in activity, energy or emission metrics.

For P2P trading of consumer goods, the main impact is the substitution of new goods production by sharing or renting existing goods. Some studies also consider goods transport by mode and distance [56]. For example, the range of impacts for clothing-related applications represents variation across garment type, material, and function [69]. Most studies estimate lifecycle GHG emissions. Koide, Murakami [64] systematically review consumer-oriented product-service systems by application (e.g., clothes, books, media, tools) including renting and sharing strategies (which also include mobility-related applications). Fremstad [57] estimates changes in solid waste generation as an outcome activity metric.

Usership impacts activity levels (numbers of devices) and both operational and embodied energy of consumer good bundles. E-materialisation studies report wide ranges depending on adoption context and deployment conditions (e.g., emission intensity of electricity) [17]. One simulation study estimates energy impacts using optimistic assumptions of functional convergence as digital devices displace large numbers of single-purpose appliances [61]. However, the omission of potential induced demand effects means energy savings are overestimated [58].

For e-retail, the main impact is from substituting personal shopping trips with last-mile delivery to homes. Most studies estimate impacts on carbon footprint (kgCO_2e) per purchase. (A single purchase can consist of multiple items both online and in-store). To provide context and scale: (1) the average US consumer makes >300 in-store shopping trips per year; (2) UK online shopping accounts for 27.6% of retail sales [70]; (3) online shopping in China accounts for 13.7 MtCO_2e in 2018 [66].

TABLE VI
SUMMARY OF IMPACT ESTIMATES (LOWER – UPPER BOUND RANGES) IN THE CONSUMER GOODS SECTOR.

digital application	**impact ranges (ΔA)**	**impact ranges (ΔI) or (ΔE)**	**impact ranges (ΔC)**
P2P trading (goods)	ΔA (kg waste) -0.4% to +13% [57]		ΔC -89% to +55% [all]
usership	ΔA (kg/cap) -65% to +3% [61]	ΔE -50% to -12% [61] ΔE -90% to +100% [17]	ΔC -100% to +100% [17]
e-retail			ΔC -94% to +140% [62]

Note: ΔA = % change in activity; ΔI = % change in intensity; ΔE = % change in energy use; ΔC = % change in CO_2 or CO_2e
[] denotes main studies used for ranges

4) Conditions explaining lower and upper bounds of uncertainty ranges: For P2P trading of goods, impact estimate ranges reflect heterogeneous characteristics of users and goods and the extent to which renting or sharing displaces new purchases. The lower bound assumes full displacement with low rebound, long lifetime goods, and efficient transport of exchanged goods. In contrast, the upper bound assumes smaller rental shares, rebound, and energy required for maintenance and repair. Meta-analysis demonstrates the importance of including rebound effects within study design system boundaries [64].

For usership, ranges represent geographic differences between income and population in the Global North and South, and scenario assumptions. In particular, the lower bound estimates make more detailed assumptions on functional convergence [61].

For e-retail, lower bound estimates are associated with large reductions in personal car trips for shopping replaced by an efficiently consolidated distribution network for e-retail goods. Upper bound estimates are from additional consumer car trips for shopping (e.g., store browsing prior to online purchase, fragmented purchase, or purchase returns).

C. Impact Estimates from Statistical Models of Digitalisation in the Industry Sector

In the introduction, we noted statistical modelling as an alternative approach to estimating digitalisation's indirect impacts on energy. Rather than comparing digitalisation use cases to a 'without-digitalisation' reference case to estimate percent changes, statistical models fitted to panel data (countries or industries over time) estimate the marginal effect of ICT penetration over time on energy demand or greenhouse gas emissions [10], [71]. This approach aggregates across all digital applications so does not identify specific causal mechanisms or deployment contexts. As a result, impact estimates tend to be smaller in magnitude and range.

As digitalisation is not the main effect on energy or emissions, model results are sensitive to the non-ICT variables included as controls for explaining energy and emission trends. For country level studies, examples include economic structure, trade, R&D, urbanisation, and demographics [12].

Statistical modelling is common for both country-level analysis and industry sector analysis or specific subsectors like manufacturing. We summarise our review of this evidence here.

1) Selected digital applications in industry and manufacturing: The fourth industrial revolution concept (Industry 4.0) emphasises the integration of digital applications including AI (artificial intelligence) and IoT (internet of things) into manufacturing and industrial processes [72]. This enables energy savings through: (i) intelligent data-driven process control, optimisation, and automation including IoT and digital twins; (ii) substitution of resource-intensive manufacturing (including through additive manufacturing); (iii) flexible or responsive demand to support low-carbon electricity networks (industrial demand response).

Here we focus on the cluster of digital applications designed to improve industrial process efficiency and save energy including through automation and monitoring (IoT).

2) Studies reviewed with quantitative impact estimates: Table VII summarises the main characteristics of studies reviewed that model observed relationships between ICT penetration in industry or manufacturing sectors and resulting impacts on energy. Different variables for digitalisation are used including ICT capital and robot density, but also patent intensity, hardware, software, or composite digitalisation indexes depending on data availability.

As with economy-wide models, how models are specified influences results. Most models control for variables that affect industrial output, such as gross value added, number of employees, and foreign direct investment. A few studies consider mediators explaining the digital-energy relationship and/or moderators of relationship strength.

TABLE VII
STUDIES REVIEWED PER DIGITAL APPLICATION IN THE INDUSTRIAL SECTOR.

digital application	n studies	main study design[1]	geography	refs
process efficiency, IoT and automation	n=10	empirical	OECD, Europe, China, other major economies	[73], [74], [72], [71], [75], [76], [77], [78], [79], [80]

[1] empirical = based on observations, trials, real-world applications; simulation = based on modelling, scenario assumptions

3) Quantitative impacts: uncertainty ranges: Most studies report digitalisation impacts in terms of energy intensity (ΔI, energy required per unit of gross value added) or energy consumption (ΔE). Some studies report impacts on carbon intensity (ΔCI, carbon emissions per unit output) or GHG emissions (ΔC).

Unlike with evidence from use-case studies, statistical models using panel data report percent change estimates as changes associated with a +1% increase in digitalisation (measured by ICT penetration). This is equivalent to the elasticity of energy use with respect to ICT use. Elasticities are an indicator of responsiveness measured as the percent change in an outcome variable for a 1% change in an explanatory variable. Relationships with elasticities of magnitude <1 are considered inelastic (relatively unresponsive to change).

We denote this interpretation of the impact estimates by using a subscript e such that Δ_eE denotes a % change in energy use associated with a 1% increase in digitalisation. This is distinct from the use-case based impact estimates E which denotes a % change in energy use relative to a without-digitalisation reference case.

The full uncertainty ranges from the literature reviewed on industry sector digitalisation are:

- Δ_eI = -0.56% to +0.08%
- Δ_eE = -0.58% to +0.04%
- Δ_eCI = -0.70% to -0.28%

These elasticities are all less than one, but generally negative: i.e., digital applications in industry and manufacturing lead to net energy-savings in absolute terms or through intensity improvements (either in energy or carbon). However, two studies find increases in ICT capital (as a measure of digitalisation) does not automatically translate into improved energy intensity unless it is actively managed [73], [74].

One advantage of the panel data models used in this type of evidence synthesis is that their system boundaries are drawn widely over whole industrial or manufacturing sectors over time and so capture different indirect impact mechanisms. However, studies that report impacts in relative terms of energy or carbon intensity per unit output do not capture induced demand or growth in output ('scale effects') resulting from efficiency gains.

IV. Discussion: Evidence Synthesis from Use Cases in Transport and Consumer Goods sectors

The impact estimates expressed as elasticities in the industrial sector are not directly comparable with the use-case evidence expressed as percent changes relative to a without-digitalisation reference case in the transport and consumer goods sectors. Here we focus our discussion on the use-case data.

A. Availability & generalisability of evidence:

Overall we find there is sufficient evidence available for quantitatively assessing the indirect impacts of digitalisation on energy across many different types of application and context (Figure 1). For all digital applications we find quantitative impact estimates are available from multiple studies, and in some cases systematic reviews, meta-analysis, or other syntheses.

Although studies are more common in Europe and North America, there is a good number of studies from China and other Asian countries, as well as some studies from typically underrepresented regions in global evidence syntheses of this type such as the Middle East.

B. Opportunities & mechanisms that save energy:

Some digital applications show significant potential benefits for energy or emission reductions (e.g., teleworking reductions down to -15%; shared ridehailing to -55%; MaaS to -50%; P2P trading of goods to -89%; e-retail to -94%); see also Figure 1.

These energy-saving potentials per application are achieved by specific mechanisms through which digitalisation affects energy use. These include substitution effects (e.g., shared mobility for private mobility), efficiency improvements and optimisation (e.g., freight logistics) and system integration (e.g., VGI).

C. Risks & mechanisms that increase energy:

Some digital applications show significant potential to undermine efforts to reduce energy or emissions unless carefully managed (e.g., ride-hailing increases up to +94%; autonomous vehicles to +60%; P2P trading of goods to +55%; e-retail to +140%); see also Figure 1.

These energy-increasing potentials per application are also explained by specific mechanisms through which digitalisation affects energy use. These include perverse substitution effects through which a more energy-intensive activity displaces a less energy-intensive activity (e.g., shared mobility substituting for cycling or walking), rebound effects (e.g., AVs), and induced demand effects (e.g., teleworking, P2P trading of goods).

D. Relative vs absolute impacts on energy:

The impact estimates are expressed in relative terms (percent changes) and can be easily compared. How they translate into absolute impacts on energy (GJ) or emissions (tCO2) depends on the scope and footprint of the activities to which they apply (e.g., commuting travel for teleworking, urban travel for ridehailing, or electric vehicle use for VGI). Consequently some large percent changes may be relatively inconsequential for total energy use (e.g., dematerialisation).

Large positive or negative impacts in relative terms are also diluted when scaling from best or worse cases to aggregate effects across whole sectors. This is clearly shown by comparing the use-case based ranges in Figure 1 with the much smaller whole sector elasticities for the industry sector. Although these measure a different type of effect size, comparing the effect of 1% ICT penetration with an order of magnitude higher 10% ICT penetration would still only be associated with an impact estimate range less than -10%.

E. System boundaries & rebound effects:

How studies of digitalisation impacts define system boundaries is an important determinant of estimate ranges. In general, studies with more comprehensive system boundaries tend to have smaller lower bound impact estimates; the more impact mechanisms included, the lower the net energy-savings. In particular, studies that explicitly include induced demand and rebound effects report offsetting increases in activity or energy that reduce net energy-saving benefits. This is emphasised statistically by a meta-analysis of impact estimates in the consumer goods sector [64].

Induced demand and rebound effects are included within study designs for most but not all of the digital applications reviewed. These include teleworking (less commuting travel resulting in more leisure and retail travel), ridehailing (cheaper, quicker, more convenient private taxis resulting in more taxi travel), and P2P trading (wider choice of cheaper goods resulting in more goods purchased).

Study system boundaries that exclude induced demand and rebound effects may either have trivial or significant consequences on impact ranges. For some digital applications, the cost, time, or convenience benefits of digitalisation are small relative to other usage attributes. These applications include MaaS (easier multi-modal travel journeys), VGI (additional value stream for EV owners from offering ancillary services to the grid), and freight logistics optimisation (reduction in fuel costs). However, for other applications, digitalisation significantly increases the appeal of an activity resulting in large effects on demand that bias impact estimates downwards if omitted. These applications include e-retail (easier, quicker, more impulsive consumption), and usership (proliferation of digital devices).

For many digital applications, indirect impacts on transport activity for people, goods, or materials are important but can sometimes fall outside study system boundaries. Although these tend to be induced demand effects for more transport activity (e.g., teleworking impact on leisure travel, e-retail impact on freight activity), they can also be substitution effects resulting in less transport activity (e.g., MaaS or shared ridehailing reducing vehicle.kilometres travelled in single occupancy cars).

F. Impact uncertainty & deployment conditions:

Overall, for the impacts of digital applications in transport and consumer goods sectors we find strong evidence of both large reductions in energy use (e.g., shared ridehailing: -55% to -18%) and large increases in energy use (e.g., ridehailing: +41 to +90%). These two examples are for digital applications with consistently negative or consistently positive impacts on energy use.

However, for most applications, we find evidence of impacts spanning both negative and positive impacts depending on application characteristics and deployment conditions (e.g., mobility-as-a-service, MaaS: -50% to +20%). Consequently, we find that impact estimates tend to vary widely, with larger ranges for digital applications that vary across subsectors, contexts, user types, or geographies. This contextual variation encompasses differences in business models (e.g., P2P trading), physical infrastructure (e.g., VGI), urban setting (e.g., MaaS, shared ridehailing), location (e.g., teleworking), and user behaviour (e.g., e-retail).

Although this makes it hard to generalise how any given digital application will impact energy use, there are some common features of the lower and upper bounds to impact ranges.

First, lower bound estimates tend to be associated with optimistic or best-case deployment conditions. These are most common in modelling simulations of digital applications with limited real-world deployment data (e.g., VGI, MaaS, shared ridehailing). Best-case conditions take the perspective of a social planner by optimising how an integrated system functions. In contrast, upper bound estimates tend to be associated with fragmented or competitive service provision and privately-oriented business models resulting in externalities like congestion.

Second, lower bound estimates also tend to assume or estimate no or small rebound; upper bound estimates include larger rebound.

Third, lower bound estimates may leverage larger energy or emission savings by aligning digitalisation with other decarbonisation or efficiency strategies (e.g., vehicle electrification). This recognises that energy-saving potentials from digitalisation are not transformative in isolation. Upper bound estimates do not exploit these synergies.

This provides simple prescriptions for achieving net energy-savings across widely different digital applications and deployment contexts: (1) limit potential rebound through pricing or other constraints on activity increases; (2) incentivise and design business models that maximise overall service efficiency; (3) integrate activities enabled by digital applications into wider systems of provision (e.g., for mobility); (4) align digitalisation with climate mitigation strategies.

G. Impact uncertainty & methodological variation:

Study design and methodological approaches for assessing digitalisation impacts also affect estimate uncertainty. In general, empirical studies based on observational data from real-world deployment report narrower ranges than simulation studies using scenario-type assumptions about future deployment that are designed to explore a wider hypothetical possibility space.

Choice of impact metric also affects uncertainty ranges. In general, activity metrics have wider impact ranges than those using energy or emission metrics. Activity is a precursor to energy use which in turn is a precursor to emissions, so the three metrics are generally consistent in direction and magnitude. However, in some cases, confounding effects break this consistency, for example, when digital transport applications are also associated with vehicle electrification which results in smaller changes in activity leading to larger changes in energy or emissions due to fuel substitution rather than digitalisation per se. If changes in activity or energy use involve electricity as an energy carrier, then the emission intensity of electricity is another important confounding factor for emission metrics.

For digital applications that interact with the energy supply (e.g., electric vehicle-grid integration, VGI), impacts are expressed indirectly through changes in the penetration or curtailment of intermittent renewable energy generation. While an important enabling effect of digitalisation on the energy supply sector, this makes the impact estimates harder to compare.

V. Conclusions

Overall, our evidence synthesis of the indirect impacts of digitalisation in transport, consumer goods, and industrial applications shows clear potentials to reduce energy demand, but with specific and identifiable risks of induced demand and rebound in some cases. The conditions we identify that explain the lower and upper bounds of the impact ranges help informed deployment and policy to ensure digitalisation contributes to net-zero goals.

Although observed impacts of discrete applications can be large (both negative and positive) when expressed in relative terms, scaling from best or worse case conditions per application to aggregate effects across whole sectors means absolute impacts are much smaller. As a result, the energy-saving potential of digitalisation is not transformative in isolation, but needs to exploit synergies with other decarbonisation processes.

An important next step is to extend the evidence synthesis to use cases from high-impact digital applications in the buildings sector (e.g., smart heating and cooling, energy management systems, demand response) and in industry (e.g., digital twins, robotics and automation, additive manufacturing) [6].

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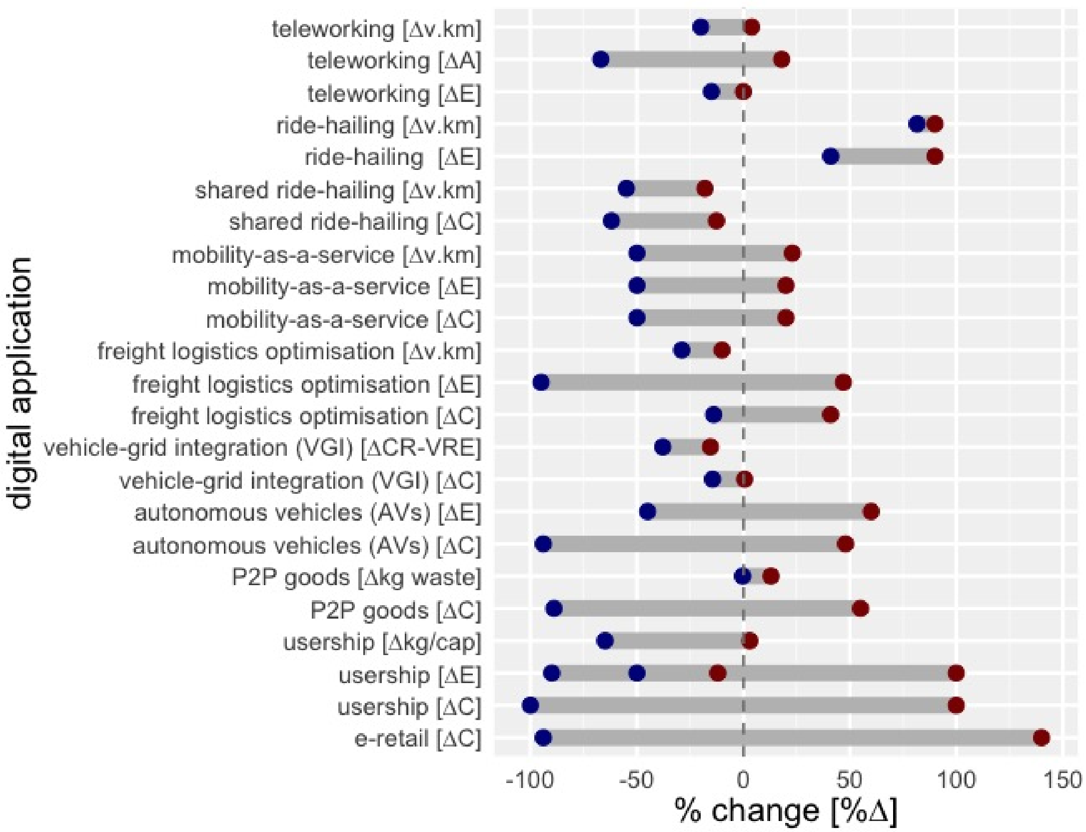

Fig. 1. Summary of estimates of indirect impacts of digital applications in transport and consumer goods sectors on activity, energy, or emission outcomes.

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