## Title

Digitalisation and AI impacts on energy transitions and climate targets

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## Author Contributions

CW designed and led the study, and wrote the manuscript; CW, YVF led the empirical analysis; VK, FM led the modelling and its interpretation; AM, AJ, BZ, KR contributed to the modelling and its interpretation; YVF, FM, CW, VK designed the figures; KR, RP shaped the manuscript narrative and arguments; all authors commented on and edited the manuscript.

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## Abstract

Digitalisation is a double-edged sword for energy transitions and climate change mitigation. Digital applications can improve the energy efficiency of processes and systems, but can also induce demand for energy-hungry activity. Digital infrastructure like data centres also has a large energy footprint. AI is amplifying and accelerating these impacts, both for better and for worse. How does this affect the feasibility of long-term climate targets?

We use a global integrated modelling framework to quantify scenarios to 2050 describing alignment or misalignment between digitalisation and climate goals. We combine empirical estimates of the energy impacts of digital and AI applications in buildings, transport, and industry sectors with digitalisation's role in the integration of renewables, storage, and demand flexibility in electricity systems.

We show digitalisation uncertainties for future energy demand and $CO_2$ emissions are large - similar in magnitude to the effect of all global demographic, economic, and technological uncertainties quantified in future climate pathways. We also show that available near-term assessments of AI impacts within this uncertainty space are optimism biased.
Energy transition and emission risks from digital and AI applications in transport and buildings are a factor five higher than from data centres and other infrastructure. Climate policy is the most effective driver of emission reductions to meet Paris targets but climate-aligned digitalisation reduces energy investment needs by a factor of two down to $35 trillion and brings the global net-zero year forward to as early as 2047. Conversely, climate-misaligned digitalisation drives up energy demand and sees lost opportunities to build a reliable and renewable future electricity system. Resulting increases in near-term cumulative $CO_2$ emissions mean the probability of limiting warming to 2°C almost falls below the 'likely' threshold, increasing risk of temperature overshoot.

Digital transformation can undermine or enable the feasibility and affordability of long-term climate targets delivered by decarbonised energy systems. Entwining digital and low-carbon energy transitions requires strategic governance and institutional innovation to link climate and digital concerns.

## Main

Digitalisation is a double-edged sword for energy transitions and climate change mitigation. Digital applications, including those enabled by AI, have both energy-increasing and energy-reducing effects. As a general-purpose technology, digitalisation transforms activity across sectors from homes to industries and across scales from discrete processes to whole systems [1,2].

Quantifying the net climate effect of digitalisation is complex. It has been assessed as detrimental [3–5] or beneficial [6–9] depending on what's counted.

Digitalisation impacts on energy and emissions are at three levels: infrastructure (direct), applications (indirect), economic and social processes (systemic) [10–12]. Moving up through these levels, impacts become less clearly bounded and harder to measure with available tools and taxonomies. AI compounds uncertainties by accelerating the diffusion of new applications, amplifying induced demand, and requiring its own specialised infrastructure [13].

We scale evidence at the first two levels into a global modelling framework to quantify impacts to 2050. Although recent concerns are focused on the direct energy footprint of AI data centres, we show that indirect application-level impacts are an order of magnitude higher. (Many digital applications now include some form of AI; for brevity we use 'digital' as an umbrella term).

Impacts at the infrastructure level are from data centres, fixed and wireless networks, and end-use devices. The whole information and communication technology (ICT) sector accounts for 1.4 - 3.8% of global $CO_2$ emissions [14,15]. Data centres alone consume around 1.5% of global electricity [6,16]. This is expanding rapidly after a period in the early 2010s of relatively flat global electricity consumption during which efficiency gains offset exponential growth in computation [17]. Current and near-term projected growth is driven by demand for generative AI model training and inference [18–20].

Digital applications that affect energy-related demand in different economic sectors are ubiquitous and varied.  Examples range from simple thermostat control in buildings and predictive maintenance in manufacturing to the management or optimisation of complex systems in urban infrastructure, transportation, and energy networks [21,22]. Digital applications affect $CO_2$ emissions through changes in energy demand but also by changing the cost or feasibility of energy resource exploitation and system integration. Examples include fossil fuel extraction techniques and renewable electricity forecasting.

The net environmental impact of most digital applications is conditional on their design, deployment context, and user behaviour [23,24]. Digital applications reduce the cost, time, effort, inconvenience, or underutilised capacity of an activity, potentially reducing energy or emissions in the process. However, these savings can rebound into more activity or induce demand for other energy-using or carbon-emitting activities [25,26]. The balance between these different mechanisms determines whether efficiency gains are partially or wholly offset by activity growth. 'Backfire' describes aggregate impacts worsening due to efficiencies - a resource paradox first identified by Jevons in the industrial revolution [27,28]. Quantifying the outcome of these competing but related effects is a focus of this study.

The implications of digital infrastructure and applications on the feasibility of long-term climate targets are poorly understood for three reasons.

First, despite its pervasiveness, digitalisation (including AI) is not represented explicitly in global climate mitigation analysis to 2050 and beyond [11,13]. This includes the quantitative scenario modelling used in IPCC assessments [29] and the shared socio-economic pathways (SSP) framework used to assess global development uncertainties [30–32].

Second, near-term projections of digital application impacts, and the evidence on which they are based, are optimism biased [33]. The International Energy Agency (IEA)'s recent report on 'Energy and AI' found application-level reductions in energy use to 2035 more than compensated for infrastructure-level increases [6]. Other studies have similarly identified large energy-saving potentials for both digital applications in general [7,34,35] and AI applications specifically [36]. All these studies that scale up the energy impact of digital applications select beneficial examples and define system boundaries that include physical-to-digital substitution and optimisation. Rebound effects and induced demand from the selected applications are either omitted [36], ignored [37], or estimated only in general terms [6].

Third, methodologies used to quantify the impacts of digital applications at a global scale take a sectoral perspective, for example, in transport [38], in industry [39], or in energy networks [40,41]. They also provide limited or no spatial resolution. This misses important interactions between digital transformation of the energy system (e.g., renewables integration) and of energy end-use (e.g., demand volumes and flexibility). These interactions vary across world regions in energy systems at different stages of transition.

We use MESSAGEiX, an integrated global systems model, to quantify infrastructure and application-level impacts of digitalisation including AI in four demand sectors (buildings, transport, industry, and ICT) integrated with the energy supply and electricity system (Figure 7). We model impacts on energy and emissions over the long-term to 2050 under both optimistic and pessimistic assumptions (Figure 1).

Our modelling distinguishes the modification of energy demand by general-purpose digital applications across sectors from the co-evolution of digitalisation with electrification and decarbonisation trends in energy systems. We estimate the demand modifiers using best-available evidence (Methods §1 and Figure 6) that we scale globally out to 2050 consistent with detailed scenario storylines that explore a wide uncertainty space (Methods §2 and Table 3). We also derive parameterisations from these storylines to model digitalisation impacts on electricity systems that are either synergistic with, or decoupled from, energy transition dynamics (Methods §3 and detailed modelling assumptions in Tables 5&6 in SI).

Our modelling yields widely divergent outcomes. The effect on $CO_2$ emissions in 2050 solely due to digitalisation (±34% relative to a reference scenario) is as large and uncertain as the effect of fundamentally different global population, economic, and geopolitical development pathways.

If digitalisation does not align with climate action, risks to the feasibility of 2°C targets are high. These risks do not come from data centres and other digital infrastructure whose energy demand growth is manageable over the long-term. Rather, risks arise from the combination of digital efficiencies driving more and more demand on an energy system in which digitalisation serves local needs and private benefits but not wider system goals.

Across different digital futures, climate policy is the most effective driver of $CO_2$ emission reductions, but digitalisation can amplify policy effectiveness. Climate-aligned digitalisation reduces energy investments to 2050 by a factor of two from over $70 trillion down to $35 trillion for the same cumulative emissions budget. Conditions enabling these synergistic outcomes include constraints on efficiency-induced activity growth across all demand sectors (particularly transport), strong innovation and deployment incentives for digital applications that deliver public goods, and widespread trust and user participation. These conditions are not yet evident at a sufficient scale. Indeed the current trajectory of generative AI model applications towards consumption-oriented agentic, retail, and marketing applications is more characteristic of our climate-misaligned scenario in which limiting global warming to 2°C is more costly, risky, and delayed.

Digital transformation is means not end. Entwining digitalisation and climate ambition requires the design of digital and AI applications that are compelling for users without undermining public policy goals, and the synergistic integration of digital capabilities into decarbonising and electrifying energy systems.

## Study design

We design two main scenarios – Enable and Undermine - to explore the uncertainty space for digitalisation impacts on climate targets. We focus on energy transitions and resulting fossil $CO_2$ emissions that account for three quarters of the greenhouse gas burden [42].

We do not consider food and land use implications of digitalisation, nor do we attempt to quantify the systemic impacts of digitalisation including AI on labour markets [43], GDP growth [44], and climate governance institutions [13]. We return to these omissions in the discussion.

In our 'Enable' scenario, widespread deployment of digital applications *enables* faster and cheaper emission reductions by reducing energy demand and accelerating renewables integration. In our 'Undermine' scenario, digital transformation *undermines* emission-reduction efforts through rebound, induced demand, and intensification effects that drive up energy used by digital applications and infrastructure in a system that digitalisation has fragmented and decoupled from climate goals.

We include a reference scenario against which to assess digitalisation impacts. This 'SSP2' pathway broadly represents a continuation of current trends [45] We also use updated energy and emissions data from the full set of SSP1-5 pathways to contextualise our analysis within global development uncertainties [46] (Methods §3a).

The Enable-Undermine scenario taxonomy distinguishes alignment and misalignment between the use of digital applications and climate change mitigation (upper part of Figure 1). By design this is independent of climate policy which we model in each scenario at both current and strengthened levels of climate ambition. Our current policy ('CurPol') scenarios assume existing implemented climate policies, but no new commitments post 2030. For our more stringent climate policy assumptions ('2°C'), we use a carbon budget of 600 $GtCO_2$ with limited overshoot consistent with stabilising long-term warming below 2°C (with a probability of about three-quarters in our reference scenario).

Both Enable and Undermine scenarios are characterised by narrative elements that have three functions (lower part of Figure 1; see also Table 3). A first set of elements influence our selection of empirical evidence on application-level impacts. Examples include sectoral deployment incentives and behavioural norms among application users. A second set of scenario elements explain our assumptions for scaling impacts from the geographies for which we have evidence to 12 world regions and out to 2050. Examples include the scale economies enabled by interoperability, standardisation, and high levels of trust. A third set of scenario elements like innovation investments and data governance provide contextual interpretation of application deployment, use, and global diffusion (Table 3).

Within each scenario we further distinguish Cautious and Extreme variants based on the evidence sourced from empirical literature (Figure 6). Cautious impact estimates are medians from empirical uncertainty ranges and have slower scaling trajectories to 2050. Extreme impact estimates are maxima or minima from empirical uncertainty ranges and scale more rapidly (Methods §2a). The best and worst case Enable-Extreme and Undermine-Extreme storylines are designed to stress test digital-climate uncertainties.

Our Enable-Undermine taxonomy does not imply equal likelihood or robustness across scenarios (Methods §2). It is designed to explore alternative possible digital futures grounded in empirical evidence of application-level impacts and the conditions under which these arise.

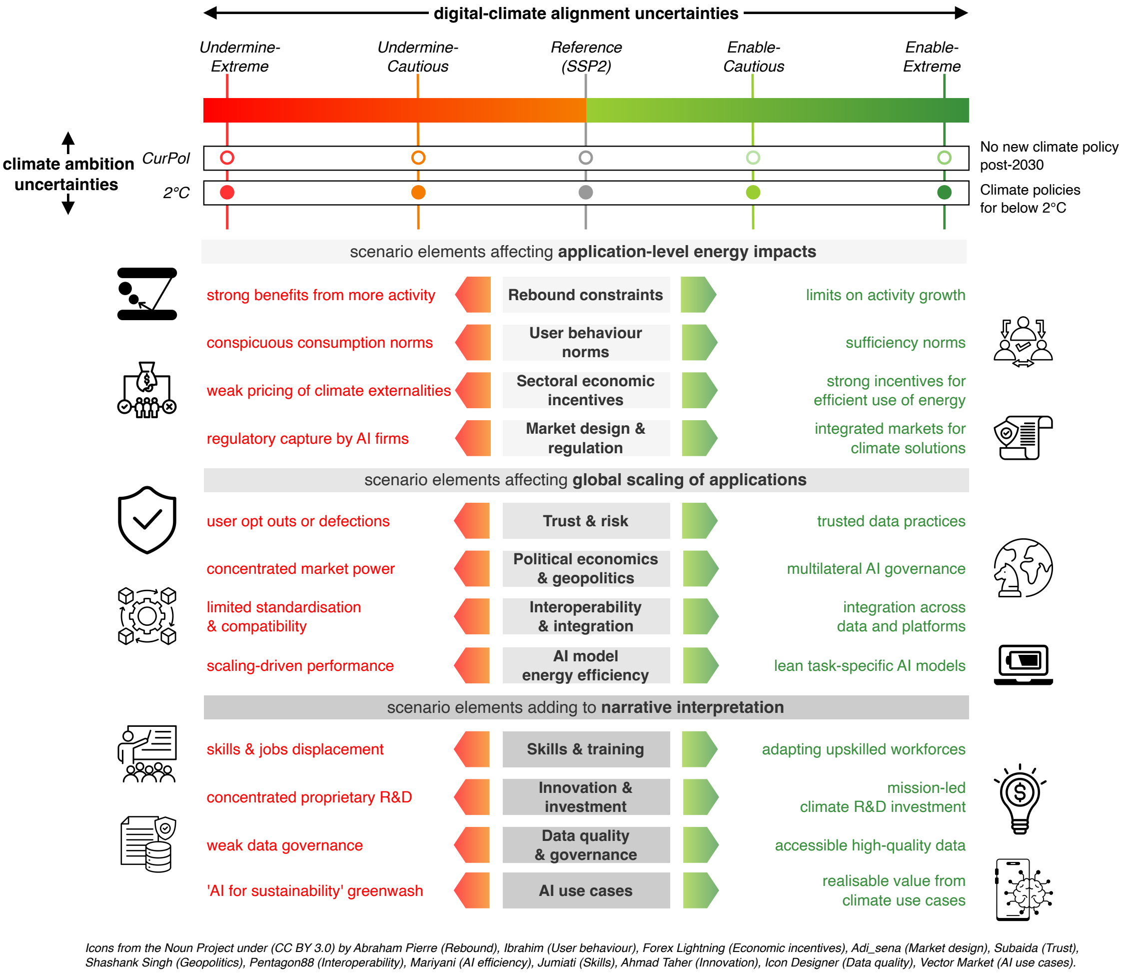



**FIGURE 1. SCENARIOS CHARACTERISING UNCERTAIN DIGITALISATION IMPACTS ON ENERGY AND $CO_2$ EMISSIONS.**

LEGEND: SCENARIO TAXONOMY WITH MAIN NARRATIVE ELEMENTS THAT EXPLAIN SELECTION OF EMPIRICAL EVIDENCE, SCALING ASSUMPTIONS, OR PROVIDE ADDITIONAL NARRATIVE INTERPRETATION. DETAILS OF EACH SCENARIO ELEMENT MAPPED ON TO ALL FOUR DIGITALISATION SCENARIOS ARE PROVIDED IN TABLE 3.

## Digitalisation impacts on energy demand

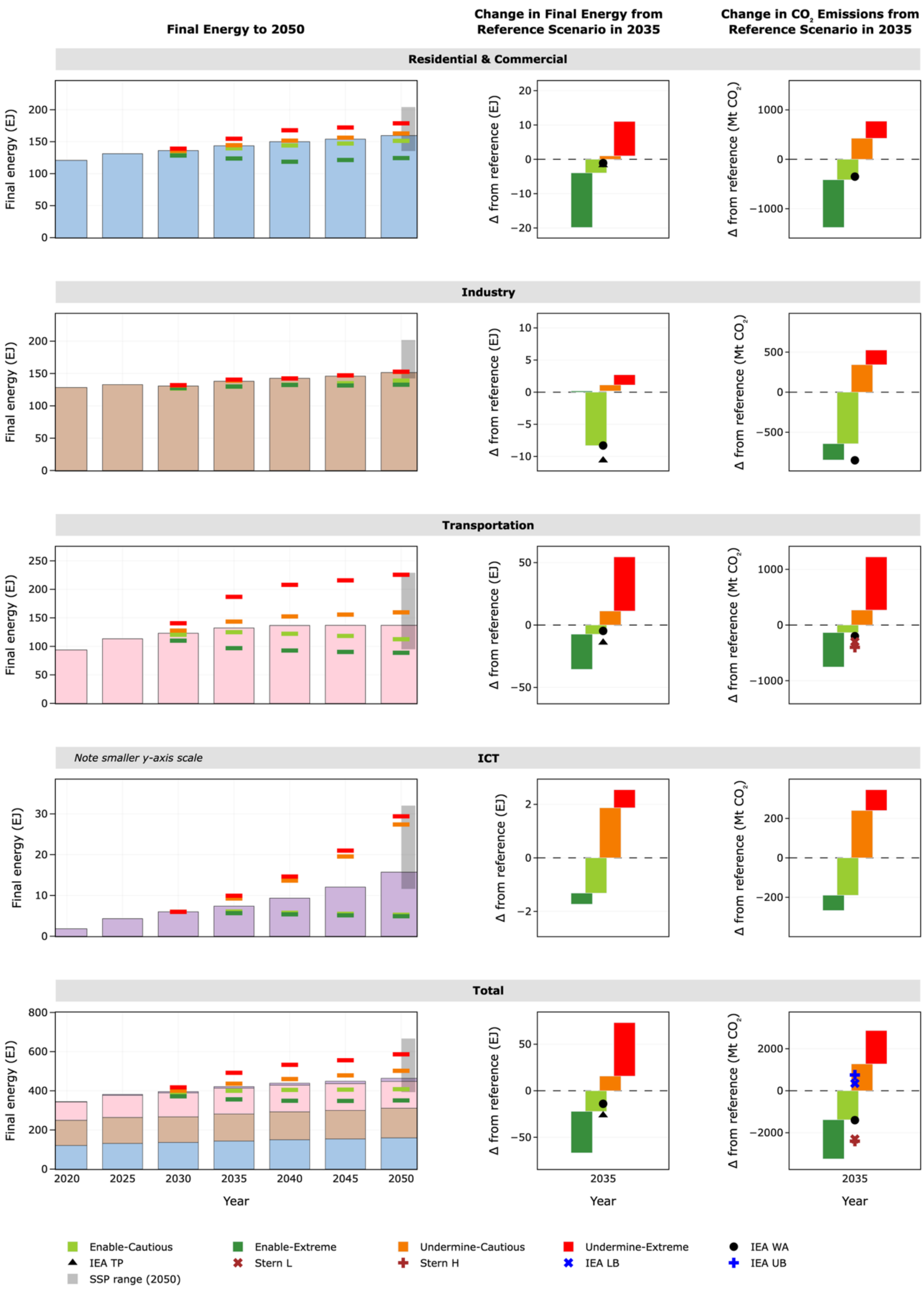
We first show sectoral impacts on energy demand to 2050 under current climate ambition (Figure 2, left column). The largest impacts of digitalisation are in transport, then buildings, with potentials for substantial net energy reductions or increases. Application-level impacts depend on deployment conditions and use under sectoral economic incentives that shape activity levels. As an example, applications in freight logistics can optimise the load factors and routes of delivery vehicles, or facilitate on-demand consumption that drives up vehicle numbers and trips [47]. In buildings, smart energy management technologies improve responsiveness to users' preferences that can orient towards energy savings or energy-hungry comfort-seeking [48]. The result is wide variation in total energy demand to 2050 relative to the reference scenario, with net energy-demand reduction in Enable scenarios (-11% Cautious to -23% Extreme) and net increases in Undermine scenarios (+6% Cautious to +27% Extreme) (Figure 2).

The largest sectoral effect is in passenger transport which can be digitally transformed towards or away from private car dependence through a combination of ride-hailing and mobility-as-a-service platforms, autonomous vehicles, and teleworking [38,49–52]. Synergistic combination in the Enable scenario facilitates multi-modal journeys, and shared and public transport options on high-frequency routes and in cities. In the Undermine scenario, incentives from mobility apps for low-occupancy vehicle use are compounded by induced demand for more passenger-kilometres of travel [53,54]. Relative to the reference scenario, transport energy demand in 2050 goes as low as -20% to -40% (Enable), or as high as +14% to +81% (Undermine). Equivalent ranges for buildings are -5% to -22% (Enable) and +3% to +9% (Undermine) (Figure 2).

The energy impacts of digital and AI applications in energy-intensive industries and manufacturing are net beneficial but of smaller magnitude. This is expected in competitive sectors like aluminium or steel production for which high energy cost inputs are already optimised. We include the impact of digital applications on materials used in building construction and vehicle fleets. These indirectly affect demand for cement, steel, and aluminium but only marginally relative to bulk material flows (Methods §3c). In the empirical literature for the industry sector, we found no application-level studies that assessed rebound or induced demand resulting from efficiency gains. This is an artefact of study designs with system boundaries that exclude these effects; sectoral analyses that do not resolve specific applications clearly show productivity-driven rebound [4,55,56]. In the absence of evidence we capped worst-case energy impacts per application at zero (Figure 6). This is very conservative. Consequently, industrial energy demand in 2050 varied only -8% to -13% (Enable) and +0.2% to +3% (Undermine) relative to the reference scenario.

The ICT sector itself accounts for only a small share of future energy demand. Across all scenarios under current climate ambition, we project ICT infrastructure (data centres and networks) to account for 5-35 EJ (1,400-9,700 TWh) of electricity demand in 2050. This is equivalent to 4-20% of total final energy in the buildings sector within which ICT is accounted for in energy statistics. This gives important macro perspective to current concerns over data centre energy footprints. Over the long-term, we find ICT sector energy needs globally are much smaller in magnitude than the indirect impacts of digital applications on energy-using activity even under cautious assumptions (Figure 2, left column). However, the future evolution of ICT infrastructure for AI is highly uncertain [57]. Our projections are strongly dependent on the methodology used (Methods §2e). (We model ICT end-use devices separately from infrastructure as a category of appliances within the buildings sector; see Figure 6).

Our long-term modelling demonstrates the optimism bias of near-term global impact assessments of AI. Figure 2 (middle and right columns) shows that sectoral energy and emission-*reducing* impact estimates to 2035 by IEA [6] and Stern et al. [36] fall within the range of our Enable-Cautious assumptions and Enable-Extreme assumptions respectively when compared on a like-for-like basis. Only the IEA project potential emission-*increasing* impacts, but on aggregate for the economy as a whole (Figure 2, blue data points in bottom right panel). These estimates are substantially more conservative than our Undermine-Cautious scenario set up that is designed to explore sectoral rebound and induced demand effects. The IEA do not disaggregate energy-increasing impacts by sector so it is not clear where induced demand originates nor how it interacts with digitalisation in the energy system to generate the emission outcome they report.



Final Energy to 2050
Change in Final Energy from Reference Scenario in 2035
Change in $CO_2$ Emissions from Reference Scenario in 2035
Residential & Commercial
Industry
Transportation
Note smaller y-axis scale
ICT
Total
Final energy (EJ)
Δ from reference (EJ)
Δ from reference (Mt $CO_2$)
Year
Enable-Cautious
Enable-Extreme
Undermine-Cautious
Undermine-Extreme
IEA WA
IEA TP
Stern L
Stern H
IEA LB
IEA UB
SSP range (2050)

**FIGURE 2. DIGITALISATION IMPACTS ON SECTORAL ENERGY DEMAND TO 2050, AND RELATIVE TO REFERENCE SCENARIO ENERGY AND $CO_2$ EMISSIONS IN 2035.**

LEGEND: LEFT COLUMN SHOWS SECTORAL AND TOTAL FINAL ENERGY TO 2050 GLOBALLY IN FOUR DIGITALISATION SCENARIOS AND A REFERENCE SSP2 SCENARIO UNDER CURRENT CLIMATE AMBITION (CURPOL). SOLID COLOURED BARS SHOW REFERENCE SCENARIO. HORIZONTAL LINE MARKERS SHOW DIGITALISATION SCENARIOS. VERTICAL GREY BAR IN 2050 SHOWS FULL SSP1-5 RANGE FOR COMPARISON. MIDDLE AND RIGHT COLUMNS SHOW DIFFERENCES FROM REFERENCE SCENARIO IN 2035, FOR COMPARISON WITH ESTIMATES FROM IEA [6] AND STERN ET AL. [36] SHOWN AS DATA POINTS. MIDDLE COLUMN SHOWS DIFFERENCES (Δ) IN FINAL ENERGY. RIGHT COLUMN SHOWS DIFFERENCES IN $CO_2$ EMISSIONS BECAUSE THIS IS THE ONLY METRIC FOR WHICH IEA ESTIMATE INDUCED DEMAND EFFECTS SHOWN AS BLUE MARKERS IN BOTTOM RIGHT PLOT FOR UPPER AND LOWER BOUND (UB, LB) ESTIMATES. IEA DATA POINTS FOR SECTORAL FINAL ENERGY SHOWN AS BLACK MARKERS ARE BASED ON TECHNICAL POTENTIAL (TP) AND WIDESPREAD ADOPTION (WA) OF AI USE CASES. STERN ET AL. ENERGY-RELATED DATA POINTS SHOWN IN DARK RED MARKERS ARE FROM LOW (L) AND HIGH (H) END OF RANGES. ALL IEA AND STERN ET AL. DATA POINTS ARE COMPARED ON A LIKE-FOR-LIKE BASIS ADJUSTING FOR DIFFERENCES IN METHODOLOGIES. FOR EXAMPLE, STERN ET AL. ALSO ESTIMATE IMPACT OF ACCELERATED INNOVATION DISCOVERY FOR ALTERNATIVE FOOD PROTEINS THAT SUBSTITUTE EMISSIONS-INTENSIVE MEAT; THIS IS NOT EXCLUDED. BOTH IEA AND STERN ET AL. REPORT DIFFERENCES IN 2035 RELATIVE TO THEIR OWN REFERENCE SCENARIO.

## Digitalisation impacts on energy systems

Digital applications' general-purpose impacts on sectoral energy demand interact with electrification and the coordination of resources on power networks. If deployed for system benefits, digitalisation enables the integration of intermittent generation [58,59], storage [60], and more flexible demand including from smart electric vehicle (EV) charging [61–64]. This improves network reliability [65] and enables higher variable renewable energy (VRE) shares with reduced curtailment [66,67].

Our modelling of the Enable scenario shows this co-evolutionary dynamic in which digitalisation becomes the operational backbone of a decarbonising electricity system [68] (Methods §3d). VRE penetrates faster and less storage is required in a more flexible system to firm up VRE output. Figure 3 shows storage needs increase with VRE penetration, but at much lower levels in the Enable scenario. For a 70% VRE system, for example, the storage share of total power capacity in Enable-Extreme is reduced by a factor of two from around 10% in the reference scenario to less than 5%. By 2050, total global storage capacity is reduced by a factor of three to as low as 2 TW in Enable-Extreme from 6 TW in the reference scenario. These results are with strengthened climate ambition that incentivises higher VRE shares. In SI we provide results on energy-system impacts under both current and strengthened climate ambition for the Enable scenario. These impacts include lower storage needs (Figure 8 in SI), faster electrification of energy end-use (Figure 9 in SI), faster VRE penetration (Figure 10 in SI), and a higher share of distributed (rooftop) solar (Figure 11 in SI). More VRE and less electricity storage in Enable scenarios contribute to substantially lower energy transition costs (Figure 5). We discuss this further below.

In the Undermine scenario, incentives faced by firms and households do not align with electricity system operators concerned with decarbonisation (Table 3). Digitalisation creates fragmented energy assets and data resources that are used for local optimisation at the building or vehicle level but to the detriment of system integration [69,70]. Data sovereignty and privacy concerns result in users opting out of contributing to system flexibility. Rather than co-evolving with a decarbonising electricity system, digitalisation decouples from it.

VRE shares of the electricity mix still increase in the Undermine scenario under strengthened climate ambition, but with much larger requirements for firm capacity (Figure 3) that drive up investment costs (Figure 5). End-use electrification and rooftop solar deployment are slower than under reference assumptions as value cannot be captured from demand flexibility, despite VRE output being higher overall to meet the additional demand induced by digital applications (Figures 9-11 in SI). Data centres with large inflexible loads can further cause congestion and VRE curtailment on electricity networks, but our global modelling does not resolve these localised effects [71,72].

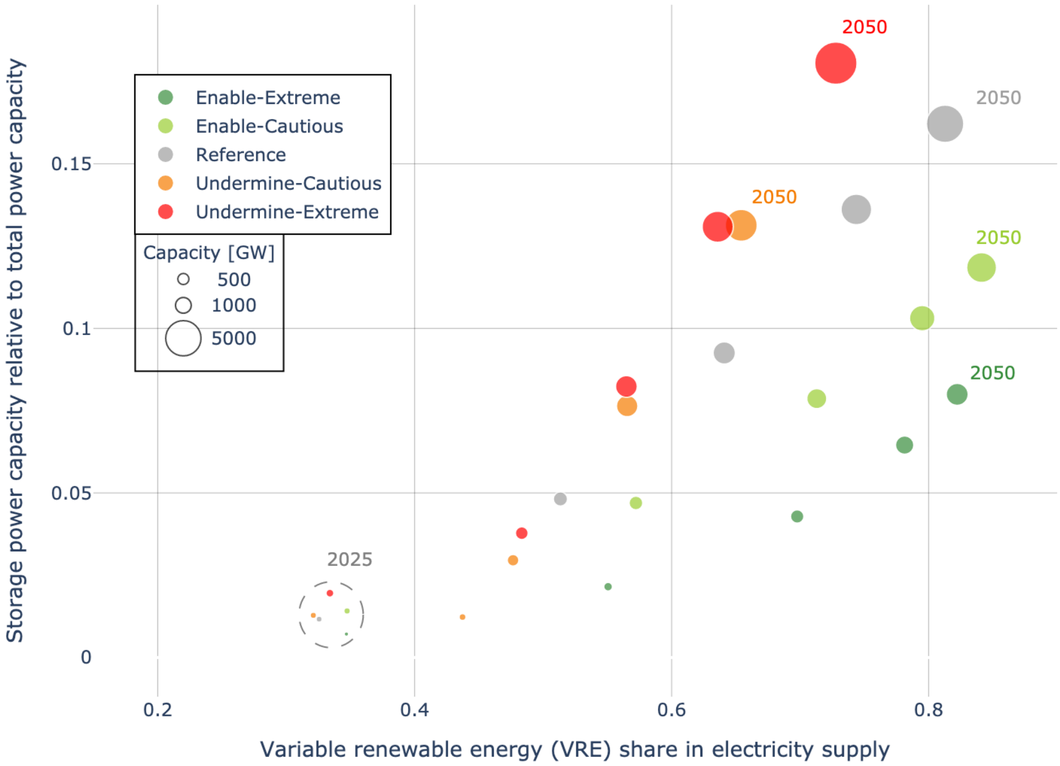



**FIGURE 3. RENEWABLES AND STORAGE IN A DIGITALISED ELECTRICITY SYSTEM UNDER STRENGTHENED CLIMATE AMBITION.**

LEGEND: VARIABLE RENEWABLE ENERGY (VRE) SHARE OF TOTAL ELECTRICITY GENERATION (X-AXIS) VS STORAGE SHARE OF TOTAL ELECTRICITY GENERATION CAPACITY (Y-AXIS) AND TOTAL STORAGE CAPACITY (BUBBLE SIZE) GLOBALLY IN FOUR DIGITALISATION SCENARIOS AND A REFERENCE SSP2 SCENARIO. VRE INCLUDES WIND, SOLAR, HYDRO BUT EXCLUDES BIOMASS. DATA POINTS FOR EACH SCENARIO ARE 5 YEAR TIME STEPS FROM 2025-2050. TO CLARIFY THE VRE-STORAGE RELATIONSHIP, SCENARIOS INCLUDE STRENGTHENED CLIMATE AMBITION (2°C); SCENARIOS WITH CURRENT CLIMATE AMBITION (CURPOL) ARE SHOWN IN FIGURE 8 IN SI. VERSIONS OF THE FIGURE WITH ABSOLUTE STORAGE QUANTITIES (GW) ON THE Y-AXIS ARE ALSO SHOWN IN FIGURE 8 IN SI.

## $CO_2$ emissions under current and strengthened climate ambition

Digitalisation uncertainties have major implications for climate change mitigation at current levels of climate ambition. Strong divergence between emission pathways is already seen by 2035, emphasising the long-term path dependence of near-term impacts. Under Cautious assumptions, global $CO_2$ emissions in 2050 are -21% to +20% relative to the reference scenario, widening to -32% to +35% under Extreme assumptions (Figure 4, solid lines and hatched areas). Figure 14 in SI decomposes the differences between Enable and Undermine scenarios. The largest effect is attributable to digitally-induced changes in land-based transport modes.

Under strengthened climate ambition, more stringent climate policy drives $CO_2$ emissions down towards zero (Figure 4, dotted lines and solid shaded area). However, relative differences between scenarios due to digitalisation uncertainties remain large (-35% to +55% relative to the reference scenario in 2050). Our worst-case digitalisation scenario with strengthened climate policies results in lower $CO_2$ emissions in 2050 than our best-case digitalisation scenario with current climate policies.

These global outcomes mask regional differences. Figure 4 (lower panels) shows emission pathways in three illustrative world regions; Figure 13 in SI shows results for all 12 world regions. In our modelling, regional variation in the impact of digital applications is a function of each region's digital transformation level (Methods §2c). To 2050 this is highest in North America and Pacific OECD regions, and lowest in Africa and the Middle East. Although the effects of digitalisation are stronger or weaker respectively in these regions, this is not always clear in the overall emission trends due to the interaction with secular (non-digital) technological and economic factors that explain most of the inter-regional variation. In regions like Pacific Asia where reference scenario emissions under current climate ambition rise or fall relatively gradually, digitalisation uncertainty amplifies divergence. In regions with sharply declining emissions (e.g., Western Europe) or consistently increasing emissions (e.g., Sub-Saharan Africa), the effect of digitalisation is less marked. Under strengthened climate ambition, emissions to 2050 fall in almost all regions. In some regions like Latin America, this follows an initial period of rising emissions due to digitally-induced demand growth before decarbonisation incentives take stronger effect. Sub-Saharan Africa is the only region in which the induced demand-effect dominates to the extent that emissions in the Undermine scenario are higher in 2050 than now, even with stringent climate policy.

Both globally and regionally, the strongest interaction between strengthened climate ambition and digitalisation is seen over the near to medium-term out to 2040. This affects cumulative emissions and so the probability of meeting 2°C targets (Table 1). In the Undermine-Extreme scenario this reduces from 76% in the reference scenario to 67%, at the threshold of the IPCC's 66% probability definition of "likely" staying below a temperature threshold. Conversely, climate-aligned digitalisation (Enable-Extreme) reduces cumulative emissions to 2050, pushes up the probability of staying below 2°C to 82%, and brings the year in which global net-zero emissions are reached forward to 2060 from 2063 (reference scenario) or from 2066 (Undermine-Extreme).

In sensitivity testing we explore more stringent climate policy assumptions towards the Paris Agreement's ambition to limit global temperature change to 1.5°C (Table 1). As carbon prices increase above those in our main 2°C scenario, cumulative emissions to 2050 are further reduced and the probability of staying well below 2°C warming improves. The year of global net-zero year is brought forward to as early as 2047 under Enable-Extreme assumptions and a roughly 16-fold increase of the carbon price. Figure 15 in SI shows this reduces reliance on carbon dioxide removal (CDR) already by 2050, an effect that will further increase over the longer term.

The impact of digitalisation on energy transition costs is also very large. This is due both to changes in total energy system size to meet demand and to structural change in system efficiency and electricity infrastructure. Cumulative energy-supply investments to 2050 differ by a factor of two between the Enable-Extreme and Undermine-Extreme scenarios (moving top to bottom between scenarios in Figure 5). To stay within the same carbon budget of around 550 $GtCO_2$, the investment burden ranges from around US$75 trillion to less than US$35 trillion depending on how well aligned digitalisation is with decarbonisation. This effect dominates the additional costs of mitigation from the ratcheting up of carbon prices to drive emissions down (moving right to left within a scenario in Figure 5).

In the Enable-Extreme scenario, energy-supply investments are reduced so strongly that even meeting the most ambitious climate targets is achievable at lower cost than in the Undermine-Cautious scenario with the least ambitious climate targets.

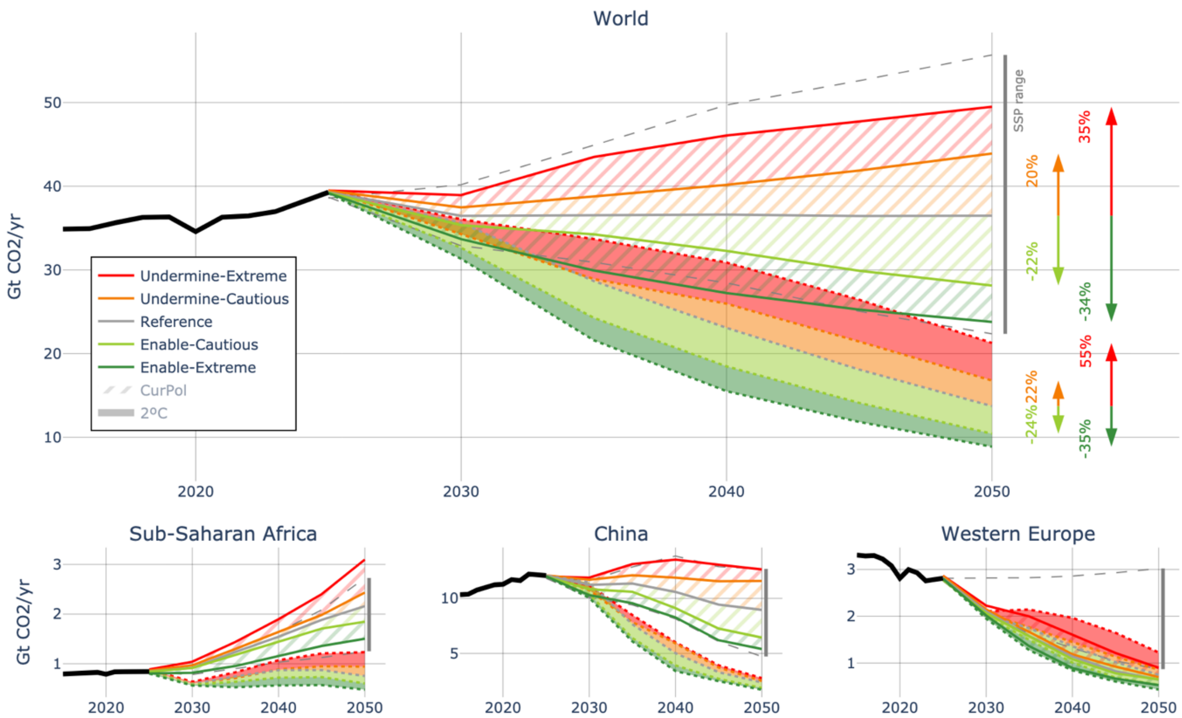



**FIGURE 4. DIGITALISATION IMPACTS ON $CO_2$ EMISSIONS TO 2050 UNDER CURRENT AND STRENGTHENED CLIMATE AMBITION.**

LEGEND: GLOBAL $CO_2$ EMISSIONS (MAIN PANEL) AND SELECT REGIONAL $CO_2$ EMISSIONS (LOWER PANELS) FROM FOSSIL FUEL COMBUSTION TO 2050 IN FOUR DIGITALISATION SCENARIOS AND A REFERENCE SSP2 SCENARIO. SOLID LINES AND HATCHED AREAS SHOW CURRENT CLIMATE AMBITION (CURPOL). DOTTED LINES AND SOLID AREAS SHOW STRENGTHENED CLIMATE AMBITION WITH MORE STRINGENT CLIMATE POLICY (2°C). VERTICAL SOLID GREY LINE TO RIGHT OF PLOTS SHOWS CORRESPONDING RANGE OF EMISSIONS ACROSS SSP1-5 PATHWAYS IN 2050. FIGURE 12 IN SI DISTINGUISHES EACH OF THE FIVE SSPS. FIGURE 13 IN SI SHOWS RESULTS FOR ALL 12 WORLD REGIONS.

**TABLE 1. DIGITALISATION IMPACTS ON THE FEASIBILITY OF PARIS CLIMATE TARGETS.**

NOTES: CUMULATIVE GTCO2, P(<2°C), AND NET-ZERO YEAR ARE FOR THE MAIN 2°C SCENARIO VARIANT IN OUR STUDY DESIGN WHICH HAS A 600 GTCO2 FULL CENTURY EMISSIONS BUDGET AND AN EXPONENTIAL CARBON PRICE TO 2060. THE SENSITIVITY OF THESE CLIMATE-OUTCOME METRICS TO MORE STRINGENT CLIMATE POLICY ARE SHOWN IN [SQUARE BRACKETS]. THESE SENSITIVITIES ARE GENERATED BY INCREASING THE CARBON PRICE TO 2060 AT MULTIPLES OF ROUGHLY 2, 4, 8, AND 16 OVER THE MAIN 2°C SCENARIO VARIANT. THIS SHOWS THE EFFECT OF INCREASING CLIMATE POLICY STRINGENCY WITHIN EACH SCENARIO IN ORDER TO EXPLORE A WIDER MITIGATION SPACE TOWARDS 1.5°C.

| Reference 2°C scenario | **Enable** | | **Reference (SSP2)** | **Undermine** | |
|---|---|---|---|---|---|
| *[more stringent climate policy sensitivity]* | **Extreme** | **Cautious** | | **Cautious** | **Extreme** |
| Cumulative $GtCO_2$ emissions (2025-2050) | 531 *[402-488]* | 582 *[414-533]* | 674 *[421-572]* | 703 *[429-627]* | 796 *[472-711]* |
| Probability of staying below 2°C | 82% *[85%-88%]* | 76% *[82%-88%]* | 76% *[81%-87%]* | 74% *[78%-87%]* | 69% *[75%-85%]* |
| Year of global net-zero emissions | 2060 *[2047-2053]* | 2061 *[2048-2054]* | 2063 *[2048-2055]* | 2064 *[2048-2058]* | 2066 *[2049-2060]* |

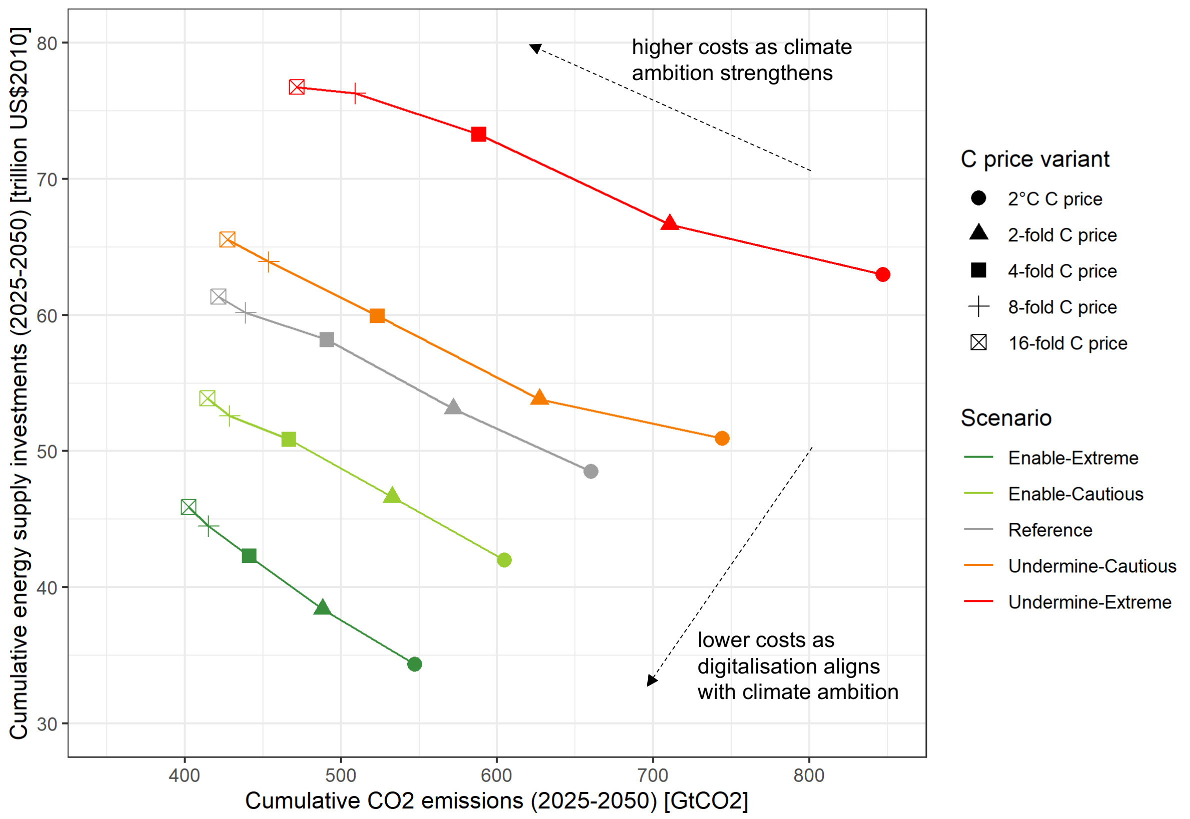



**FIGURE 5. IMPACTS OF DIGITALISATION ON ENERGY TRANSITION COSTS.**

LEGEND: NON-DISCOUNTED ENERGY-SUPPLY INVESTMENTS AS A MEASURE OF CUMULATIVE ENERGY TRANSITION COSTS TO 2050 (Y-AXIS) FOR GIVEN LEVELS OF CUMULATIVE $CO_2$ EMISSIONS OVER THE SAME PERIOD (X-AXIS). ENERGY-SUPPLY INVESTMENTS INCLUDE CAPITAL, OPERATING AND MAINTENANCE COSTS, BUT NOT INVESTMENTS IN END-USE TECHNOLOGIES NOR DIGITAL INFRASTRUCTURE. THE RIGHTMOST DATA POINT (SHOWN AS A FILLED CIRCLE) IN EACH SCENARIO IS THE MAIN 2°C SCENARIO VARIANT IN OUR STUDY DESIGN. THE RANGE OF CUMULATIVE $CO_2$ BUDGETS WITHIN EACH SCENARIO ARE GENERATED BY INCREASING CLIMATE POLICY STRINGENCY (APPROXIMATED BY THE CARBON PRICE) TO 2060 AT MULTIPLES OF ROUGHLY 2, 4, 8 AND 16 OVER THE MAIN SCENARIO VARIANT. MOVING RIGHT TO LEFT BETWEEN POINTS ALONG EACH LINE SHOWS THE EFFECT OF SUCCESSIVE DOUBLINGS OF THE CARBON PRICE.

## Discussion

Digitalisation impacts on climate are pervasive, fast, large, and uncertain. The range of impacts on energy demand and on $CO_2$ emissions to 2050 are similar in magnitude to the full range of uncertainties used to stress test climate mitigation challenges under different storylines of future global development (vertical grey bars in Figure 2 and Figure 4). These storylines - the shared socioeconomic pathways or SSPs - variously emphasise sustainability, inequality, national sovereignty, resource extraction, and technological convergence. Across these storylines by 2050, global population differs by up to a billion people, long-term annual GDP growth ranges from 1.1-3.0% $yr^{-1}$, and average global GDP per capita (in 2017$) varies from less than $25,000 to more than $39,000 [73]. The impact of these uncertainties on emissions is similar to that of digitalisation as a single transformative force.

Navigating this uncertainty depends on how digital and AI applications are designed, deployed, and used. Realising our Enable scenario requires deployment contexts that constrain rebound, economic incentives that ensure benefits to users are not at the expense of benefits to public goods like decongested cities and reliable low-carbon electricity systems, and users' trust and participation in the digitally-enabled provisioning of these public goods (Figure 1; Table 4 in SI for examples). This governance imperative cuts across energy end-use sectors, electricity systems, and the digital realm. In contemporary AI discourses, it is the "*transformative opportunity … to align socially desirable with privately profitable AI*" emphasised by the UN [74] or the principle for "*aligning the development, deployment and use of AI to promote planetary stability and stewardship for the benefit of humankind*" [75].

There are many examples of digital innovation, applications, and initiatives that give grounds for optimism [11,21,22]. But widespread conditions for climate-aligned digitalisation are not in place. Our Undermine scenario makes clear the long-term risk of alignment failure, challenging the optimism bias in near-term global assessments [6,7,36,76]. Worst-case outcomes become more likely under conditions that include profligate consumption norms, economic incentives to grow activity, and weak digital governance regimes that fuel user distrust and opt outs from applications that provide public goods, particularly in the transport and electricity systems (Figure 1). Generative AI business cases depending on advertising that drives consumption growth show that realising the Undermine scenario is of real and present concern.

Ambitious climate policies remain the most important steering mechanism for reducing emissions (Figure 4). In the Enable scenario, digitalisation makes climate policy more effective and less costly by structurally changing the energy system towards resource efficiency, electrification, and flexibility. This co-evolution of digitalisation and decarbonisation is broken in the Undermine scenario. If digital applications are deployed at scale to optimise only private local benefits, the aggregate outcome is delay, cost, and risk to climate policy's ability to deliver on Paris targets.

Climate policy alone is not sufficient to avoid digitalisation risks for climate. The asymmetry between fast-moving digital innovation and slow-moving climate governance institutions requires a response that also targets digital actors and markets [13]. The scale of R&D and infrastructure investment in the ICT sector and the pace of new product development are eyewatering. Decisions now determine how and what digital and AI applications will shape current and future energy transitions [77,78]. Our analysis emphasises three critical leverage points.

First, passenger transport contributes the largest wedge of difference between emission outcomes in Undermine and Enable scenarios (Figure 14 in SI). Regulating market access of mobility platforms and services in urban planning contexts is needed to limit digitally-induced travel demand for low-occupancy modes.

Second, digitalisation can reduce investment needs for meeting climate targets by a factor of two from $75 trillion down to $35 trillion. Capturing this economic benefit depends on energy market incentives and regulatory frameworks that integrate digitalisation into the electricity *system* not its disparate constituent *parts*.

Third, digitalisation impacts across world regions amplify differences in $CO_2$ emission trajectories determined by stages of development and energy transition. In regions like Latin America and Sub-Saharan Africa, this makes the mitigation challenge harder when climate ambition is strengthened. To avoid a global digital divide compounding other social and economic inequalities, mechanisms are needed to strengthen the absorptive capacity of regions for transferring, adapting, and effectively deploying digital applications with climate benefits [2,74].

This need was recognised in international climate negotiations (CoP28) in 2023 with the launch of the AI Innovation Grand Challenge and by the UN in 2024 through the Digital Global Compact [79]. But the wider governance landscape emerging globally around AI lacks an explicit climate focus [80–82].

Institutional innovation combining economic, energy, and ICT expertise is needed to systematically and transparently track application-level emission impacts (Scope 3) alongside the direct operational impacts of digital and AI infrastructure (Scope 1-2) [13,83,84]. Better data is a critical enabler of a digital-climate governance response (Table 4in SI for details). It would also strengthen the kind of analysis we have presented here.

Our assessment of digital-climate uncertainties is limited to the energy and emission impacts of digital infrastructure and applications that we can reasonably quantify based on empirical evidence (Methods §1a). We omit a large number of emerging applications with substantial but as yet unproven impact. This includes AI-accelerated scientific discovery of novel materials and catalysts to improve solar cell efficiency, battery performance, and carbon dioxide removal [22,85,86]. As our scenarios make clear, innovation and scientific progress are not inherently climate-aligned. They similarly expand the frontier for improving fossil fuel exploitation or other resource-intensive activities with detrimental impacts for climate.

Although we capture the co-evolution of digitalisation and electrification in the energy system, we model application impacts on energy demand as perturbations from a reference scenario (Methods §3a). Our application-level analysis in a detailed process-based model does not account for macroeconomic effects of digitalisation on jobs and economic productivity. Many employment skills or tasks have been automated, impacting wages and labour market inequalities (Acemoglu and Restrepo 2020). Resulting productivity and growth impacts are uncertain [87,88]. How this affects emissions will depend on economic structure and the overall energy and carbon intensity of economic activity. AI is amplifying outcome uncertainty [89]. A recent macroeconomic assessment of AI found $CO_2$ emissions to 2035 are driven up by demand growth in response to falling prices from AI-enabled efficiencies [44]. This is consistent with our Undermine scenario narrative.

Other systemic effects of digitalisation and AI on energy transitions and $CO_2$ emissions are not yet quantified and probably cannot be beyond speculative estimates. Pinning these uncertainties down requires empirical analysis and tools to isolate the digital signal from the noise of all other drivers of systemic change. One example is the implications of digital information ecosystems for human agency and social trust [90,91]. Algorithms that promote and micro-target reinforcing beliefs on media platforms have been linked to opinion polarisation [92]. Polarisation in turn undermines the broad social and political consensus necessary for stringent long-term climate policy [93,94]. AI adds fuel to the fire. Misinformation and disinformation on climate can be propagated more easily and with fewer barriers to entry for bad actors seeking to erode support for climate action [95,96]. Generative AI models can also be exploited to influence climate discourse [97]. In our Undermine scenario, weak digital governance allows these risks to propagate into mistrust and lost opportunities for digitalisation to enable collective action on climate. Digitalisation is not a parallel concern for climate mitigation but is central to the feasibility, timing, and cost implications for meting Paris climate targets.

## Methods

Our overall approach has three phases of analysis: (1) empirical; (2) scenarios; (3) modelling. Figure 7 provides an overview. Circles with labels (e.g., §1a) correspond to method steps explained here.

***1. Empirical evidence on energy impact of digital applications.***

We first build an evidence base of how digital applications impact energy demand and system integration. There are three main approaches used to quantify impacts in the literature: (i) lifecycle analysis (LCA) or other bottom-up accounting methodologies using empirical data from case studies in specific deployment contexts [98]; (ii) modelling simulations for new applications for which sufficient observational data are not yet available, e.g. [99]; (iii) statistical modelling of economy-wide or sectoral panel data on ICT penetration over time regressed against energy demand or greenhouse gas emissions [100,101]. This third approach aggregates across all digital applications and deployment contexts. To resolve the impact of specific applications we use data from the first two approaches, in line with [6,36].

Our main data resources are [5–7,23,102–104], all of which synthesise evidence on multiple digital applications. Good quantitative impact estimates are available in buildings and transport sectors, but less so in industry and the energy supply [103].

*1a. Selection of high-impact digital applications per sector.*

We identify the digital applications with the highest magnitude energy impacts in each sector. For example in transport, we include teleworking, ride-hailing (private and shared), mobility-as-a-service, e-commerce, freight logistics, smart charging and vehicle-to-grid integration, and autonomous vehicles (Table 2). Although most applications impact energy use, some also relate to energy system integration (e.g., smart charging).

We focus not just on applications with demonstrated energy-saving potentials, but also on applications that may result in net increases in energy use through rebound or induced demand effects. Table 2 summarises the main applications considered with key data sources for each.

There are numerous other digital and AI applications not included explicitly in our analysis because energy impacts are either relatively minor or are not quantified in published studies. Examples in buildings include: peer-to-peer electricity trading [105], building information modelling (BIM) impacts on operational energy performance [106], consumer goods or home exchange platforms like AirBnB [107]. Examples in transport include: traffic and transit optimisation [6], drone freight delivery [108], unmanned shipping [109]. There are many other examples not included rom multi-sector assessments [6,11,22] for lack of quantitative evidence as a basis for our modelling.

Finally, we also exclude longer-term systemic impacts of discrete applications such as the effect of teleworking on spatial patterns of living and working, urban density, and dwelling size. Another example is the impact of e-commerce on the spatial distribution of supply chains, with diffuse implications for emissions. This is beyond the scope of our analysis.

Omission of these and other applications mean our overall impact uncertainties are conservative.

**TABLE 2. EXAMPLES OF HIGH-IMPACT DIGITAL APPLICATIONS PER SECTOR WITH KEY LITERATURE SOURCES.**

| sector | digital application | definition | example reference |
|---|---|---|---|
| transport | teleworking | ICT-enabled remote working and interaction | 110 * |
| | ride-hailing | on-demand private taxi platforms | 111 * |
| | shared ride-hailing | on-demand multi-occupancy flexible route taxi platforms | 112 |
| | mobility-as-a-service (MaaS) | multi-modal trip integration platforms | 113 |
| | freight logistics | data-optimised freight distribution, loading, routing | 114 |
| | vehicle-to-grid integration | electric vehicle (EV) smart and bidirectional charging | 61 * |
| | autonomous vehicles (AVs) | vehicles that can operate without human involvement by collecting and processing real-time contextual data | 50,115,116 * |
| buildings | energy management systems ^ + | control & integration of behind-the-meter energy consumption, generation, and storage | 117,118 * |
| | smart heating ^ | thermal controls that learn, adapt, optimise, differentiate spaces | 119 * |
| | smart cooling ^ | | 120 |
| | smart lighting | lighting controls responsive to occupancy & luminosity | 121 * |
| | disaggregated energy feedback | real-time appliance-specific or disaggregated energy information (inc. non-intrusive load monitoring) | 122 |
| | building information modelling (BIM) | data platform with tools to optimise building design, construction & operation | 123 |
| | smart appliances, IoT + | internet-enabled devices with user controls and potential for load shifting | 124 |
| industry ^ | automation | robotics, automated monitoring and targeting systems, intelligent control systems | 125 |
| | AI and big data analytics | data analysis for predictive insights, process optimisation, intelligent decisions | 126 |
| | digital twins | virtual replica of a system for detecting inefficiencies, developing improvements, stress testing solutions | 127 |
| | sensors & IoT | network of connected & communicating devices and equipment | 128 |
| | demand response (DR) | time shifting or switching off production in response to network signals or needs | 129 |
| | additive manufacturing | 3D printing of components or products in advanced manufacturing industries (e.g. aerospace) | 130 |
| | general | combinations of applications under 'smart manufacturing' or 'industry 4.0' rubrics | 103 |
| energy supply | oil & gas extraction | data-optimised surveying, drilling, and extraction | 6 |
| | renewable energy | integrating variable renewable energy (VRE) into power systems, reducing curtailment | Methods §1d |

Notes:

* Review, synthesis, or meta-analyses using large n studies.

^ Different estimate for residential & commercial sectors in buildings, and for energy-intensive subsectors in industry.

+ Energy management systems for homes (HEMS) and commercial buildings (BEMS) include impact estimates for grid-responsive smart appliances and internet of thing (IoT) which are not modelled separately.

*1b. Quantitative synthesis of energy impact uncertainties from evidence regions.*

For each application we compile quantitative impact estimates drawing on systematic reviews and empirical rather than prospective modelling studies wherever possible (Table 2). We normalise impact estimates into % changes in activity or energy relative to a reference case (without the digital application) for direct comparability of relative effect sizes between applications [23]. If the energy input per unit of activity is unaffected by the digital application, then the % change in activity and energy metrics are equivalent. Figure 6 shows the maximum uncertainty ranges from reviewed literature of impact estimates per digital application, with the countries or regions from which evidence is based. These evidence regions affect spatial scaling assumptions in our scenarios (Methods §2c).

*1c. Conditions explaining upper & lower bounds of uncertainty range.*

We also characterise the conditions explaining both the lower and upper bounds of the uncertainty ranges [102]. We use these conditions to develop elements of our scenario narratives (Figure 1 and Table 3). For example, rebound effects and induced demand enabled by growth-oriented market incentives are common features of upper bound impact estimates in the reviewed literature, so become a scenario element.

*1d. Generalisable evidence on energy system integration.*

In addition to the quantitative impacts on energy demand from discrete digital applications (Figure 6), we also review literature on digitalisation that affects energy system integration but not in a way that is reducible to a simple % change metric.

This is particularly relevant for electricity systems with increasing output shares from variable renewable energy sources (VRE) like wind and solar whose output is intermittent [131]. Through dynamic line rating, digitalisation of transmission networks can increase capacities, alleviate congestion, and reduce VRE curtailment [65,76]. Digitalisation can also contribute to grid operation and system balancing by: (1) reducing peak demand in grid-stressed periods through demand response [129], load shifting [132], and EV smart charging coordination [133]; (2) providing real-time locational information on demand [62]; (3) integrating and scheduling VRE through better forecasting of supply availability [58]; (4) coordinating the provision of flexibility and stability services from distributed demand, storage, and generation resources [59,64,134]. These additional value streams for time-flexible loads stimulate faster adoption of end-use electrification including EV charging and heat-pump operation [135].

Although the literature is oriented towards positive use cases for digitalisation in decarbonising electricity systems, there are contrary potentials. One example is if digital applications like energy management systems or demand response become widespread and used to maximise local or private benefit to the detriment of overall system integration

[70]. Another example is if unmanaged digital coordination of flexible load in response to local incentives causes abrupt troughs and spikes on networks that are hard for system operators to balance with low-carbon supply [69]. A third example is if the enablement of distributed solar PV generation leads to congestion on local VRE-dense networks [62].

Conditions under which these detrimental outcomes for decarbonisation may arise are described by the Undermine scenario narrative. They include fragmented markets, weak alignment between private gains and public goods, mistrust in service providers, and defections or opt outs from applications supporting system functioning.

We capture these varying effects of digitalisation on electricity systems in our modelling through parameterisations consistent with the scenario storylines (Methods §3d and Table 6 in SI).

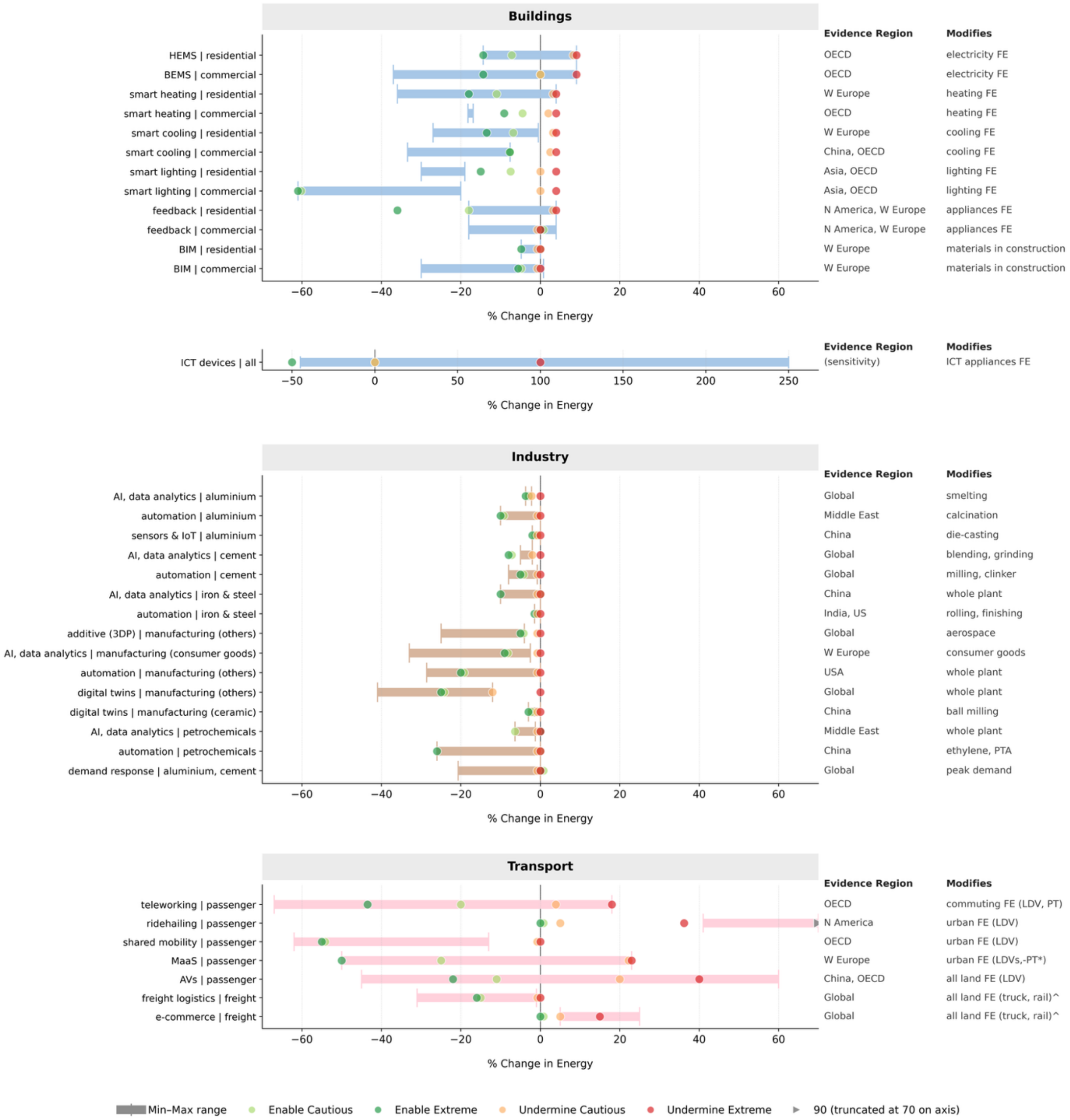
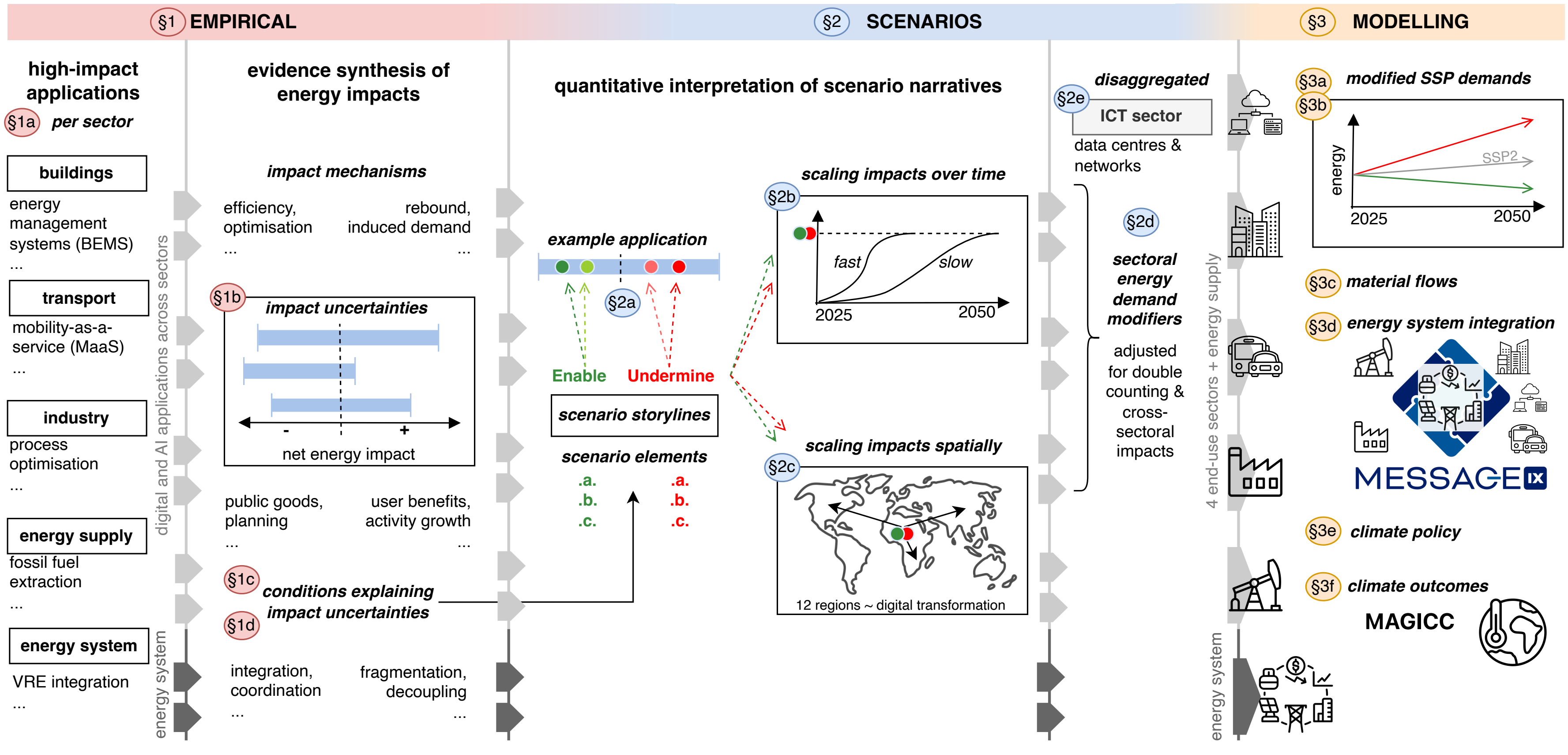



**FIGURE 6. ENERGY IMPACTS OF DIGITAL APPLICATIONS: FULL UNCERTAINTY RANGE FROM EMPIRICAL STUDIES (NORMALISED AS % CHANGES IN ENERGY) WITH POINT ESTIMATES FOR MODIFYING ENERGY DEMAND IN FOUR DIGITALISATION SCENARIOS.**

NOTES: 'EVIDENCE REGION' DENOTES LOCATION OF EMPIRICAL STUDIES. 'MODIFIES' DENOTES ENERGY-RELATED QUANTITY OR PROCESS TO WHICH % CHANGE METRIC APPLIES. * SHIFT FROM LDV TO PT OR VICE VERSA. ^ AIR INCLUDED IN EXTREME SCENARIOS.

ACRONYMS: FE = FINAL ENERGY; ICT = INFORMATION & COMMUNICATION TECHNOLOGIES; PTA = PURE TEREPHTHALIC ACID; 3DP = 3D PRINTING; LDV = LIGHT DUTY VEHICLES (CARS, VANS); PT = PUBLIC TRANSPORT (BUS, METRO, TRAIN + ACTIVE).




Icons from Noun Project by Brand Mania (world map), Good Wife (ICT sector), Made by Made (buildings), Icon Solutions (transport), Sita Raisita (industry), Profit0101 (energy system), min park (oil drilling), Kusuma Potter (climate globe)

**FIGURE 7. THREE STAGE WORKFLOW FROM EMPIRICAL EVIDENCE TO GLOBAL IAM IMPLEMENTATION.**

Table 3. Comprehensive set of digitalisation scenario elements.

| ***Scenario Element*** | **Undermine** | | Reference (SSP2) | **Enable** | | ***Why relevant?*** |
|---|---|---|---|---|---|---|
| | **Extreme** | **Cautious** | | **Cautious** | **Extreme** | |
| | | | *affect* ***application-level energy impacts*** | | | |
| ***Rebound constraints*** | No structural constraints to more activity, activity growth strongly welfare-enhancing | Limited demand management or activity disincentives | Mixed, varied by sector, stronger energy price disincentives in industry & buildings | Activity growth disincentivised by energy pricing | Strong constraints (inc. standards & urban planning) limiting any activity growth | ***Determines magnitude of rebound or induced demand*** |
| ***User behaviour norms*** | Supportive norms for profligate or conspicuous consumption | Consumption inequalities, profligate use accepted | Oriented towards activity growth across income groups (historical trends) | Activity growth disincentivised by norms & inequalities | Strong sufficiency norms, consumption ceilings, saturated welfare gains | ***Shapes behavioural response to digitalisation efficiencies*** |
| ***Sectoral economic incentives*** | Strong misalignment with climate mitigation goals, cheap fossil energy | High electricity : gas price differential, carbon externalities not guiding market activity | Mixed, varied by sector, current climate policies to 2030 then constant | Rapid end-use electrification, enforced efficiency standards | Strong incentives for efficient use of energy and decarbonisation | ***Defines deployment contexts (solutions & use)*** |
| ***Market design & regulation*** | Fragmented markets, inconsistent regulations, no climate-alignment, regulatory capture by AI firms | Digital-climate solutions monopolized then squeezed (e.g. free then pay-per-use) | Winner-takes-all dynamics, slow regulatory catchup to speed of innovation activity | Stable markets, knowledge spillovers between geographies, accessible climate solutions | Strong market integration, collective action on climate solution search | ***Sets incentives for digital application development & deployment*** |
| | | | affect **scaling of applications globally** | | | |
| ***Trust & risk*** | Unmitigated cybersecurity threats, high risk of data misuse by service providers | Privacy concerns & defection or opt outs from data provision | Privacy paradox as trust concerns offset by utility of digital services | Trusted & well-regulated data practices, widespread participation | Strong user protection & data sovereignty, stringent data access controls | ***Determines extent of user participation in data-dependent applications*** |
| ***Political economics & geopolitics*** | Competitive sovereign national interests dominate, concentrated power (winner-takes-all) | Economic divergence, distributed AI data centres as critical national infrastructure | Global AI-climate governance in tension with national sovereignty, regional variation | Economic convergence & technology transfer, AI infrastructure as global resource | Strong multilateral governance, dispersed AI political influence | ***Affects speed and scope of digitalisation diffusion out of home markets*** |

| | | | | | | |
|---|---|---|---|---|---|---|
| ***Interoperability & integration*** | Siloed digital applications, protective behaviour to preserve market niches | Limited interoperability between systems, weak economies of scope | Context-specific variation in integration of and interoperability between digital systems | Standards and practices enabling interoperable systems | Strong knowledge spillovers through integration of datasets, applications, platforms | ***Determines technical transaction cost for scaling digital solutions*** |
| ***AI model energy efficiency*** | Generative AI model performance dominated by scale, energy-hungry next generation chips | Weak market incentives for AI hardware or software efficiencies | Scaling heuristic for generative AI models but increasing salience of energy costs | Energy and cost incentives for efficient AI infrastructure, continual improvements | Leaner task-specific models, energy dominant as cost factor in AI data centre business models | ***Influences direct operational energy footprint of AI infrastructure*** |
| add to **narrative interpretation** | | | | | | |
| ***Skills & training*** | Wide digital divide, skills displacement | Lack of training (particularly AI), increasing inequality of opportunity | Uneven labour market impacts, uneven availability of training across firms and sectors | Widely accessible training, net skills creation | Workforces with task-related skills to exploit digital opportunities across deployment contexts | ***Affects workers' acceptance of digitalisation and labour market impacts*** |
| ***Innovation & investment*** | Highly concentrated proprietary R&D activity, no incentives for climate-directed investment | Solution search dominated by big tech, poor skills base weakens R&D capacity | Private R&D investment leveraged by early-stage public R&D, mixed incentives for climate innovation | Skills & resources invested in climate-aligned R&D, climate in social contract for AI firms | Strong mission-led R&D investment for climate, strong incentives for public-purpose IP | ***Controls type and flow of digital innovations from labs to markets*** |
| ***Data quality & governance*** | Proprietary or otherwise inaccessible datasets, high bias & misrepresentation risks | Weak data governance, inconsistent dataset quality | Variability in quality and accessibility of datasets, IP concerns over data collection | Industry standards enabling accessibility and data quality | Widespread availability of clean & well-organised datasets | ***Underpins effectiveness and data risks of digital applications*** |
| ***AI use cases*** | Decline phase post AI hype, undermined market & investor confidence | Hard-to-capture value from AI model use cases, greenwash claims on AI sustainability | Mixed evidence on realisable economic value varying by use case, continued innovation | Robust ESG criteria used in AI risk scoring, strengthening evidence on climate-aligned AI use cases | Sustained AI boom driven by realisable value from climate-aligned use cases | ***Impacts how widely new AI applications become embedded throughout the economy*** |

## 2. Scenario storylines translated into quantitative energy demand projections.

Our two scenario storylines – Enable and Undermine – characterise digitalisation uncertainties (Table 3). We quantitatively interpret these storylines by mapping them onto application-level energy impacts. We then project these impacts out to 2050 using simple diffusion curves and to 12 world regions as a function of countries' relative levels of digital transformation. In a final step we aggregate application-level impacts to the sectoral level accounting for double counting and cross-sectoral feedbacks. This gives us a set of sectoral energy demand projections for each scenario.

*2a. Selection of extreme and cautious impact estimates per application.*

Certain scenario elements determine how we model application-level impacts. Each of these elements is derived from underlying empirical studies in which they are used to explain either upper or lower bound impacts in the corresponding deployment contexts (Methods §1c). Upper bounds are often net energy increasing (positive % change) and lower bounds are net energy reducing (negative % change), but this is not always the case. The most common conditions cited relate to 'Rebound constraints' and 'User behaviour norms' that determine whether savings of time, money, effort, or inconvenience are reinvested in more activity (Table 3). 'Sectoral economic incentives' and 'Market design & regulation' are more structural conditions that influence whether each digital applications is used for private benefit or public good, and whether these private-public use values are synergistic or in tension.

For each scenario, we select point estimates of each application's energy impact as a % change in activity or energy demand relative to a counterfactual or no-digital reference case (Figure 6). We use the term 'demand modifiers' for these empirically-based point estimates as we model them as % modifications to reference case demand projections.

We select two sets of values from the uncertainty ranges consistent with our Extreme and Undermine scenario narratives. Cautious values are typically medians or points up to which we consider empirical evidence to be robust (e.g., from meta-analyses or synthesis studies with a large number of observations across different deployment contexts). Extreme values are typically at or close to the end point of uncertainty ranges for which we consider empirical evidence to be less generalisable (e.g., from single studies, specific deployment context across, or model simulations designed to test best or worst case outcomes). The cautious and extreme variants to our scenarios therefore describe our confidence in the robustness and generalisability of underlying empirical evidence. This applies to both Enable and Undermine scenarios. In addition, there are generally fewer studies that quantify energy-increasing effects of select digital applications (autonomous vehicles and ride-hailing are exceptions) due partly to the methodological challenges of including rebound and induced demand effects within study system boundaries. As a result, values we select to parameterise our Undermine scenario may have a less diverse empirical grounding.

*2b. Scaling impact estimates per application to 2050.*

We characterise the potential for each digital application to diffuse fast or slow depending on the ancillary changes required to institutions or infrastructures for its widespread deployment. As examples, we assign autonomous vehicles to slow diffusion given their dependence on changes to mobility norms and regulatory frameworks. We assign ride-hailing to fast diffusion given the business model's ready substitutability into urban mobility networks. These fast-slow assumptions are for diffusion from 2025. For established applications with existing market share, this diffusion represents additional market penetration or energy impacts increasing in magnitude.

For most applications we scale energy impacts out to 2050 using a simple three-parameter logistic function commonly used to describe technology diffusion over its lifecycle [136]. We vary the demand modifier from 0% of its value in 2025 to 100% of its value in 2035 (fast diffusion) or 2050 (slow diffusion) following the S-curve trajectory. For a few applications, we use alternative linear or cumulative growth functions, for example, if the lifecycle may not saturate within the 2050 timeframe. In such cases, the demand modifiers are still set to 0% and 100% of their values in 2025 and 2035 or 2050 respectively. This results in only very minor differences in resulting scaling assumptions.

*2c. Scaling impact estimates per application from evidence regions to all world regions.*

The empirical evidence for each application's energy impact draws on studies from specific geographies or contexts (Figure 6, first column to right of plot). Certain of our scenario elements describe the conditions influencing spatial diffusion out of these earlier-adopting regions (Table 3). Later adoption is faster if participation in digital transformation is trusted ('Trust & risk') and with functional benefits from integration across devices, platforms, and services ('Interoperability & integration'). Market incentives for technology transfer and convergence ('Political economics & geopolitics') further accelerate spatial diffusion.

To model spatial diffusion we use digital transformation as a proxy for regions' capacity to successfully deploy digital applications whose energy impacts are evidenced in other earlier-adopting regions.

Digital transformation is measured by the UN's e-government development index, a basket of 15 indicators measuring access to digital technologies, infrastructures, skills, and public services [137]. [138] project future levels of digital transformation under SSP assumptions using a statistical model fitted to country panel data over the period 2004-2020. We use the SSP2 projections over the period 2025-2050 in the spatial scaling of our demand modifiers.

Specifically, we adjust the energy impacts from each application's evidence region, $r_0$, for other world regions, $r_n$, as a function of these other regions' relative level of digital transformation. If a demand modifier is $dm\%$ in evidence region $r_0$, it is $dm\% * r_n/r_0$ in region $r_n$. These ratios can change over the period to 2050 as a region's speed of digital transformation is determined by its GDP growth, innovativeness (measured by R&D intensity), and population density in our projections. For example, the rapid digitalisation of OECD and Asian economies is much slower and less pervasive in other parts of the world. [138] find 13% of the assessed global population in 2050 still only have access to relatively low levels of digital transformation under reference SSP2 assumptions. This constrains the availability and scale up of digital applications in our modelling.

We use the 12 world region specification of the MESSAGEiX global integrated assessment model for our set of $r_n$. Figure 13 in SI lists the world regions. If the evidence region $r_0$ for an application spans more than one of the 12 world regions we use a weighted average of the closest regions to define $r_0$ (e.g., for OECD we average digital transformation levels in North America, Western Europe, and Pacific OECD).

This scaling formulation assumes linear proportionality between digital transformation level and digital application impact. This is a simplifying assumption and a limitation that does not allow for leapfrogging or catch-up of less digitalised regions in particular sectors [2].

Another limitation of this approach is that it maps from evidence regions to other world regions, but does not account for variation in existing deployment levels in specific regions if these are not adequately captured in the empirical studies reviewed.

*2d. Aggregation of application impacts to sectoral energy demand modifiers.*

To aggregate the impacts of discrete applications within each sector we account for:
(i) applications impacting specific end uses rather than total sectoral energy demand - e.g., smart lighting only impacts the lighting share of final energy in the buildings sector;
(ii) more than one application impacting the same end use – e.g., teleworking, MaaS, ride-hailing (private and shared) all impact urban passenger mobility.

First, where applicable, we adjust each application's demand modifier by the corresponding final energy share to which it applies in each region, using data from [139]. (Modified shares are shown in Figure 6, second column to right of plot).

Second, we define a double counting logic that sets out which final energy shares are impacted by which applications and in what order. We then follow the multiplicative logic of [7]'s digitalisation study: "*As the impacts of each measure are non-additive (due to overlaps in how they affect activity), the diminishing returns on each additional measure are modelled assuming multiplicative reduced efficacy of impact:*

*total % effect = 1 - (100%-effect of measure A) * … (100%-effect of measure N).*"

This multiplicative combination of adjusted application-level demand modifiers gives a set of aggregated modifiers that apply to overall sectoral demand in each of our 12 world regions to 2050.

*2e. Future ICT sector energy demand.*

ICT sector energy use is accounted for in IEA energy statistics within the commercial buildings sector but not represented explicitly in global modelling frameworks like MESSAGEiX. We disaggregate the ICT sector by projecting data centre and ICT network electricity demand to 2050 using simple models calibrated to two distinct historical periods.

The first period from 2010-2017 saw relatively flat global energy demand for data centres due to efficiency gains (including from hyper-scaling) offsetting strongly rising demand for computation and sectoral expansion [17]. Our ICT sector projections use this efficiency-driven period as the basis for our Enable scenarios.

The second period from 2020-2024 saw sharply rising energy demand due to exponential growth in service demand associated particularly with training and inference of foundation AI models [6]. Our ICT sector projections use this service demand-driven period as the basis for our Undermine scenarios.

Figure 16 in SI shows these projections, with further details in [140] and [141]. We use upper and lower bound ratios of data centre to network ratios observed to 2024 to estimate additional network infrastructure energy demands.

### 3. Modelling long-term energy impacts of digitalisation scenarios.

We use the MESSAGEix-GLOBIOM-GAINS global integrated assessment model to interpret our scenarios quantitatively. MESSAGEix-GLOBIOM-GAINS is an intertemporal optimisation model with a detailed process-based representation of the energy system coupled to sectoral demand models and linked to a macro-economic (MACRO) model. Full documentation is available at: https://docs.messageix.org/en/stable/index.html.

The model has been widely used for scenario analysis of future energy and emission pathways including in IPCC assessments [29]. The full model covers energy, economy, land use, waste, and other sectors. Here we use the MESSAGEix-GLOBIOM-GAINS set up focusing on the energy system (no land use) to project energy and fossil $CO_2$ emissions to 2050. In the rest of this paper we refer to this model with the shorter label 'MESSAGEiX'.

Our overall modelling approach combines exogenous perturbations to reference scenario sectoral demands with endogenous modifications to energy system integration. This allows for structural change in the electricity system to respond dynamically to changes in the quantities and types of demand variation, climate policy, and other scenario assumptions. It also provides transparency and traceability for application-level impacts by preserving process detail. Although MESSAGEiX iterates with MACRO on aggregate price-demand feedbacks, induced demands from digitally-enabled efficiencies are mainly captured in the demand modifiers.

*3a. Modification of SSP2 sectoral energy demand projections.*

Sectoral demand modifiers are directly applied to the reference SSP2 final energy projections for industry, transportation, and buildings sectors [29] updated for CMIP7 and ScenarioMIP [142]. In selected figures in results, we also provide SSP1,3,4,5 reference points to compare SSP storyline uncertainties with digitalisation uncertainties. For the full SSP database, see [73].

Table 5 in SI gives examples of the modifiers applied in each demand sector.

Modifiers in the industry sector distinguishing five energy-intensive sectors plus manufacturing are applied to specific technology or process representations – e.g., aluminium smelting - in MESSAGEix-Materials [143].

Modifiers in the buildings sector distinguishing residential from commercial subsectors are applied to final energy shares for heating, cooling, appliances, and 'other' end-uses in the SSP2 projections from MESSAGEix-Buildings [144,145].

Modifiers in the transport sector distinguishing passenger from freight subsectors are applied to activity levels for different modes (car, bus, rail, two wheelers, air for passengers; truck, rail for freight) in the SSP2 projections from MESSAGEix-Transport (https://docs.messageix.org/projects/models/en/latest/transport/index.html). These modifiers are calibrated to the impact of digital applications on final energy based on literature (Table 2). Total energy and material demand from transport vehicles is determined by service levels (e.g., passenger-kilometres for cars) as well as usage patterns (e.g., occupancy per vehicle, activity levels per vehicle per year). By employing modifiers at the activity level, total material and energy demands are reduced in Enable scenarios due to lower service demands as well as more efficient use of available vehicle stock. The opposite happens in Undermine scenarios.

An important simplifying assumption in both buildings and transport sector scenario modelling is that digitalisation does not substantially impact the technical energy conversion efficiency of discrete end-use technologies (e.g., heat pumps, cars). For example, we assume a shared vehicle is not fundamentally different to a privately-owned vehicle in its built characteristics.

*3b. Disaggregation of ICT sector energy demand projections.*

We separate the ICT sector out from the commercial buildings sector using our new explicit ICT electricity demand projections for data centres and networks (Methods §2e). Commercial buildings energy demand in MESSAGEix is calibrated to international energy statistics for the year 2020. The historic energy demand of the ICT sector is assumed to be already included to that point. We deduct this 2020 quantity from the reference SSP2 projection from 2025 to avoid double counting. As an additional demand sector, the ICT interacts with the electricity system in the same way as the buildings sector. We do not make differentiating assumptions about its electricity supply nor load flexibility.

*3c. Impacts on material flows and industrial output.*

We implement the effect of digitalisation on materials used in the production of new goods and infrastructure in an analogous way to the energy demand modifiers. We first use the MESSAGEix-Transport and MESSAGEix-Buildings models to quantify material demand changes for each digitalisation scenario. These are soft linked into the industrial sector representation in MESSAGEix-Materials [146]. As examples, building information modelling (BIM) affects the material efficiency of new building construction (e.g., cement, steel), and shared mobility affects the lifetime and turnover of the vehicle stock as well as demand for new vehicles (e.g. aluminium, steel). The absolute differences in projected sectoral material demands are then used to modify the reference SSP2 projections from the industry model, MESSAGEix-Materials.

*(3d). Energy supply and system integration.*

Digitalisation impacts the energy supply including through fossil fuel extraction costs and exploitable reserves, and through efficiency improvements in the siting and operation of VRE. Digitalisation also impacts final energy quantities in all end-use sectors as well as the electrification of energy end-use with knock-on implications for the energy supply. However, as noted in our evidence review (Methods §1d), the main effect of digitalisation is on energy system integration particularly for electricity.

Modelling the dynamic interaction of these different impacts requires multiple adjustments to the MESSAGEiX SSP2 set up to capture our digitalisation scenario narratives. Table 6 in SI summarises the main parameterisations used in our modelling of the digitalisation scenario variants with examples of each. These cover the different dimensions of VRE integration, coordination of distributed storage and generation assets, and demand flexibility.

In MESSAGEix, energy system integration is represented through four dimensions, each modelled using stylised constraints: (1) VRE curtailment; (2) firm capacity requirements; (3) flexibility requirements; (4) grid integration costs. Each of these is explained further below. These constraints jointly determine the technical feasibility and the cost of wind and solar PV integration, in addition to the techno-economic parameters related to each technology (e.g., capital cost, capacity factor, resource potential). These constraints are also used to determine the need for additional measures, such as flexibility or storage, to enable a system with a high share of VRE [147]. The VRE parameters are defined separately for wind and solar, with regionalisation where relevant. The original methodology is based on [148], with further updates from [149], which was later benchmarked against a detailed global power system model (PLEXOS-World) in [150]. More details and sensitivities of model results to VRE integration constraints can be found in a recent benchmark study by [151].

First, VRE curtailment is modelled through VRE penetration-dependent “bins” that approximate how VRE surplus grows with increasing shares of VRE in the system. For each penetration level, a certain level of marginal curtailment is determined, which overall makes a piecewise VRE-penetration – VRE-curtailment curve. These curves are derived from detailed power system models and fed into MESSAGEiX. Depending on the cost of meeting a certain policy or other constraints, the system absorbs the most cost-optimal level of VRE, accounting for the additional cost of curtailment or the cost of curtailment-reducing measures (e.g., $H_2$ electrolysis, storage charging, EVs, and net electricity exports).

Second, firm capacity requirements are modelled to ensure that peak load plus contingencies (reserve margin) can be met at all times. Different technologies are assumed to contribute to firm capacity with various capacity credits. VRE contributes to firm capacity only with a fraction of its capacity, using a capacity value function that declines with VRE penetration. In high VRE penetration scenarios, VRE provides incremental firm capacity, forcing the system to invest in other technologies such as storage to meet power adequacy requirements.

Third, flexibility requirements approximate the need for dispatchable resources to cope with variability in the system, either because of VRE or load (e.g., due to short-term forecast error). Different electricity generation technologies and storage can provide flexibility. As VRE shares rise, MESSAGEiX must deploy more flexible capacity (storage, gas, etc.) even if energy balances alone would be met by VRE generation.

Fourth, grid integration costs in MESSAGEiX internalise additional system-level expenses that are not explicitly modelled elsewhere, such as grid management and contingency, transmission expansion, and cycling costs of conventional plants. They are implemented as a penetration-dependent cost based on the VRE share.

In addition to these constraints and requirements for VRE integration, MESSAGEix parameterises electricity storage as a generic 24 hour storage technology with 75% round-trip efficiency to prevent storage cycling effects. The storage technology can contribute to several services, subject to the level of coordination in a specific scenario, including curtailment reduction, firm capacity provision, and flexibility (balancing) services. This ensures the multi-tasking feature of storage when coordinated for providing services across energy, capacity, and transmission and grid management and investment deferral.

3e. *Current and strengthened climate ambition.*

In our analysis we model digitalisation impacts independently from climate ambition as their drivers and governance are distinct. We model two levels of climate ambition. For current climate ambition (‘CurPol’) we use a currently implemented policies set up to 2030, with a regional carbon price extrapolation post-2030. The extrapolation determines the regional carbon price needed to continue the emissions path from current policies for the years after 2030. For example, the Undermine scenarios require higher regional carbon prices to compensate for larger energy demand growth to stay on the extrapolated emissions path. These prices in turn provide stronger near-term incentives for decarbonisation.

For strengthened climate ambition ('2°C') under more stringent climate policy assumptions, we use a cumulative carbon budget of 600 $GtCO_2$ to 2100 consistent with limiting long-term warming below 2°C with limited overshoot (with a roughly three-quarters probability in our SSP2 reference scenario) (Table 1). Implementing this budget gives us a shadow carbon price as a proxy for climate policy stringency. This is our main 2°C scenario variant reported in results.

In sensitivity tests to explore the wider mitigation space towards 1.5°C targets, we increase the carbon price from our main scenario 2°C variant in successive doublings (x2, x4, x8, x16). We show resulting implications for Paris climate target relevant metrics including the probability of limiting warming to 2°C (Table 1) and energy transition costs (Figure 5).

*(3f). Climate outcomes.*

To assess climate outcomes of the emission pathways in our digitalisation scenarios, we use the reduced complexity climate model MAGICC, version 7.5.3 [152,153] that was also used as part of the Sixth Assessment Report (AR6) of the IPCC [154].

## Data Availability

All data inputs and relevant model parameterisations are summarised in Methods, and will be made available in full in a public repository on publication. All model results will be uploaded to a public database on publication.

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