Artificial intelligence drives divergent emission futures

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Artificial intelligence drives divergent emission futures

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Abstract

Artificial Intelligence (AI) may impact greenhouse gas emissions in both positive and negative ways, yet these impacts are not represented in recent assessments of climate change mitigation. Uncertainty surrounding future AI capability and adoption, its impacts on energy systems, and limited data availability complicates the inclusion of AI impacts. We conduct an expert-led process, ascertaining plausible impacts, and quantify ranges in their magnitude to 2040. We present a new scenario framework for AI and climate change that considers interactions between AI growth, climate policy, and AI policy. We translate elicited insights into illustrative scenarios and assess their implications using an integrated assessment model. Cumulative global CO_2 emissions by 2040 range from +11% above to 1.4% below a baseline without AI impacts, depending on the scale of AI growth and policy intervention. Our results highlight emissions risks and opportunities from AI and the need for explicit representation in mitigation scenarios.

Main

The use of artificial intelligence (AI) has increased significantly in recent years[1,2]. While generative AI represents just one domain within the broader field of AI, its ubiquity has amplified public and academic attention on the wider economic, environmental, and societal implications of AI systems. Advancements in AI capabilities are likely to drive increased usage, with uncertainties regarding broader societal impacts[3]. This extends to their potential to impact energy demand and climate change mitigation[4–6].

The trajectory of AI development is uncertain, complicating efforts to consider climate impacts. Some anticipate the emergence of systems that exceed human-level capabilities in all areas in the next five years, leading to profound societal shifts[7–9]. Others point to technical, cost or diffusion barriers likely to temper such rapid progress or impacts[10–14]. A range of possible scenarios of AI development deserve attention in the context of climate change. Strong near-term action is needed to minimise temperature increases, and it is therefore salient to understand ways AI could influence emissions pathways[7,15]. Recent assessments of climate change mitigation, such as IPCC Sixth Assessment (AR6), do not explicitly consider the influence of AI[1,6.]

Possible AI impacts extend to climate change in both direct (e.g. increased electricity demand for AI computing) and indirect (e.g., AI-driven sectoral efficiency gains) ways[17]. Most widely discussed is the electricity demand for both the training and inference of AI models[18–21]. Here, uncertainty stems not only from the AI adoption trajectory but also from the degree to which improvements in computation, cooling, software (e.g. energy-efficient algorithms, task-specific models), and new computing architectures can temper energy demand growth[18,21–24]. Additionally, there is inadequate data on electricity usage from AI, with a lack of transparency from key stakeholders impeding measurement[25.].

Data centre electricity demand is often used as a proxy for AI electricity demand given that data centres account for most AI-related demand, with a much smaller share from end-user devices and networks[18]. It is estimated that AI applications accounted for 15% of data centre demand in 2024, increasing to up to 50% by 2030[18,26]. There is considerable uncertainty in measuring this, however. The International Energy Agency (IEA) projects data centre electricity demand to reach 600-1200 TWh by 2030 and 700-1700 TWh in 2035, representing 1.9-3.8% and 2-4.4% of global electricity demand in each year respectively[18]. Whilst other estimations are also of similar order of magnitude[19,27,28], there is a wide range in recent estimates, from around 600 TWh to over 2000 TWh in 2030[26]. Some perspectives on the near-term trajectory for AI see very significant AI progress and societal change, along with high possible electricity demand[7,29]. Regardless, even under more modest demand increase scenarios, the type of new generating capacity (i.e., low carbon or fossil) may be an important variable for emissions impacts[28,30].

On indirect AI impacts on climate change, AI is already aiding more efficient management of energy resources in electricity systems and buildings[31–33]. Further, applications of AI tools and models have been demonstrated for enhanced fossil fuel extraction, leading to the possibility of increased supply and lower costs of oil and gas[34,35]. The use of AI systems holds promise too for the discovery of new battery materials and improved methods for sequestering carbon, improving the cost and performance of mitigation strategies, complicating modelled impacts[36,37]. AI may have a range of impacts within specific sectors such as transport. AI may enhance efficiency in transport systems, making them lower cost and more accessible[38]. However, there are possible rebound effects. AI systems may rapidly enhance the performance, safety and efficiency of autonomous vehicles in the coming years, reducing their cost and thus increasing their adoption[17]. This wide range of possible indirect impacts, taken together, may have a net positive or negative impact on climate change mitigation and emissions pathways, with considerable uncertainty over the magnitude.

Climate change mitigation scenarios with quantitative outputs from integrated assessment models (IAMs) play a crucial role in assessment reports from the IPCC[39,40]. Insights from these scenarios are used extensively to develop national and international climate policies[41,42]. There have been recent efforts to use a scenario-based approach to think about how AI and digitalisation of the economy may influence energy demand and climate change[5,18,19,43,44]. However, scenarios with associated inputs for IAMs have so far omitted consideration of both direct and indirect AI impacts. Given the outsized influence of such scenarios on climate policy and the wide-ranging possible AI impacts, this omission urgently needs to be addressed.

Deep uncertainty exists in the future energy and emission impacts from AI, complicating their representation in modelled futures. This uncertainty leads some to question the value of projecting and modelling impacts beyond the near-term[45]. However, scenario construction permits exploration of a range of possible futures, without explicit probability attached to their likelihood. Omission of AI impacts from such scenarios could also imply an assumption about the future. In this paper, we use complementary approaches to address different sources of uncertainty regarding AI and emissions pathways. We use expert interviews to understand the range of ways in which AI may influence energy systems and emissions. Next, addressing parametric uncertainty, we conduct a structured expert elicitation, providing quantified ranges for specific impacts, used for subsequent modelling. We follow the IDEA protocol, which aims to minimise individual overconfidence and collective groupthink effects whilst facilitating information exchange between various types of experts[46]. These insights taken together inform a scenario framework and a set of narrative scenarios that explore the irreducible uncertainties around how AI may impact emissions pathways. We model our scenarios in the TIAM integrated assessment model, providing a range of quantitative energy system and emissions insights. In our discussion, we highlight crucial aspects that cannot easily be modelled and areas of focus for future work.

Results

Diverging expert predictions for climate and AI

Our expert-led elicitation process included a range of ways AI could influence climate change mitigation; these were derived from initial interviews. Our quantitative survey approach elicited distributions of uncertainty for each variable from each expert rather than single estimates (see Methods). These factors are grouped into three categories: electricity demand, sectoral efficiency gains, and discovery science (Fig. 1).

For electricity demand from AI (Figs. 1a–b), the median estimate for 2030 is 4.5% of 2024 global electricity demand (1,395 TWh), and 10.4% (3,224 TWh) for 2040. We provide equivalent compute load estimations for these values under different power usage effectiveness scenarios in Supplementary Results 1. Our 2030 median is similar to, but above IEA total data centre electricity demand projection[18]. Future electricity demand growth means these percentages are substantially lower when expressed as shares of 2030 or 2040 demand. The wide range in expert predictions, particularly for 2040 (Fig. 1b), highlights substantial uncertainty surrounding future AI capabilities, adoption rates, and developments in key drivers such as algorithmic and compute efficiency. Experts viewed the likely geographical distribution of additional demand to continue along present distributions of demand and therefore be dominated by the US, China and Europe. Further, we elicited views on the supply mix of new demand, with these outcomes feeding into our narrative scenarios (Table 1).

For sectoral efficiency (Figs. 1c-g), we elicited expert predictions on how AI impacts fossil fuel extraction (Fig 1c), passenger transport (Figs 1d-e), consumption of material goods (efficiency of marketing and distribution systems) (Fig 1f) and electricity grids (Fig 1g). Efficiency changes may bring benefits, for example, AI may allow electricity networks to improve the use of resources and reduce emissions. However, efficiency improvements may lead to rebounds, negating gains. For transport, experts posited that advances in AI would improve autonomous vehicle capability and deployment, reduce passenger transport costs and cause demand growth. Our median 2040 transport cost reduction is 27.1% (Fig. 1f), with a demand increase of 21.8% (Fig. 1g). These values are in line with other estimates of energy saving from digitilisation[47.]

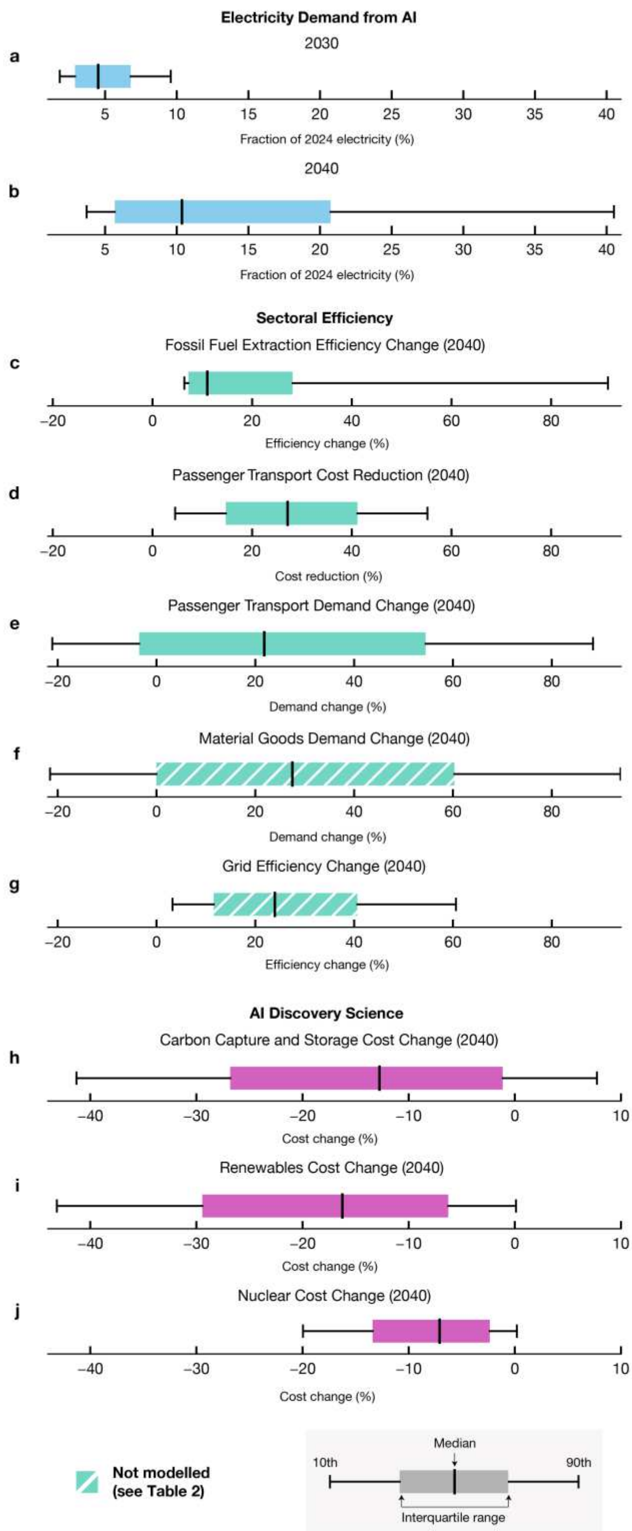

Figure 1 | Box plots of expert-elicited uncertainty distributions for a range of quantitative variables. Box plots represent quantiles of fitted uncertainty rather than raw estimates (see Methods). Data is shown for electricity demand estimations, 2030 and 2040 (panels a and b); sectoral efficiency, 2040 predictions for fossil fuel extraction efficiency (panel c), passenger transport cost reductions (panel d), passenger transport demand change (panel e), 2040 material good demand change (panel f), and estimations for grid efficiency changes (panel g). Panels h, i, and j are for AI discovery science variables: carbon capture, renewables and nuclear cost changes in 2040, respectively. Coloured boxes represent the interquartile range, medians are shown as horizontal lines, and whiskers show $10^{th}/90^{th}$ percentile values. Quantiles are extracted from skew-normal distributions fitted to pooled expert-elicited median, upper, and lower estimates, standardised to a 90% confidence level (see Methods). Hatched boxes represent variables that were not modelled (see Table 2).

For discovery science (Figs 1h-j), median values of resultant 2040 cost reductions were 16.3%, 12.8% and 7% for renewables, carbon capture and nuclear, respectively. Experts viewed the use of AI in science that could be relevant for emissions drivers as important to model. For example, AI is being used to advance our understanding and use of new materials in technologies such as batteries or solar cells.

Additionally, experts viewed AI as a potential vector influencing the implementation of climate policy. This included improvements via enhanced reporting and monitoring, or increased challenges through disinformation, polarisation and weakened ability of governments to implement climate policies.

A scenario framework for AI and climate change

Following the expert-led process, we present a conceptual scenario framework that systematically characterises plausible trade-offs and synergies between AI growth, climate policy, and AI governance (Fig 2). The framework defines a possibility space spanning strong alignment to strong non-alignment across these dimensions.

Whilst dependent on a wide range of factors, both climate policies and AI governance could influence AI growth, and whether such growth impacts emissions. Climate policy limiting the development of datacentres is a plausible trade-off. AI governance may hinder or help AI growth, depending on whether the reduction of possible harms or objectives for societal gain are prioritised. AI growth has the potential to increase pressure on both climate policy and AI governance if real or perceived benefits of AI growth are prioritised.

As countries and companies may build more powerful AI systems and infrastructure, there is a risk that climate policy objectives are sidelined. However, AI growth may help achieve climate policy aims, for example, via specific sectoral efficiency gains. AI governance may serve as a mediating force for ensuring that AI can benefit climate objectives: e.g., through limiting specific use cases of AI. Climate policy objectives may be synergistic with AI growth, for example, where energy-efficiency constraints drive innovation in algorithms or hardware system design.

AI governance is linked to AI growth, but the strength of such links might vary. AI governance may actively encourage AI growth, limit it, or have a more neutral impact, for example, only aimed at reducing specific harms. Strong AI growth and capability may, however, exert negative pressure on AI governance, harming its ability to play a mediating role in climate-beneficial outcomes (Fig. 2).

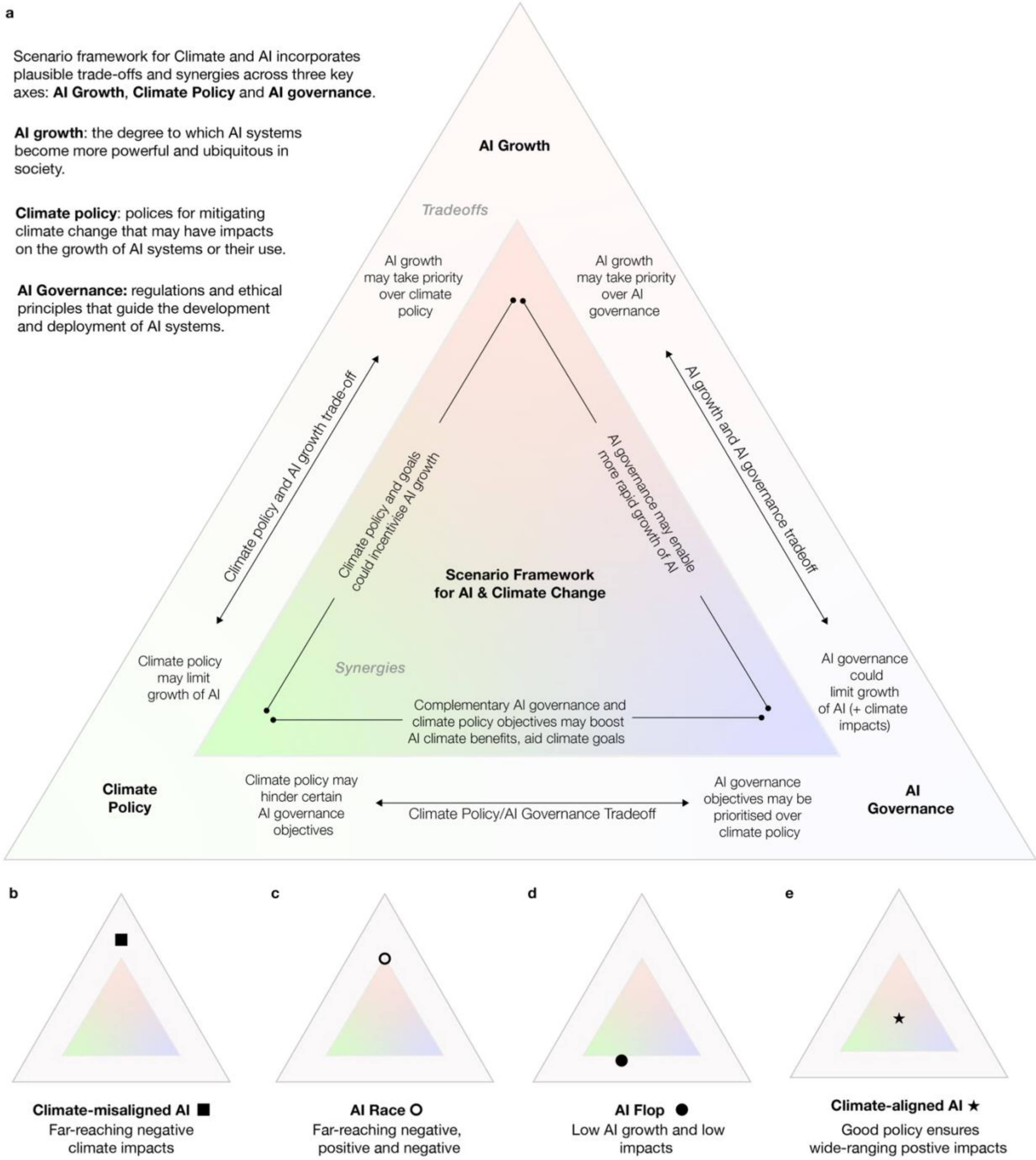

Figure 2 | A conceptual scenario framework that systematically characterises plausible trade-offs and synergies between AI growth, climate policy, and AI governance. Framework (panel a) showing how emission scenarios that incorporate AI should consider a range of plausible trade-offs and synergies between climate policy, AI growth (capability and ubiquity), and AI governance. Trade-offs are in the outer grey triangle and connected with bidirectional arrows; synergies are in the inner coloured triangle, connected with lines ending with circles. This is a continuous conceptual distinction, and scenarios may sit anywhere within it. Represented on panels b-e are subplots displaying the indicative positioning of each narrative scenario (Table 1) within the framework. Icon positions reflect the interpreted dominant balance of trade-offs and synergies from each narrative, rather than any numerical score. Icons positioned at the boundary between trade-offs and synergies indicate that both are present. Scenario selection is illustrative rather than systematic.

Next, we use the framework to situate illustrative narrative scenarios, selected following our expert elicitation process (Methods, Table 1). These scenarios are not meant to be exhaustive and instead represent a sampled subset of the possibility space identified by experts as policy-relevant. Quantitative scenarios inputs are provided in Supplementary Tables 3 & 4.

Table 1| Narrative scenarios presented in this paper and how they relate to our climate and AI scenario framework.

Scenario	Summary	AI Growth	Climate Policy	AI Governance
Baseline	Baseline scenario using Shared Socioeconomic Pathways (SSP) 2 data, current climate policies, updated for the removal of US policies and incorporating a policy extension to 2040 (see Methods).			
AI Race ○	AI is powerful, ubiquitous in society, and has wide-reaching emissions impacts. Companies and countries are in competition towards producing powerful AI systems. We combine high estimates of all indirect effects, with high electricity demand that uses a primarily cost-optimal grid electricity, with some direct supply from fossil and other sources. High sectoral efficiency gains lead to climate benefits, but the rapid scaling for AI comes ahead of efficiency regulation for datacentres, resulting in high electricity demand. AI expansion and dominance are prioritised over policy to ensure positive climate impacts.	Rapid growth, primarily due to innovation, but with AI governance supporting rapid scaling and not impeding growth. AI growth is ubiquitous across the economy.	AI growth and AI governance take precedence over climate policy objectives. High electricity demand growth leads to more challenges for climate policy. Powerful AI deployment in specific sectors has beneficial outcomes for achieving climate policy.	AI governance is geographically heterogeneous and focused on growth due to competition between countries.
AI Flop ●	AI has effects across society, but is less impactful than promised, with lower emissions impacts. The development of ever more powerful systems slows. Electricity demand growth ends up at the lower end of projections. Low indirect effects, with low electricity demand increases, using a cost-optimal mix from the grid. AI expansion does not conflict with climate policy objectives.	Slow growth, with innovation and enhanced capability failing to materialise to the degree anticipated over the next 15 years.	Low AI growth means that there isn't pressure on climate policy objectives. However, AI growth doesn't lead to changes positive for climate policy objectives.	AI governance across a range of areas, e.g., safety, disinformation, whilst materialising, does not include aspects relevant to emissions, in part due to low growth.
Climate-misaligned AI ■	AI is powerful and widespread, and fails to deliver beneficial emissions impacts and instead causes societal changes that worsen the climate outlook, such as low sectoral efficiency gains and polarisation. There is increased electricity demand and weak AI governance. High or medium for emissions-negative indirect climate impacts, with low estimates for our emissions-positive indirect effects. High electricity demand is supplied by a mixture of grid electricity (cost-optimal) and direct generation from fossil fuels. AI leads to disinformation and polarisation in society, with climate policy objectives sidelined.	Rapid growth in AI, but growth is particularly dominant in specific sectors. AI plays a prominent role in the mediation of information and news.	Powerful AI and its use in information dissemination and manipulation lead to the weakening of consensus for achieving climate policy objectives. Uneven AI growth across the economy fails to deliver impacts beneficial for achieving climate policy objectives.	Largely absent AI governance fails to protect against societal (incl. climate) harms. Weak governance leads to misinformation and polarisation, fails to lead to AI development that doesn't increase emissions.
Climate-aligned AI ★	AI is powerful and ubiquitous in society, but good policy intervention sees AI deliver strong positive emissions impacts, with negative impacts, such as rebound effects, limited. AI electricity demand is tempered through strong governance and policy intervention (e.g., ensuring high standards of efficiency for datacentres). Additional electricity demand is met through clean energy deployment. AI governance and climate policy are aligned to maximise benefits.	Innovation drives rapid growth of AI across the economy. Good policy ensures growth and application is emissions-beneficial.	Climate policy is not sidelined, and in conjunction with AI governance, reduces harms and ensures AI is climate-aligned. Strong AI growth across sectors brings impacts beneficial for climate policy objectives.	Strong, broad AI governance, with strong international collaboration, means that negative societal impacts, including those on emissions, are minimised.

Modelled energy system and emissions impacts

Our modelling of scenarios encompassing a range of expert-assessed variables shows diverging possible impacts. On emissions (Fig 3e), they range from 11% higher 2025-2040 cumulative CO_2 emissions than baseline (Climate misaligned AI), to 1.4% lower cumulative emissions across the same period (Climate-aligned AI). AI race also sees considerably higher emissions (6% higher cumulatively 2025-40), but lower than climate-misaligned AI, reflecting the mitigating impact of indirect effects that are negative drivers of emissions in this scenario. All scenarios see emissions fall between 2030 and 2040 (Fig 3f), due to our assumed continuation of reducing emissions intensity of GDP (see Methods). However, in the climate misaligned AI scenario, emissions in 2040 are only 4% lower than the 2030 value, which is already 8% higher than the Baseline scenario. The Baseline and climate-aligned AI scenarios see reductions between 2030 and 2040 of 12 and 13%, respectively. These results suggest that for the range of impacts modelled here, plausible emissions downsides outweigh the plausible upsides (Fig 3f). This exercise only considers certain AI impacts. Others, including from material goods consumption or labour market changes, could considerably alter findings (See Discussion, Table 2).

There are significant electricity-generating capacity additions in the Climate-misaligned AI and AI Race scenarios (Figs 3a & b) to meet increased compute and transport demands. Increases in both fossil capacity and renewables are due to the mix of direct supply for increased demand and grid electricity, for which renewables are the cheapest. AI race has lower overall additions than Climate-misaligned AI due to beneficial indirect effects as well as negative ones; a lower share of fossil new capacity is driven by a higher share of AI demand being met by grid electricity rather than direct fossil supply. In the climate-aligned AI scenario, there are small reductions in fossil capacity; this is due to assumed reductions in passenger transport energy demand (Table 1, Supplementary Table 3).

For all scenarios, higher investment in electricity supply than Baseline is observed for 2030, reflecting the additional electricity generating capacity needed for AI (Fig 3f). By the year 2040, for climate-misaligned AI and AI race, this is around 39 and 24% higher per year compared to the Baseline scenario (in 2000 USD). In a climate-aligned scenario, it is 1% lower, reflecting the small reductions in electricity capacity (Fig 3d).

Regionally, in a climate misaligned future, additional emissions are seen predominantly in India, China and the US (Fig 3g). Here, cheaper fossil fuels and additional electricity demand from compute and the transport sector are key drivers. Following the outcomes of our expert-led process, electricity demand from AI is assumed to increase the present regional mix in line with GDP growth (see Methods), with the US, China and Europe dominating future growth.

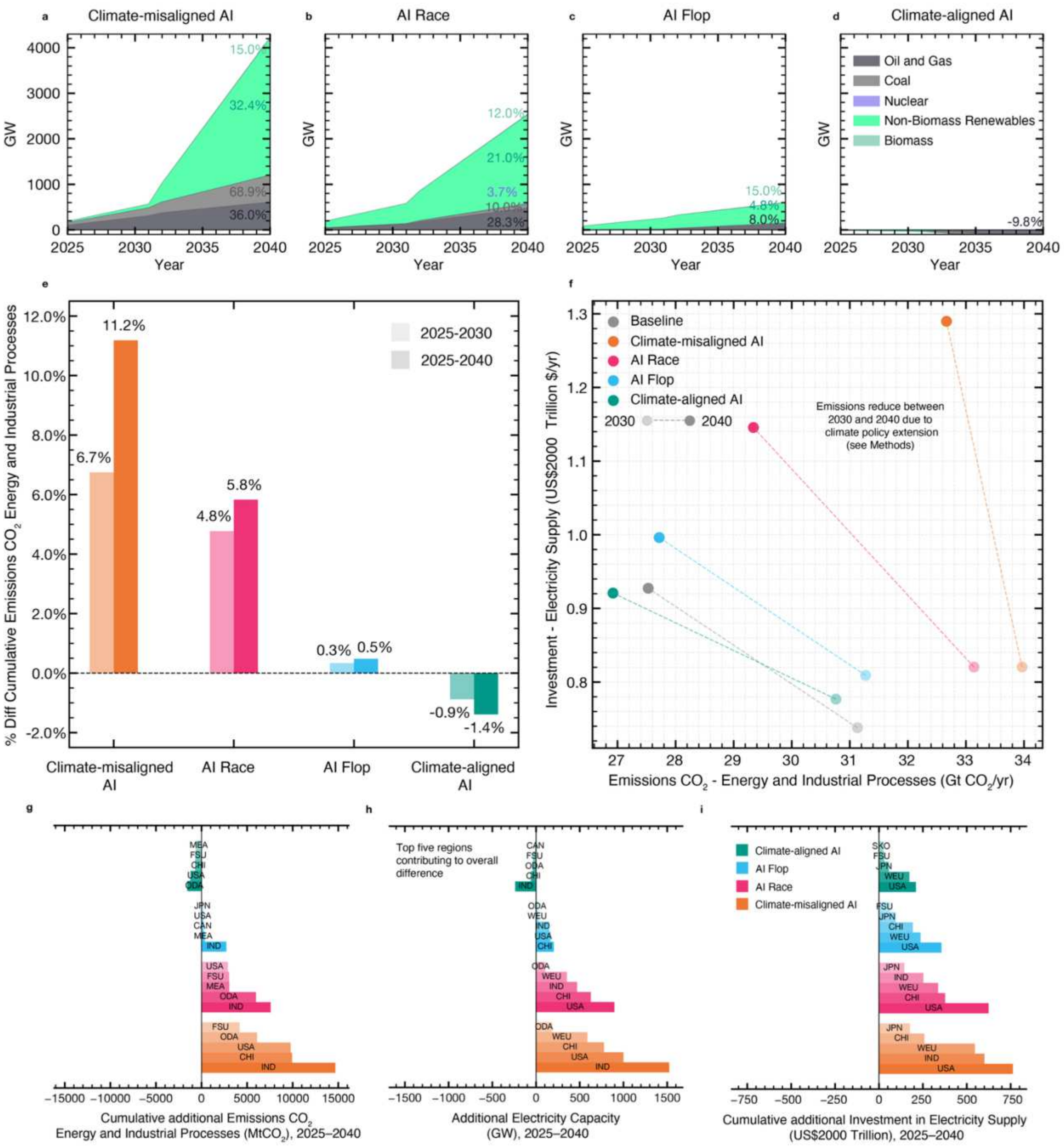

Figure 3 | Narrative Scenario IAM results showing electricity system, emissions and investment impacts from modelled direct and indirect effects. Panels a-d show the additional electricity capacity added by type, between 2025 and 2040, for each of the narrative scenarios, compared to our Baseline Scenario. Annotated percentages denote differences in generating capacity in 2040 by type, compared to the baseline scenario. Panel e shows the differences from baseline for each scenario in cumulative CO_2 emissions for two periods, 2025-30 (lighter bars) and 2025-2040 (darker bars). Panel f plots investment against emissions for two years, 2030 and 2040, with lighter circles representing 2030 values. Panels g to I show regional data for three variables for each scenario: cumulative additional CO2 emissions (g), cumulative additional electricity capacity (h), and cumulative additional investment in electricity supply (i). The five regions contributing most to the overall scenario difference from baseline are shown. FSU = Former Soviet Union, ODA= Other Developing Asia, WEU= Western Europe, SKO= South Korea, MEA= Middle East. For a full list of model regions, see Supplementary Table 5

Sensitivity of emissions pathways to AI-impacted variables

Here, we explore additional scenarios showing the sensitivity of emissions outcomes to individual impacts, both with and without policy extension to 2040. This provides insights into key drivers of emissions, and thus where targeted policymaking can enable climate-alignment of AI.

For AI electricity demand, emissions impacts vary between demand levels and supply approaches. We explore low, medium and high electricity demand trajectories (Methods, Supplementary Table 3) for cost-optimal grid-supplied electricity, as well as scenarios of direct supply from fossil fuels and low-carbon sources.

The cumulative additional CO_2 emissions by 2040 vary from 6% higher and 2.7% higher than baseline in the 'high' case for fossil and cost optimal scenarios, respectively, without policy extension (see Methods), to no or very low increases at the low demand level with policy extension (Figs 4a, b).In a cost-optimal scenario with no other AI impacts, most new capacity added is renewables, resulting in relatively lower additional emissions even in a high-demand scenario. With a climate policy extension, in a direct supply fossil scenario, emissions reductions occur elsewhere in the energy system to ensure meeting the policy target, resulting in relatively low overall emissions. A nuclear or renewables-only approach has no emissions impact. These results highlight the importance of considering not only efficiency and demand of compute, but also the supply options, with policy intervention needed to ensure that AI is powered with low-carbon sources to reduce additional emissions.

Examining indirect effects, we combine individual AI impacts with a medium cost-optimal AI electricity demand scenario. The largest individual effect is seen with transport cost per mile changes combined with rebound passenger transport demand, showing >6% higher emissions between 2025 and 2040 than baseline. It is important to note that when impacts are combined, this can lead to differences that vary in magnitude when compared to individual impacts (Fig 3). Here, the climate policy extension has a limited impact due to the applied regional emissions constraints acting as a proxy for the continuation of climate policy beyond 2030 (see Methods). Interactions between different AI impacts can amplify or dampen their combined effects in individual sectors. For example, with higher fossil fuel extraction efficiency (Fig 4c), investment in fossil generation increases, which means a greater share of AI electricity would be used in a cost-optimal scenario, all other things being equal.

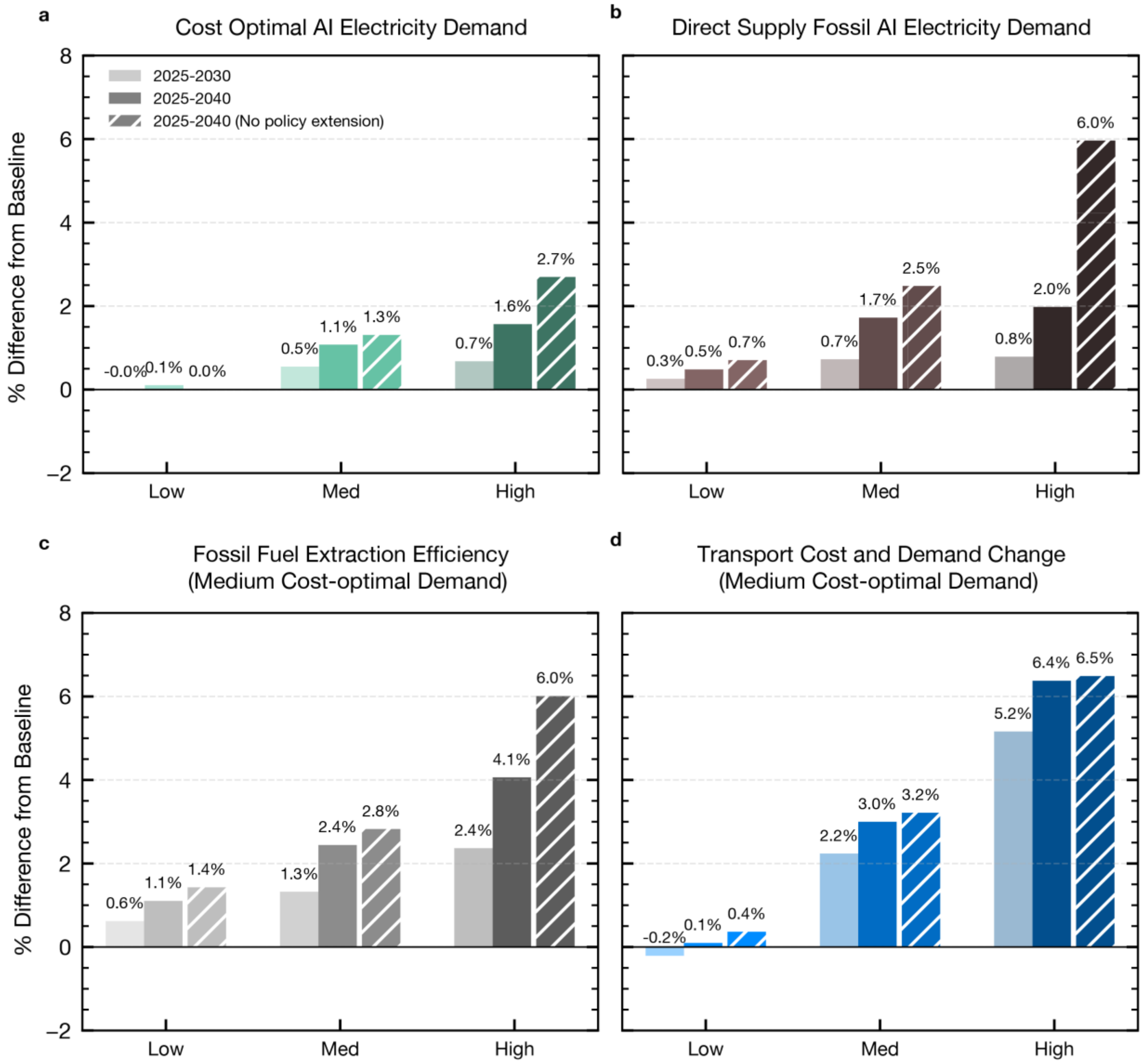

Figure 4 | Sensitivity of CO_2 emissions to individual AI impacts. Selected variables explored at low, medium and high intervals (see Methods, Supplementary Table 3), values shown are the difference in cumulative CO2 emissions from energy and industry when compared to the baseline scenario (See Table 1). For each impact, emissions differences 2025-2030 and to 2040 are provided, with policy extension. We also provide cumulative differences from 2025 to 2040 without climate policy extension after 2030 (hatched bars). Panel a shows cost-optimal grid supplied electricity demand, b shows direct supply fossil fuel AI electricity demand, c shows changes in fossil fuel extraction efficiency, and d shows transport cost and demand changes. For indirect effects (panels c and d), these impacts are run in a medium AI electricity demand scenario with a cost-optimal supply mix.

Towards the inclusion of AI Impacts in emissions scenarios

Our expert-led process highlighted several ways that AI may impact drivers of emissions. Although only exploratory, our results indicate there is a strong case for emission scenarios to consider AI impacts in future, which can be informed by the expert elicitations in this paper. Cumulative global CO_2 emissions to 2040 could be up to 11% higher than the baseline due to AI, in a case with powerful AI and poor climate-alignment. Alternatively, with good policy intervention, cumulative CO_2 emissions could be 1.4% lower by 2040. Acknowledging the significant uncertainty in these numbers, these divergent outcomes nonetheless highlight the importance of ensuring both AI and climate policy respond to AI growth in ways that maximise emissions benefits (Fig. 2), while meeting other societal goals. Our findings also suggest that indirect effects of AI on emissions may be larger than direct effects (electricity demand from AI) (Fig 4). This is salient given the broad attention placed on direct (data centre) electricity demands.

However, our results should be considered in the knowledge that several impacts could not be easily modelled in this exploratory study and require further research (Table 2). The nature of IAMs as tools for considering long-range emissions and energy system changes limits their usefulness in some regards. For example, the impacts on electricity systems, resultant emissions and electricity price changes may occur to a large degree at a localised level and have temporal variation[48,49]. Global IAMs are regionally aggregated and typically do not offer the required temporal resolution to consider such dynamics, which means that national and subnational energy-economic models could be valuable complements for investigating AI's impacts on emissions.

Additionally, increased goods consumption due to AI (Table 2) was highlighted during our expert-led process as a plausible emissions-relevant outcome of AI. Again, IAM model characteristics make changing the consumption of such consumer goods far from straightforward. A range of modelling tools and research methods in combination are needed to quantify emissions-relevant AI impacts. Further research is needed to better develop and combine appropriate methods.

Table 2 | Key modelling and data gaps for representing AI's emissions impacts

Variable	Plausible impacts	Modelling and Data Challenge
Electricity Demand and Supply Profile	When and where electricity demand occurs is crucial for the impact on supply needs and emissions. If demand occurs at times when there is surplus clean energy capacity, more emissions may be negligible. National and subnational policy, market, and technology dynamics may materially alter power sector responses to AI demand.	Integrated assessment models do not readily allow the consideration of the time of use of electricity demand at the temporal resolution needed to explore these dynamics (e.g., energy storage), nor do they generally model the spatial resolution to capture policy and market dynamics or infrastructure costs and constraints (e.g., transmission). Other modelling approaches at a national or regional scale (e.g., energy systems models, electric sector capacity expansion models) should complement IAM analysis.
Material Goods Demand Growth	AI may drive more consumption of goods through its use in advertising and online communication to target consumers and increase spending. AI may enable more efficient distribution systems, lower costs and further drive consumption.	Within integrated assessment models, demand is broken down into specific sectors relating to energy demand. These sectors cannot be easily mapped to consumer products that could be influenced by such algorithms. Economic models (e.g., computable general equilibrium models) can represent service demand feedback but have more aggregate representations of the energy system.
Disinformation and Polarisation	The use of AI in algorithms driving social media platforms, and the use of AI to produce content shared on social media, may drive polarisation in society, weakening governments' ability to implement climate policies. These issues may also extend to the use of generative AI, with their outputs driving disinformation and polarisation.	Whilst this can to an extent be incorporated into scenario narratives, influencing the strength of policy and the magnitude of other variables, it is difficult to explore directly. Future availability of empirical data may allow quantification of such impacts.
Economic growth	Economic growth may be impacted either positively or negatively by AI. Productivity increases from AI systems may drive economic growth; alternatively, labour market disruption and mass-unemployment could have negative impacts on economic growth. This would have a resultant impact on emissions	Modelling these changes may require new assumptions around GDP and productivity for IAMs[50]. However, more research is needed to think about the likely labour market and productivity impacts, and in different regions. These dynamics may intersect with channels for climate impacts.

A considerable obstacle to improved quantification of AI emissions impacts is data availability. The need for transparency of electricity consumption used for the training and inference of AI models has been well discussed, but large gaps remain, especially for proprietary systems[45]. There is also a need for data and research on how AI may influence or is already influencing emissions through the way it is applied. For example, our understanding of how AI can improve operational efficiency in sectors such as transport or fossil fuel production, change technology adoption rates, and accelerate innovation is limited[6,17,18]. Policy intervention and research initiatives can help address this, for example, through reporting requirements for proprietary AI systems and data centres, and case study and sector-level impact assessment of AI applications.

Policy intervention offers the potential to improve climate-alignment of AI in a range of ways. On direct AI electricity demand, this could include regulating efficiency standards or rules about the use of low-carbon electricity. Such measures may be examples where climate policy and AI policy compete, with opposition made on the basis that they could make companies or countries uncompetitive. However, such regulation incentivises the improved efficiency and consequently more 'frugal AI' systems [51], which may further the development of more superior and powerful AI systems due to their better use of compute resources. Beyond regulation, policies could include funding of research focused on measures to reduce energy demand from compute, such as algorithmic efficiency or cooling technology , which may also aid in achieving reduced direct AI demands.

On indirect impacts, policy intervention may enable the use of AI in ways that lead to emissions reductions. In practice, this could be via initiatives to provide computing resources or training and development for specific sectors, or funding of sector-specific AI research programmes. Concurrently, anticipating potentially harmful rebounds resulting from AI-driven efficiency gains can minimise downsides. These measures are likely to be sector-specific. For example, for road transport, policies could range from infrastructure design to appropriate taxation and regulation of autonomous vehicles.

Whilst this work includes a range of impacts that may determine the degree to which AI development is aligned with climate change mitigation objectives, this does not necessarily equate to other societal aims. Making AI systems aligned with other environmental or socio-economic aims may require alternative policy and governance approaches to those discussed above. Possible impacts on other societal aims are beyond the scope of this study, but need urgent investigation.

Given the substantial uncertainty over AI growth, and the magnitude of emissions impacts our findings should be treated as exploratory. They serve to discuss plausible outcomes, provide some quantification and explore modelling initial insights to motivate further research. Whilst our robust expert-led process enabled this, the breadth and heterogeneity of impacts considered means that future work should engage more deeply with experts relevant to each impact pathway. In parallel with further expert-led work, approaches using emerging empirical evidence will be required to track and forecast AI impacts across different sectors.

Method

We use expert elicitation for both compiling the possible ways that AI may impact climate change and for predicting their range in magnitudes. This expert data was used to develop a scenario framework and a range of scenarios that aim to cover a large portion of the possibility space. Next, we use an integrated assessment model to explore each scenario's energy demand and emissions trajectory. Through this exercise, we identified aspects that cannot be easily modelled using existing approaches and tools (Table 2).

Expert Elicitation

The expert elicitation comprised three stages: interviews, quantitative surveys and group discussions. We follow aspects of the IDEA protocol [46], an adapted Delphi process designed to enable experts to make more accurate predictions under deep uncertainty. The expert elicitation process included a total of 17 experts from a range of organisations, including academics, international organisations, think tanks and businesses. An anonymised list of experts and their contribution at each stage in the process is included in Supplementary Table 1. We contacted experts based on authorship of existing relevant published academic and grey literature, and those based at specific organisations producing relevant work. Further experts were contacted on the recommendation of previously interviewed experts.

Interviews
We conducted short semi-structured scoping interviews with experts to gather a range of possible influencing factors. In total, we interviewed 15 experts.

These interviews were designed to allow each expert to discuss factors they felt were possible regarding ways that AI could influence climate mitigation. Further, we asked about the relative importance and timing of factors, as well as an exercise aimed at getting experts to consider extreme best and worst cases. The interview questions and protocol are provided in Supplementary Methods 1. Interviews were recorded, and an auto transcription used for ease of data analysis.

We grouped these into the following key themes, with factors mentioned by only one expert excluded.

- **Electricity Demand** (direct)**:** discussion on both short-term and long-term impacts, localised stresses, and the supply of this additional demand from different sources.

- **Sectoral Efficiency Gains** (indirect): discussion of how AI might influence a range of sectors influencing climate change mitigation, including but not limited to transport and the electricity sector; discussion of rebound effects.

- **AI and Science** (indirect)**:** discussion of the use of AI as a tool in science to give mitigation-relevant gains, e.g., materials for batteries.

- **Implementation of Climate Policy** (indirect)**:** discussion of how AI and algorithms for social media may drive polarisation and weaken the ability of governments to implement policy, and AI for monitoring and compliance

These factors and themes were used as the basis for the quantitative surveys.

Quantitative Surveys
Following the IDEA protocol[46], we asked our experts to perform two sets of quantitative predictions, one before and one following a group discussion. This is due to the evidence that indicates experts make better predictions following discussion with one another[52,53]. We compiled our quantitative surveys around key themes raised in the interview data. We asked experts about impacts in 2030 and 2040, with some factors only for 2040. Timing for factors was based on the information gathered in interviews regarding how soon measurable impacts would be expected. We did not ask for predictions beyond 2040 due to early guidance from experts, highlighting the increasing uncertainty in making predictions further in the future.

We used the outputs of the second set of quantitative predictions (post-group discussion, see below) to develop our scenarios and respective inputs. We structured the questions to elicit the upper, lower and central estimates for each quantity; as well as the confidence that their estimates lie between their upper and lower bounds. These data points allow us to construct distributions, from which we derive our scenario inputs (see below). The full survey is provided as Supplementary Data to this manuscript.

Group Discussions

Group discussions were 90 minutes long and each held with six participants. These were structured around the survey outcomes and allowed the expert participants to explain justification for their initial predictions, with time allowed for discussion and rebuttal.

Scenarios and Integrated Assessment Modelling

We used the survey outputs and interview data to construct a set of scenarios and inputs for the integrated assessment modelling stage. The scenarios are split between those designed to understand the sensitivity of emissions to various factors and example narrative scenarios. We constructed narrative scenarios (Table 1) alongside a scenario framework for understanding impacts of AI on the climate using insights from across our expert elicitation process (Figure 2). The model inputs are derived from combining low, medium or high estimates from our survey data; a full set of data, and estimates used for each narrative scenario are provided in Supplementary Table 3.

Construction of Model Inputs

Results from the second round of the survey were cleaned and sanity-checked, and in any cases of doubt were discussed with the experts. Sign conventions were aligned between responses. The range of uncertainty allows us to categorise some quantities as logarithmic and others as linearly uncertain, where we had genuine uncertainty over the sign of the answer. The questions which were treated linearly were "Material goods demand increase in 2040", "Transport demand increase in 2040", "Transport cost reductions in 2040", "Carbon capture and storage price reduction 2040", "Cost reduction for renewables 2040" and "Cost reduction for nuclear 2040".

The confidence intervals of all experts were standardised to 90%, and the values of the central, upper and lower limits were averaged – the standardisation was achieved by multiplication, and the averaging was geometric for logarithmic quantities, whereas linear standardisation and averaging were used for linear values.

For logarithmic values, we express:

$$V_{s+} = V_b * \left(\frac{V_+}{V_b}\right)^{0.9/p} \tag{1}$$

Where V_{s+} is the standardised upper bound, V_+, is the value before standardising, V_b is the best guess, and p is the assessed probability that the given answer is between upper and lower bounds. For linear values, we express

$$V_{s+} = V_b + \frac{0.9}{p} * (V_+ - V_b) \tag{2}$$

Similar expressions are used for the lower bounds. A skew normal distribution is fitted to match the median, upper and lower estimates at the required quantiles using the Scipy optimise function in Python[54]. Required quantiles are then extracted from this distribution.

For most modelled aspects, we assume uniform impacts across regions. This is due to an assumption that most modelled factors, e.g., cost reductions of technology, or the availability of AI technologies to enable efficiency gains, will be experienced across regional boundaries. However, for some factors, we take a different approach. Electricity demand from datacentres is regionally concentrated at present, and projections of future growth are also regionally concentrated[18]. For this factor, we asked our experts to predict how electricity demand would be distributed regionally.

In accordance with their views, we assume that future growth in electricity demand from datacentres will follow existing distributions, for which we use data available from the IEA[18]. These data provide current distributions for all data centre usage, which we assume as a proxy for the AI usage within datacentres. Current distribution is strongly correlated to the distribution of GDP, and therefore, we use respective SSP GDP growth predictions[55] to distribute additional future electricity demand growth from datacentres due to AI, predicted by our experts.

Integrated Assessment Modelling

We use the TIAM-Grantham integrated assessment model (IAM) to run our scenarios[56]. TIAM-Grantham is a perfect foresight cost-optimisation model, based on the TIMES model[57]. Perfect foresight means that it has full knowledge of energy availability and costs when achieving a least-cost pathway to meeting a specific emissions target. We have configured the TIAM model to run from 2025, then to 2030 and then in decadal timesteps onwards to 2040. Given that we only adjust parameters to 2040, and due to the widening cone of uncertainty further into the future, our presentation of data only up to this timestep is a deliberate decision.

Our baseline scenario is SSP2 current policies to 2030, updated to remove US climate policies. For our narrative scenarios (Table 1), we assume a continuation of the emissions intensity of GDP trajectory after 2030[58]. This represents a climate policy extension. For sensitivity scenarios (Figure 4), we explore individual impacts both within and without the policy extension.

Here, we briefly describe the representation of specific impacts within the TIAM model. For direct electricity supply proportions, e.g., from fossil fuels (Supplementary Table 4), does not include grid infrastructure costs. This is because this capacity is assumed to be co-located directly with compute demand (data centres). For fossil fuel extraction efficiency, the fossil fuel price was used as a proxy, given that extraction efficiency is not a parameter within the model. For passenger transport, we reduce costs through energy per mile, with demand increases represented through trip distance.

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