https://doi.org/10.1038/s44168-025-00252-3

Green and intelligent: the role of AI in the climate transition

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Artificial Intelligence (AI) can play a powerful role in supporting climate action while boosting sustainable and inclusive economic growth. However, limited research exists on the potential influence of AI on the low-carbon transition. Here we identify five areas through which AI can help build an effective response to climate threats. We estimate the potential for greenhouse gas (GHG) emissions reductions through AI applications in three key sectors—power, food, and mobility—which collectively contribute nearly half of global emissions. This is compared with the increase in data centre-related emissions generated by all AI-related activities.

The global economy is confronted with escalating environmental crises, including climate change, biodiversity loss, and widespread pollution. These challenges necessitate rapid systemic change across our economies and a significant boost in climate and nature-related investments.

In the context of climate change, achieving a net-zero transition requires major investments in new low-carbon infrastructure, energy systems and technologies, particularly in emerging markets and developing economies (EMDEs), where opportunities to leapfrog traditional technologies are most prevalent[1]. Africa, for example, accounts for about 60% of the world's best solar resources but received <2% of the investment in clean energy in 2023[2]. It is estimated that the aggregate requirements for climate-related investments will be at least \$4 trillion globally by 2030[3] and around \$2.4 trillion in EMDEs, excluding China[4].

This is not merely an opportunity for incremental improvements but a chance to achieve systemic transformation that can unlock a new growth story[1]. This green investment push can boost development and stimulate global economic growth in a more sustainable, inclusive, and resilient direction. Further, it can also help conclude the low investment and low productivity cycle of 'secular stagnation'[5].

The net-zero transition is not simply a mitigation strategy and should not be thought of as a "cost", but rather a great opportunity for innovation and sustainable, resilient and inclusive economic growth[6]. Further, this transformation can reduce costs through increased resource and energy efficiency; bolster human and social capital from better health and productivity gains related to lower pollution; and drive growth from the increase in investment itself[1,7].

Artificial intelligence (AI) is well-positioned to accelerate this transition and, as general-purpose technologies, AI can be applied to speed up this process of profound systems' transformation by increasing the speed, efficiency, and effectiveness with which innovation processes are scaled and capital is deployed. AI is in a strong position to deliver use cases for the net-zero pathways of almost all economic systems and can help reimagine interconnected systems such as power, transport, cities and land use.

Limited research exists on the extent of the combined effects of AI and the low-carbon transition. While the conceptual effects of AI on climate change have been explored[8,9] there is still a lack of robust analysis on their macro-level effects. Few studies, in particular, have attempted to estimate the emissions reduction potential of these technologies.

Previous studies, like the ones carried out by Microsoft and PwC[10] or Google and BCG[11], have attempted to quantify AI's potential impact on emissions reductions using computable general equilibrium (CGE) modelling and surveys. They estimate an emissions reduction potential of 1.5–4% and 5–10% by 2030 respectively, equivalent to 1–2.5 $GtCO_2e$ and 2.6–5.3 $GtCO_2e$. However, these studies are not peer-reviewed, do not disclose all details of the methodologies used, and are conducted by AI solutions providers. Moreover, top-down quantitative approaches, such as CGE models, are limited by the complexities of modelling system-wide societal impacts.

To fill this gap, we explore five key impact areas through which AI can be particularly effective in supporting the climate transition, across mitigation, adaptation and resilience:

i. transforming complex systems;
ii. innovating technology discovery and resource efficiency;
iii. nudging and behavioural change;
iv. modelling climate systems and policy interventions;
v. managing adaptation and resilience.

We then estimate the GHG emissions reduction potential of AI applications for a subset of the five key areas, using three sectors as an explanatory example: power, meat and dairy, and light road vehicles. These

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sectors collectively contribute to nearly half of global emissions[12,13]. Given the wide range of potential solutions across the five key impact areas in the three sectors, we have concentrated on those that are pivotal in driving positive tipping points. Specifically, our focus is on AI's role in accelerating the adoption of those low-carbon solutions and enhancing the efficiency impact of these solutions within these sectors.

Compared to previous studies, our methodology takes a bottom-up approach, analysing the projected growth of low-carbon technologies and addressing the limitations of other approaches by isolating the specific impact potential of AI within individual sectors.

Furthermore, we estimate the potential increase in emissions due to AI applications (i.e., increasing demand for computing power drives data-centres' energy consumption), finding that the emissions reductions due to AI from just these three sectors alone would more than offset the estimated increase in emissions from all of AI's activities (i.e., not just those from AI's contribution to the climate transition). Therefore, we show how the case for using AI for the climate transition is not only strong but imperative.

It should be made clear that this study does not explore the full, dynamic impact of AI applications on climate action on broader economic outcomes, such as growth, investment and jobs. It is likely that the changes in the sectors above will be mutually reinforcing, have significant spillover effects and—together with changes that AI would foster across other sectors—drive significant macro-economic outcomes. Since we are not assessing the impact of rebound effects, we have also not considered any effects of AI on emission-intensive activities. We deliberately limit the focus of our work to direct implications of AI applied to climate action on emissions, as the main purpose of our research is to define the magnitude of potential emission reduction.

We close the paper by looking into the limitations of letting markets alone determine the applications and governance of AI. We explore how the role of an active state will be critical in ensuring that AI is deployed to accelerate the low-carbon transition equitably and sustainably.

AI's contribution to the climate transition

We explore five key impact areas through which AI can be effective in supporting the climate transition, across mitigation, adaptation and resilience (Table 1):

Transforming complex systems

Decarbonising the global economy requires radical systemic and structural changes in all key complex systems, including cities, land, transport, industry and energy. Redesigning and transforming such complex systems and running them effectively and efficiently (e.g., based on live data) can be greatly facilitated by AI.

In the energy sector, for example, AI can enhance the stability and efficiency of renewable energy integration into power grids. The intermittency of solar and wind energy presents a significant challenge, as fluctuating supply must be balanced with real-time demand. AI can optimise grid management by forecasting supply and demand more accurately and by managing distributed energy resources (DERs), such as electric vehicles and energy storage systems[14]. DeepMind has shown that AI applications can improve wind energy's economic value by 20% by reducing reliance on standby power sources[15].

AI has the potential to reimagine interconnected systems (like power, transport, cities, and land use) and optimise how such systems interact. More specifically, AI applications can be harnessed for advanced optimisation of integrated systems in urban ecosystems to improve planning, design choices and construction of infrastructure, smart grids, green buildings, or resilient transportation systems. Singapore, for example, has developed a Smart Nations initiative and National AI strategy to structurally assess the potential of AI for the public good[16].

Across sectors, AI can be used to better predict investment risks and returns, improving financial decisions where information is scarcer, particularly in emerging markets where perceived risk is high, often due to limited and asymmetric information[17]. AI can address this by aggregating diverse data sources on realised project risk, providing more accurate risk assessment and prediction and making financing more accessible. The World Bank's GovTech Innovation Lab, for example, uses AI to enhance governance and risk assessment for development projects[18]. If data is shared, as more projects get financed and more data becomes available, this in turn reduces information asymmetry, making capital more affordable for sustainable projects in EMDEs. At a more aggregate level, there are several examples of how AI can be used to mobilise finance for sustainable projects. One example is the use of satellite data to estimate solar power generation potential in different regions, which can help investors decide where to invest in renewable energy projects. As green energy projects become larger and more complex, AI is playing a critical role in optimal portfolio creation and its effective management.

Innovating technology discovery and resource efficiency

Achieving net-zero emissions requires accelerating the deployment of existing clean technologies and rapidly discovering new ones. The International Energy Agency (IEA) has estimated that almost half of the emissions reductions needed to reach net-zero by 2050 will come from technologies currently in the prototype or demonstration stage[19]. AI has proven itself as a potent tool in accelerating the pace of discovery and commercialisation in fields like materials science and biotechnology. For example, Google DeepMind's GNoME tool identified more than 2 million theoretical crystal structures, over 45 times the number identified to date by science, which can contribute to breakthroughs in renewable energy production and storage technologies[20]. Their AlphaFold model, recently honoured with a Nobel Prize, also used AI to predict the structure of 200 million proteins—an extraordinary leap forward from the small fraction scientists had deciphered until recently. This breakthrough could significantly accelerate the transition towards alternative proteins.

AI is also able to enhance asset use and resource efficiency, especially in industry; AI-powered optimisation systems can reduce waste in manufacturing, logistics, and recycling, improving both productivity and sustainability. For instance, Amazon's Package Decision Engine determines the

Table 1 | AI key impact areas to accelerate the climate transition

1. Transforming complex systems	2. Innovating technology discovery and resource efficiency	3. Nudging and behavioural change	4. Modelling climate systems and policy interventions	5. Managing adaptation and resilience
• Integrated management of energy systems, multimodal transport, and the urban ecosystem • Simulations of inter-systemic flows and cross-system interaction through AI-powered digital twins • Prediction of investment risks in low-carbon projects	• Acceleration of scientific discovery and incubation of green tech innovation at scale • Generation of sustainable design options • Maximisation of asset use and efficiency over lifetime	• Modelling of social behaviour, pattern analysis, and prediction • Facilitation of pro-environmental behaviour through advanced data analytics and AI-powered assistants	• Forecasting of extreme weather and climate change scenarios • Modelling the effects of climate change and the effectiveness of different policy scenarios	• Forecasting of climate impacts and early warning systems • Management of financial and human climate risk and impact towards more resilient systems • Strategic planning on climate adaptation

most efficient type of packaging for each item it learns about, helping to reduce the number of cardboard boxes, air pillows, tape, and mailers used to send purchases to customers. Along with other packaging innovations, this model has helped Amazon avoid over 3 million metric tons of packaging material worldwide since 2015[21]. Improving resource efficiency is also a space for entrepreneurial innovators, such as the start-up GreyParrot, which uses AI-based computer vision to optimise the sorting of materials at recycling facilities, significantly increasing recycling rates[22].

Nudging and behavioural change

Changes in lifestyle and consumer behaviour can reduce 40-70% of greenhouse gas emissions by 2050[13]. Leveraging AI towards supporting more sustainable consumption patterns is important to enable a systemic shift. In the context of increasing global resource consumption (projected to go up 60% by 2060[23]), optimisation of production will not be enough; demand must also adapt by promoting more sustainable lifestyles, conscious consumption and reducing overall environmental impact. However, despite growing awareness and willingness to act, consumers often struggle to identify the most climate-friendly options due to information asymmetry and inefficient market signals. Personalised recommendations can empower consumers to adopt low-carbon technologies by suggesting options that align with their needs while minimising their environmental impact.

The potential for AI to overcome psychological barriers and tailor interventions is also shown by examples in specific sectors. In the power sector, energy management is a key area where AI effectively drives sustainable consumer behaviour. Google's Nest uses sensors, smart home systems, and AI-driven learning to optimise heating and cooling based on real-time weather and user preferences[24]. Similarly, Oracle's Opower combines AI with behavioural science to nudge energy savings through customer engagement[25]. By channelling complex data into clear, personalised recommendations, it helps to overcome cognitive limitations that hinder pro-environmental behaviour. The potential of technologies of this type is huge, as lowering thermostats by just 1 degree could save UK households £670 million annually and reduce CO_2 emissions by 3.5 million tonnes[26].

In the food sector, Winnow Vision's cameras equipped with AI-based image recognition are being used to automatically track and reduce food waste in kitchens. This technology has already helped chefs in 3000+ locations to pinpoint waste products and adapt their menu, cutting their food waste significantly[27].

In mobility, Google Maps offers users fuel-efficient travel routes, reducing individual emissions through AI-guided decision-making[28]. Such models evolve quickly and indicate how tailored recommendations and automated feedback mechanisms may cater to individual preferences, thereby increasing the effectiveness of behavioural change initiatives.

Modelling climate systems and policy interventions

Accurate and timely climate forecasting is crucial for designing and implementing effective climate policies. AI's capacity to process vast datasets and run complex simulations in real-time makes it a valuable tool for improving the accuracy of climate models, which are essential for understanding both immediate and long-term climate risks.

AI has been instrumental in enhancing weather forecasting and climate prediction models. The British Antarctic Survey and the Alan Turing Institute developed IceNet, an AI-powered tool that uses satellite data to forecast sea ice levels at a higher accuracy than state-of-the-art dynamical models (ECMWF SEAS5)[29]. This level of precision can improve climate projections, thereby contributing to better-informed long-term policy decisions regarding mitigation and adaptation strategies.

AI models can also be applied to better design and implement policies for climate action, by generating insights and predictions around complex climate policy scenarios or monitoring the effectiveness of policy implementation. The Climate Policy Radar, for example, uses AI to create open-source tools that assist governments in designing best-practice climate policies based on evidence from thousands of case studies[30]. A recent study used Machine Learning to analyse roughly 1500 climate policies implemented between 1998 and 2022 across 41 countries, to identify those that were able to reduce carbon emissions most effectively[31].

Furthermore, AI can also contribute to developing new economic models that include "Beyond GDP" metrics (for a comprehensive review see Jansen et al.[32]). Policymaking has long focused on economic growth as measured by gross domestic product (GDP), diverting attention from other societal goals, such as sustainability, personal well-being and equality. Thanks to the ability of processing large and diverse types of datasets and running complex modelling tools, AI can help integrate "Beyond GDP" metrics into current macro-economic models. This could facilitate policymakers in making informed decisions that are directed towards shaping a sustainable and inclusive future.

Managing adaptation and resilience

As climate-related disasters become more frequent and severe, the ability to forecast hazards and adapt to changing conditions will become increasingly critical. AI is already improving early warning systems for extreme weather events, such as floods and wildfires, enabling governments and communities to take proactive measures to mitigate damage, saving lives and significant costs.

For example, flooding results in $50 billion of economic damages each year, exposing 1.5 billion people to these risks. Google's FloodHub uses machine learning models to forecast flooding events up to five days in advance, and issuing detailed alerts in more than 80 countries, allowing such damages to be avoided[33]. To cover extreme weather events more extensively, digital twins, such as NVIDIA's Earth-2 and the European Space Agency's (ESA) DestinE, are being developed. These simulations combine traditional physics-based models with AI to forecast weather in unprecedented detail, thereby improving disaster alert systems and allowing for dynamic adaptation measures[34].

AI can also support long-term resilience and adaptation through its ability to create large-scale simulations tracking how ecosystems might evolve. For instance, using satellite technology, AI can help track biodiversity loss following forest fires and estimate the water content in the tree canopy in combination with drought forecasting to help predict which regions are most at risk[35].

Quantifying AI's impact on emissions reduction

Methodology

To provide a quantitative illustration of how AI applications can contribute to reducing GHG emissions across the five key impact areas, we estimate emissions reduction potential of AI applications in three economic sectors: Power, Food, and Mobility. The choice of the three specific sectors derives from a combination of factors, including emissions coverage, availability of public data, and representativeness of relevant use cases within the five key impact areas outlined above. Specifically, these sectors together contribute to roughly 50% of global GHG emissions and show a high activity of emerging AI use cases with potential to drive decarbonisation[12,13]. The contribution of AI applications to emissions reduction occurs particularly through three of the five key impact areas, namely: (1) transforming complex systems; (2) innovating technology discovery and resource efficiency; and (3) nudging and behavioural change.

For the Power sector, we estimate the emissions reduction potential of AI technologies applied to advanced forecasting of supply and demand, and better management of distributed energy resources. These applications can improve how solar PV and wind are adopted and integrated into the grid, contributing to emissions reduction by transforming the energy system (key impact area 1). In the Food sector, we estimate emissions reduction associated with the ramping up of alternative proteins (APs) that can replace traditional meat and dairy products. Here AI can be used to identify new protein structures with better taste and texture, thereby increasing the attractiveness and consumption of APs by accelerating scientific discoveries in this area (key impact area 2). AI can also be used to nudge consumers' behaviours to choose APs (key impact area 3). In the Mobility sector, we find that significant emissions reductions can be achieved through advancing AI-enhanced shared mobility, whereby AI technologies transform the transport system (key impact area 1) and nudge consumers to switch to shared transport (key impact area 3). We also account for AI improving the affordability and accessibility of EVs by discovering cheaper battery compositions (key impact area 2).

It should be noted that these three sectors are very interconnected with others, so accelerating the adoption and efficiency of low-carbon solutions here will no doubt trigger technological tipping points elsewhere, resulting in cascading effects across the economy[36]. This dynamic effect, likely to further enhance the impact of AI on emissions, is not taken into account in our analysis.

We use a novel approach to estimate the effect of AI on the *market adoption rate* (e.g., in the food analysis, the share of alternative proteins consumed vs. traditional meat and dairy), and on the *efficiency* of low-carbon solutions (e.g., in the mobility analysis, how many passenger kilometres driven per electric vehicle).

To model the former, we assume that technology adoption follows a Sigmoid-curve (S-curve), a non-linear trajectory through five stages: (1) concept, (2) solution development, (3) niche market, (4) mass market, and (5) late market[37] (see Section 1 of the Technical Annex). We developed sector-specific market adoption S-curves based on historical data[37,38] from similar technologies (see Section 2.2 of the Technical Annex). Adoption is influenced by three enabling conditions—affordability, attractiveness, and accessibility (see Section 1 of the Technical Annex):

- *Affordability*: The solution's cost relative to alternatives. Price parity is crucial for driving user or investor adoption by ensuring financial competitiveness.
- *Attractiveness*: The solution's appeal to users, including performance, convenience, and additional benefits that enhance desirability.
- *Accessibility*: The ease with which users can access the solution, encompassing distribution, supply chain stability, and system integration.

Each solution is evaluated across the three enabling conditions using an extended traffic light system, with categories ranging from dark green to green, yellow, red, and dark red (see Section 2.1 of the Technical Annex). The relative importance of these conditions varies by solution, sector, and context. For example, affordability may dominate in price-sensitive sectors, while attractiveness drives behaviour change in consumer-facing solutions. This variability is accounted for by assigning fixed relative weights to each enabling condition for each sector. These weights are then used to calculate "maturity scores" for each combination of enabling conditions (see Section 2.1 of the Technical Annex).

To identify the fixed relative weights of each enabling condition (affordability, attractiveness, and accessibility), we translated the states of 2023 into numerical scores (i.e., dark green = 2, green = 1, yellow = 0, red = −1, dark red = −2). We formulated this as a linear programming (LP) problem and solved the optimisation using the HiGHS solver. From the resulting Pareto set, we selected the combination of weights that maximised the most important enabling condition for adoption in each sector based on expert opinions (see Section 2.2.2 of the Technical Annex). For example, affordability was prioritised in the power sector due to the critical role of levelised cost of electricity (LCOE) in investment decisions for new energy assets.

With fixed relative weights for the enabling conditions, we calculated the maturity score for all 125 possible combinations of enabling condition ratings. We then mapped these to the market adoption using our sectorial S-curves (see Section 2.2.3 of the Technical Annex).

We utilised this one-to-one correspondence between enabling condition ratings and adoption rates for each sector to define the market adoption in 2035 both in a business as usual (BAU) scenario as well as an AI scenario. This was done by assessing changes in enabling conditions for both scenarios in 2035.

We model the isolated impact of AI on efficiency improvements in the power and mobility sectors as follows. In the power sector, we calculate a change in the penetration of renewables in power production (i.e., the amount of actual electricity produced through renewable sources compared to its overall capacity). For the mobility sector, we look at the impact of AI-enhanced shared mobility solutions (car-pooling, shared vehicles, etc.) on kilometres driven. We do not model efficiency gains for alternative proteins for the Meat and Dairy sector, given that any production efficiency gains will already be accounted for in our affordability assessment, which is already considered within market adoption.

Results

The potential for AI to contribute to emissions reductions is substantial. Our analysis estimates that from these three sectors alone, AI could reduce global BAU emissions by 3.2–5.4 $GtCO_2e$ annually by 2035 (Fig. 1).

In the *Power sector*, AI can improve the *efficiency* of renewable energy systems by optimising grid management and increasing the load factor of solar PV and wind by up to 20%[39]. By doing so, it could reduce emissions by

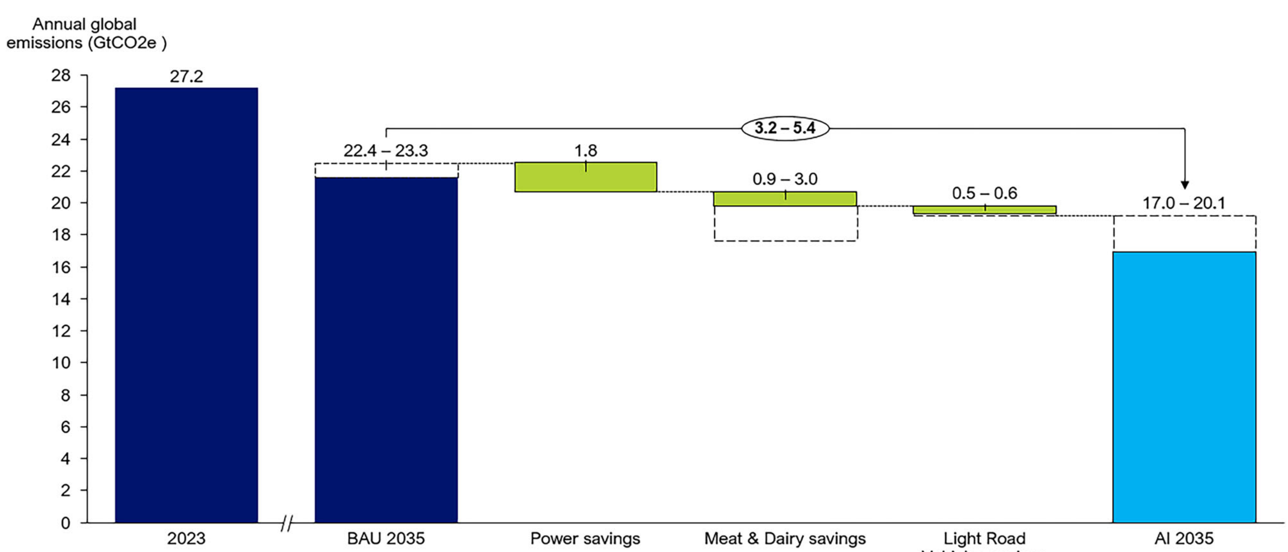

Fig. 1 | Total emissions and emissions savings from AI in 2035 for the sectors in scope (Power, Meat and Dairy, Light Road Vehicles). Note, the 2023 bar is the total 2023 $GtCO_2e$ emissions of power (15.3 $GtCO_2e$), meat and dairy (8.7 $GtCO_2e$), and light road vehicles (3.2 $GtCO_2e$) sectors.

1.8 $GtCO_2e$ per year by 2035. AI's impact on *adoption rates* of solar PV and wind is expected to be minimal given how strong their affordability and attractiveness already is (see Section 2.3.1 of the Technical Annex).

In the *Meat and Dairy sector*, we mostly look at the impact of AI on *adoption rates* of APs. We estimate that AI could improve adoption rates from ~8–14% in BAU to 18–33% in an ambitious AI scenario, and 27–50% in a highly ambitious AI scenario. We assume that AI improves *attractiveness* (taste and texture) through identifying proteins with suitable properties. In a highly ambitious scenario, it also significantly reduces production costs to the point of achieving cost parity with traditional products in all categories and products, improving *affordability*. This could result in emissions savings of 0.9–1.6 $GtCO_2e$ in the AI scenario and 1.7–3.0 $GtCO_2e$ in a highly ambitious AI scenario (see Section 2.3.2 of the Technical Annex).

In the *Light Road Vehicles sector*, we estimate the majority of emissions reductions related to AI to come from *efficiency* gains, i.e., AI-enhanced shared mobility resulting in better utilisation of vehicles, over time reducing total kilometres driven. This could result in 0.4 GtCO2e in emissions reductions annually by 2035. In addition, we look at the impact of AI on *adoption rates* of EVs. We estimate that additional improvements to *affordability* (AI finding better battery compositions that drive costs down) and *accessibility* (AI predicting optimal locations for EV charging infrastructure based on real-time data[40]) could improve adoption rates by ~25–28 p.p. vs. BAU, leading to emissions reductions of 0.2 $GtCO_2e$ annually by 2035. Overall, we estimate AI could reduce emissions in this sector by 0.5–0.6 $GtCO_2e$ annually by 2035 (see Section 2.3.3 of the Technical Annex).

Together, these estimates show that AI could generate 3.2–5.4 $GtCO_2e$ emissions reductions annually by 2035 compared to a BAU scenario based on the IEA announced climate pledges (Fig. 2). This would mean accelerating our progress in emissions reduction, moving us 36% closer to alignment with an ambitious emissions reduction trajectory versus BAU by 2035. It should be noted that these estimated emission savings occurring under the AI scenario may be subjected to underestimation since the analysis is only based on three sectors.

Importantly, these estimated emissions reductions outweigh the estimated 0.4–1.6 $GtCO_2e$ increase in emissions from the global power consumption of data centres and AI. These estimates are based on *all* of AI's activities (not just those related to decarbonisation), and are calculated by multiplying the power usage of three future scenarios of AI roll-out (limited AI roll-out, base case of AI roll-out, accelerated AI roll-out) (Since submission for publication, further research has been conducted by the IEA on data centre power consumption[41]. IEA's base case and lift off estimations fall between the limited AI roll-out scenario and base case AI roll-out scenario described in this paper.) with grid emissions intensities, the latter based on estimates from three IEA's scenarios (Stated Policy, Future Pledges, Net Zero[42]). This analysis relies on several key assumptions. First, we assume that the calculated emissions factors used to determine grid emissions intensities remain unchanged between 2022 and 2035. While this simplifies our calculations, it does not account for potential reductions in emissions intensity due to efficiency improvements over time. Similarly, we assume that the load factors for relevant technologies do not change throughout the period.

For data centre power usage, we assume a consistent growth trajectory before and after 2030. Specifically, we calculate the compound annual growth rate (CAGR) for the forecasted power usage over the 2022–2030 period and apply it to the 2030–2035 period. Furthermore, we assume that data centres rely on power with emissions intensities equivalent to the global average grid emissions intensity, rather than accounting for renewable energy sourcing through mechanisms like power purchase agreements (PPAs) (see Section 2.3.4 of the Technical Annex).

Limitations of the quantitative analysis

While this analysis comprehensively uses a bottom-up method to estimate the impact of AI on emissions reductions, it has its limitations. The model looks at improvements within just three sectors and does not quantify inter-sectoral improvements, as discussed above. It limits itself to direct impact, as opposed to looking into the dynamic impact that is likely to emerge from the simultaneous transformation of multiple systems in the economy, which would mutually reinforce each other due to spill-over effects. It considers the potential of AI in its current format and applications, which are likely to change and improve further in ways that are difficult to predict. It does not include the impact of AI on accelerating capital deployment or supporting better policymaking, which are key levers to speeding up the climate transition.

Our analysis also does not consider any rebound effects such as efficiency gains in AI leading to increased consumption or unintended expansion of carbon-intensive processes. Kaack et al.[8] provide an excellent qualitative exploration of the complexities surrounding rebound effects. Although rebound effects are commonly discussed in terms of negative outcomes, there can also be positive rebound effects, which were also not assessed in this study. For instance, AI's role in optimising energy use (e.g., in data centres, manufacturing, or logistics) could free up energy to run innovative carbon capture methods that can amplify the positive impact. Rebound effects have dynamic implications and are not obvious, therefore they are uncertain and difficult to predict. Addressing these dynamics would require more detailed modelling and further research. Nonetheless, we have shown that, even when positive rebound effects are not accounted for, the potential for GHG emissions reductions via AI is already significant—and likely to be significantly larger if positive rebound effects are considered. Understanding the full dynamic impacts of AI on climate and, more broadly, on macroeconomic outcomes require further research which must consider the compounding, systemic and intersectoral net impact of AI.

AI and climate will act on growth through multiple channels, including accelerating the adoption of cleaner and cheaper technological solutions, by

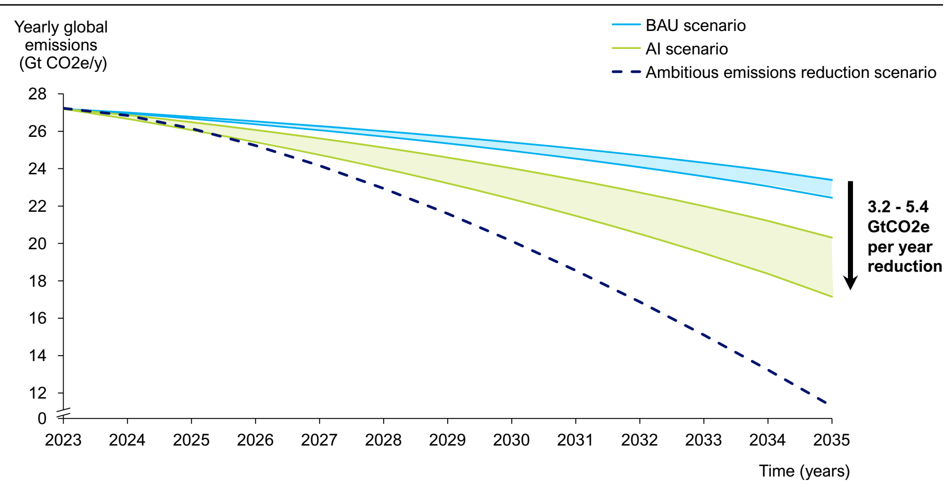

Fig. 2 | Projected annual global emissions in AI scenario vs. BAU and ambitious emissions reduction scenario by 2035 for the sectors in scope (Power, Meat and Dairy, Light Road Vehicles). Note, the ambitious emissions reduction scenario is calculated using the IEA's net zero emissions scenario[42] for Power and Light Road Vehicles and UNEP's 2050 Paris-aligned target[3] for Meat and Dairy.

fostering innovation more broadly, by increasing the efficiency of existing technologies, by transforming complex systems (such as cities or power systems), by improving health thanks to reducing pollution, and by fostering investments in the transition[1].

Conclusion

The world faces an unprecedented opportunity to leverage AI as a catalyst for the net-zero transition. The five impact areas through which AI can drive emissions reductions—transforming complex systems, accelerating technology discovery, influencing behaviour, modelling climate interventions, and enhancing resilience—provide a clear roadmap for harnessing AI's potential. While AI can contribute to emissions increase through datacentres' energy consumption, our estimates show that the emissions reduction potential from AI applications in just three sectors alone would more than offset the total AI's emissions increase in all economic activities, making a strong case for using AI for resolving the climate threat. The key will be to channel practical AI applications towards key impact areas to accelerate the *market adoption rate* and *efficiency* of low-carbon solutions.

However, letting markets determine the applications and governance of AI can prove to be risky. Governments have a critical role in ensuring that AI is deployed effectively to accelerate the transition equitably and sustainably. The concept of the "active state" is central to this transformation, as market forces alone may not be sufficient to drive the scale of change required and unlock the full potential of AI through the five key impact areas identified in this paper. Policymakers must create enabling conditions for AI deployment, provide financial incentives for research and development, and ensure that AI applications are directed toward public goods and high-impact areas.

Public intervention is particularly important in addressing the potential risks associated with AI, such as increased energy consumption and the exacerbation of inequalities between the Global North and South. Governments must regulate AI to minimise their environmental footprint, for example, by encouraging the use of renewable energy in datacentres and promoting energy-efficient AI models[43]. Furthermore, public investment in AI infrastructure and education in developing countries will be essential to ensuring that the benefits of AI are shared equitably and that the Global South is not left behind in the AI revolution[17]. Governments can also leverage the power of AI to foster a collective sense of responsibility and action towards climate change. This could involve policies and public awareness campaigns that make use of AI to facilitate community engagement and disseminate climate change-related information. By fostering innovation, directing investment, and promoting international cooperation, governments can ensure that AI delivers both environmental and economic benefits, paving the way for a sustainable future.

Data availability

The data that support the findings of this study are not openly available due to reasons of sensitivity and are available from the corresponding author upon reasonable request. Data are located in controlled access data storage at Systemiq Ltd.

Received: 20 November 2024; Accepted: 19 April 2025;
Published online: 23 June 2025

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Acknowledgements

The authors would like to thank the following experts for their valuable contributions and insightful feedback: Demis Hassabis (Google DeepMind); James Manyika (Google-Alphabet); Morgan Gillespy (Executive Director, FOLU); Prof. Dr. Lynn Kaack (Head of AI and Climate Technology Policy Group, Hertie School); Prof. Dr. Felix Creutzig (Head of Land Use, Infrastructure and Transport Group, MCC; Chair of Sustainability Economics, TU Berlin); Bianca Datta (Scientific Partnerships Manager, GFI); Emma Ignazewski (Senior Associate Director of Industry Intelligence, GFI); Daniel Gertner (Lead Economic and Industry Analyst, GFI); Krijn de Nood (Founder, Meatable); Jeremy Oppenheim (Managing Partner, Systemiq); Yoni Shiran (Partner, Systemiq); Ben Dixon (Partner, Systemiq); Ioana Simon (Associate, Systemiq); Ros Marshall (Associate, Systemiq); Max Steventon (Associate, Systemiq); Alex Andreoli (Associate, Systemiq); Rens ter Weijde (Senior Advisor, Systemiq); Peter Hulshof (Partner, Systemiq); Taraneh Azad (Partner, Systemiq); Julia Turner (Associate, Systemiq); Isha Patel (Associate, Systemiq). This work was supported by the Economic and Social Research Council [grant number ES/R009708/1]; the Quadrature Climate Foundation [grant number 01-21-000290]; and Grantham Foundation for the Protection of the Environment.

Author contributions

Each named author has substantially contributed to designing and conducting the underlying research and drafting this manuscript.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s44168-025-00252-3.

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