AI and Optimal Climate Policy

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Abstract

Artificial intelligence (AI) interacts with climate in various ways. Its impact on emissions and the costs and benefits of emission reduction are uncertain. A critical challenge is to align AI investment with global climate policies. Thus, we establish a dynamic general equilibrium climate-economy model with endogenous AI growth. By boosting both labor productivity and capital deepening, AI investment increases future gross economic output, and so emissions. It also requires more energy- and emission-intensive capital. At the same time, the application of AI technologies lowers the carbon intensity of the broader economy. Moreover, AI-powered adaptation alleviates climate damages. We distinguish

between ICT-like and Industrial Revolution (IR)-like prospects for AI development. Calibrated to the best available evidence, we find that AI development is net polluting. Under current low abatement, ICT-like AI raises global warming further by an additional 0.1°C in 2100, while IR-like AI raises it by 0.8°C. The associated climate costs are 1.6% and 23% in permanent consumption loss, offsetting roughly one-fifth and one-quarter of AI's economic gains, respectively. Consequently, the optimal AI investment rates are reduced from its maximum potential—for ICT-like AI, by 0.12 p.p. to 1.96% in 2050 and by 0.47 p.p. to 3.25% in 2100. Notably, proactive climate policy can largely reverse this investment decline, indicating that it is a complement to, rather than a substitute for, AI development. We further show that the trade-off between AI and abatement investment is driven primarily by their relative marginal economic returns, not by AI's emission impact.

Keywords: Climate change, Artificial Intelligence, Climate policy, Integrated Assessment Model

JEL Classification: O33 , O44 , Q54

1 Introduction

Artificial intelligence (AI) interacts with climate change in multiple ways. AI is energy-intensive, due to its heavy reliance on data centers (Masanet et al. 2020; Kaack et al. 2022; International Energy Agency 2025b). It directly affects both climate mitigation (Kaack et al. 2022; Rolnick et al. 2022; Luers et al. 2024; International Energy Agency 2025b; Stern et al. 2025) and adaptation (Rolnick et al. 2022; Eyring et al. 2024). Meanwhile, AI is transforming the structure of the economy (Aghion et al. 2018; Acemoglu 2025; Trammell and Korinek 2023) that drives climate change, the impact of which feeds back to the economy (Barrage and Nordhaus 2024), where AI has become increasingly integral. A unified analytical framework of this intricate interplay is lacking (Luers et al. 2024), posing a major challenge to aligning AI development with climate governance (Korinek 2025). We contribute such an integrated framework (Fig. 1), and apply it to a seminal integrated assessment model (Barrage and Nordhaus 2024) to derive novel policy insights.

The impact of AI on emissions is particularly complex. We follow the conceptual framework of a recent review paper (Kaack et al. 2022) to include three categories, computing-related impact, immediate application impact, and system-level impact. The first involves GHG emissions from both energy use in machine learning and the embodied emissions in the computing infrastructure. The second relates to the short-term GHG effects of AI-related applications, with promising abatement potentials conditional on its proper use. Recent studies (International Energy Agency 2025b; Stern et al. 2025; Xiao et al. 2025) have quantified AI-related emissions in the first two categories, despite substantial uncertainties and potentially countervailing effects. However, little is known about the system-level impact of AI, from technological development and adoption to broader lifestyle changes, which can be significant over the

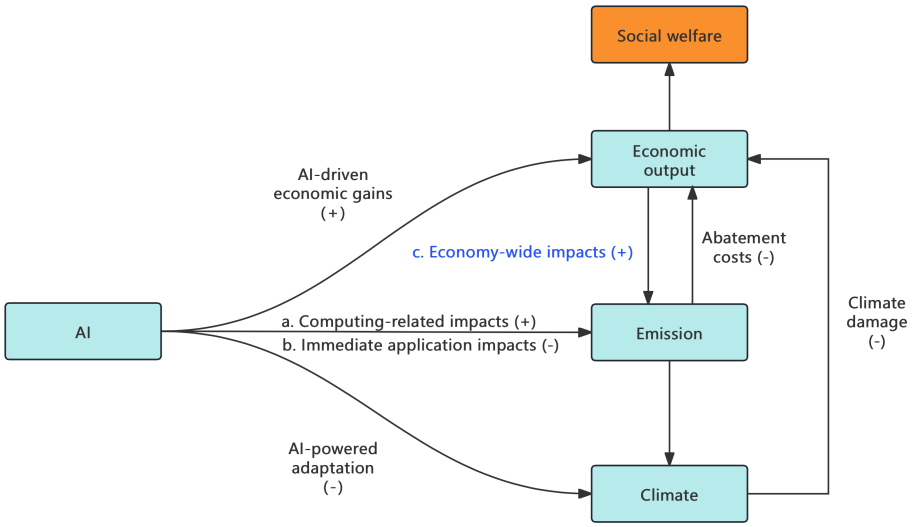


Fig. 1: AI and the climate-economy system

medium to long term (Luers et al. 2024; Stern et al. 2025). This paper not only includes the former two categories, but innovatively explores the economy-wide emission impact to represent this system-level category, because the economic system including production, technology, and policy is a critical driver of future GHG emissions (Nordhaus 2018; Rennert et al. 2022). This extended scope enables us to integrate all three categories and provide, to our knowledge, the first consistent assessment of AI's net emission impact under various economic and policy scenarios.

The complexity between AI and climate extends beyond emissions. By empowering next-generation multiscale climate modelling (Eyring et al. 2024), AI can improve monitoring, forecasting, and warnings in climate-related events (e.g. Google's GraphCast (Lam et al. 2023) & FloodHub (Nearing et al. 2024)), thereby reducing climate damage via better adaptation. In addition, AI leads to changes in economic structure (Trammell and Korinek 2023), but its ultimate impact remains unclear. This deep economic uncertainty affects both mitigation and adaptation, and can further generate general equilibrium effects in the climate-economy system (Fernández-Villaverde et al. 2024; Bilal and Stock 2025).

Our framework provides a unified basis for the welfare analysis of AI development and climate policy, consistent with both AI for Good (International Telecommunication Union 2025) and the Sustainable Development Goals (Gohr et al. 2025) of the United Nations. By boosting economic growth, AI increases available goods and services for future consumption. This raises social welfare, if equitably allocated. However, AI development also creates emissions and affects adaptation. Therefore, balancing AI development with climate policies requires a comprehensive assessment of AI's economic benefits versus external costs—a trade-off recently recognized as one of the

eight major policy challenges in the age of AI (Korinek 2025) (see Appendix B for a literature review).

Therefore, the paper addresses three research questions:

1) *What is the net impact of AI on global GHG emissions?* This requires comparing all three categories of AI's emission impact.

2) *How to align AI development with climate policies?* Specifically, if, for example, AI causes more emissions, do climate policies to reduce GHG emissions curb AI investment? In turn, how does AI development shape climate policies (e.g., the social cost of carbon (Aldy et al. 2021; Tol 2023; Moore et al. 2024))? What drives the optimal balance?

3) *What are the climate-related welfare costs of AI development?* Do these external costs offset its economic benefits? How effective are AI-powered adaptation and other mitigation policies in reducing these costs?

To this end, we establish a dynamic general equilibrium climate-economy model with endogenous AI growth (Fig. D5), building on Barrage and Nordhaus (2024). We call it DICE-AI. The inclusion of AI in an integrated assessment model is a key advance. First, we introduce AI as an intermediate production sector[1]. To calculate greenhouse gas emissions, we differentiate the capital-embodied carbon intensity between AI and final production, which is higher in the former because AI-based data centers use more energy (Masanet et al. 2020; International Energy Agency 2025b). This explicit sectoral differentiation allows us to capture the "energy-hungry" nature of AI infrastructure, which may initially strain carbon budgets. We capture the impact of the immediate application of AI with a reduction of the carbon intensity of the economy. The climate change damage function also depends on the stock of AI capital stock, representing its potential to enhance societal adaptation. We consider two different channels for AI to affect economic growth (Aghion et al. 2018; Trammell and Korinek 2023). One is an increase in total factor productivity growth (TFP) as AI fosters innovation (e.g.: Babina et al. 2024; Labaschin et al. 2025). The other automates a larger fraction of tasks in the economy (e.g. Nordhaus 2021; Acemoglu and Restrepo 2018), modelled as an increase in the capital income share. By endogenizing these channels, the model can consistently evaluate whether the productivity gains from AI are sufficient to offset its environmental costs and the potential "rebound effects" in energy consumption (Kaack et al. 2022).

The model is kept as simple as possible, yet effectively captures the key interactions in the framework. For instance, we do not represent energy as an intermediate sector; instead, the energy-intensive nature of AI is reflected with a higher capital-embodied carbon intensity. This approach has the added advantage of incorporating life-cycle

[1] While seminal studies (e.g., Aghion et al. 2018; Acemoglu 2025; Jones 2024; Trammell and Korinek 2023; Nordhaus 2021) provide foundational insights by treating AI as an exogenous technological frontier to explore its growth potential, they typically bypass the resource-diversion effect associated with AI development. We endogenize AI as an intermediate production sector for three strategic reasons. First, it captures the opportunity cost of capital: in a DICE-framework with resource scarcity, AI investment competes with climate mitigation and traditional physical capital. Second, it accounts for the feedback loops between environmental shocks and AI infrastructure—allowing climate damages to endogenously impede technological progress, a channel missing in exogenous treatments. Third, by modeling AI as a produced input, we can evaluate the cost-benefit efficiency of AI-driven growth versus green investment, addressing the critical policy trade-off between digital and green transitions. For emerging similar structural approaches in non-climate other fields, see Guerrón-Quintana et al. (2024) and Agrawal et al. (2024).

emissions from AI-related infrastructure, a recognized major emission source (Kaack et al. 2022; International Telecommunication Union 2025). Moreover, to maintain focus on the interplay between AI and climate, we abstract from detailed AI production processes, its technology characteristics, spillover dynamics to markets, and income distribution. Finally, since consumption is the sole argument in the welfare function, we need not model how AI might alter social values.

We calibrate the model based on extensive literature surveys. A detailed calibration based on best evidence is another contribution of this paper. Published studies, including by notable growth experts, show huge disparities in AI's economic prospects (Aghion and Bunel 2024; Acemoglu 2025; Filippucci et al. 2024b; Korinek 2023). Thus, we consider two distinct scenarios, one akin to the effect of Information and Communications Technology (ICT) and the other comparable to an Industrial Revolution (IR), as neither can yet be ruled out[2]. Under the ICT-like prospect, AI would exert a modest influence on long-run growth, similar to the historical role of ICT. Under the IR-like prospect, AI triggers the next industrial revolution. We project that under the ICT-like pathway, annual per capita GDP growth will stabilize around 2.1% from the second half of this century (Fig. A1). By comparison, the DICE model without AI projects a gradual decline to 1.8% by 2100. Under the IR-like pathway, AI will more than double the growth rate to 4.1% in 2100, consistent with historical industrial revolutions. These two extreme prospects bound the interactions of AI with climate. Beyond AI's economic impacts, we calibrate its emission effects based on an extensive survey of the literature (e.g.: International Energy Agency 2025b; Stern et al. 2025; Masanet et al. 2020; Shehabi et al. 2024; Gelvanovska-Garcia et al. 2024). For AI's adaptation potential, our benchmark calibration draws on Tol (2023, 2024) and Forouheshfar et al. (2025), who employ a detailed sectoral disaggregation. This implies that up to 42% of aggregate climate damages can be avoided through AI-enabled adaptation in the very long run.

Our main findings are as follows. First, AI is net polluting. Under the current low-abatement scenario, ICT-like AI increases global warming by an additional 0.1°C by 2100, whereas IR-like AI increases it by 0.8°C, with economy-wide effects accounting for a substantial share of the increase. In 2030, AI-induced emissions account for 5.6% and 26.1% of total emissions under the ICT and IR prospects, respectively. Compared with the existing literature[3], we estimate a larger effect, because previous studies focus mainly on direct, compute-related emissions while overlooking AI's broader system-wide effects (Luers et al. 2024) that we show are quantitatively important[4]. Moreover, AI-related applications reduce global emissions by 2.7 $GtCO_2$ and 5.5 $GtCO_2$ in 2035

[2]Exploring multiple scenarios for AI's economic trajectory is not without precedent. Korinek and Suh (2024) and Korinek (2023) consider a broader range of scenarios to analyze output and wage dynamics in the age of AI. In climate literature, the well-known SSP scenarios are widely used in IPCC reports and academic studies to address deep uncertainties around climate change. However, current frameworks have not yet incorporated AI's effects. Luers et al. (2024) highlights the need to link AI development pathways to existing SSP scenarios.

[3]For example, International Energy Agency (2023) estimates that AI-related data centers accounted for 0.6% of global emissions in 2020 and could consume up to 3% of global electricity by 2030 (International Energy Agency 2025b), Patel et al. (2024) project a corresponding share of 4.5%, while Accenture (2024) estimates that AI-related emissions could reach 3.4% of the global total by 2030.

[4]By 2100, for example, ICT-like AI generates 12.8 $GtCO_2$ of economy-wide emissions, compared with 10.0 $GtCO_2$ from computing-related emissions alone. We use 2100 as an illustration because economy-wide effects become more pronounced over the long run.

under the ICT and IR prospects, respectively, broadly in line with Stern et al. (2025), who estimates a 3.2–5.4 GtCO2 reduction in annual global emissions by 2035.

Second, although carbon abatement costs are higher when AI's economic impacts are stronger, carbon abatement is in fact complementary to AI development. This is evidenced by the finding that proactive climate policy can largely reverse the decline in AI-sector investment rates observed under low abatement, raising them by about 0.4 and 7.7 percentage points by 2100 for the ICT-like and IR-like scenarios, respectively. This complementarity highlights the need to balance these two forms of investment, both of which generate long-run externalities. We explore this balance by examining the social cost of carbon and the investment trade-off between climate mitigation and AI. Our results indicate that AI's emission and adaptation impacts play only a minor role in determining the social cost of carbon, particularly under the ICT-like prospect. By contrast, under the IR-like scenario, AI raises the optimal social cost of carbon by half, to 557\$/tCO_2, relative to the standard DICE model. For the investment trade-off,we quantify how much should be invested in carbon abatement per dollar directed to AI. Our simulation shows that the ICT-like prospect calls for roughly five times as much abatement investment per AI dollar——\$0.10 in 2025 and \$0.16 in 2050——compared to the IR-like case (\$0.02 and \$0.03, respectively). This large difference arises because the IR-like scenario implies an extraordinarily prosperous future driven by AI, which draws investment toward AI and away from carbon abatement.

Finally, the environmental costs associated with AI development are substantial. Climate costs under low abatement translate into permanent consumption losses of 1.6% and 23% under the ICT-like and IR-like pathways, respectively, offsetting roughly one-fifth and one-quarter of AI's economic gains. An optimal carbon tax alone (without AI-powered adaptation) can reduce these losses to 0.58% and 2.47%, respectively. When both channels are active in our DICE-AI model, the welfare loss falls significantly further to 0.28% and 0.99%, suggesting a promising multiplier effect from combining AI-enabled adaptation with sound climate policy.

Moreover, AI development involves uncertainties that extend beyond our two stylized economic scenarios, many of which are relevant to climate change and climate policy. To explore this, we first conduct a thought experiment asking how large AI's immediate application impacts would need to be to overturn our finding that AI is a net source of emissions. Reversing this outcome proves extremely difficult[5]. In addition, we examine five major sources of uncertainty. Our sensitivity analysis shows that uncertainty in AI's emission and adaptation impacts does not materially alter optimal climate policy, as reflected in the social cost of carbon. By contrast, whether AI follows an ICT-like or an IR-like development path represents a far more consequential source of uncertainty.

This paper contributes to the existing literature in three main ways. First, it builds on the established tradition of integrated assessment models for climate policy evaluation (e.g.: Barrage and Nordhaus 2024; Golosov et al. 2014; Barrage 2020). While this body of work has provided foundational insights, current IAMs have yet to incorporate

[5]It would require ICT-like and IR-like AI to reduce their aggregate carbon intensity by roughly 28% and 90%, respectively, once their abatement potential is fully realized. These are equivalent to global carbon intensity in 2050 falling from today's level in Cambodia to that of Greece under ICT, and from Pakistan's to Sweden's under IR, respectively.

or analyze the role of AI (Luers et al. 2024) . Second, our work engages with the growing economics literature on AI (e.g.: Aghion and Bunel 2024; Acemoglu 2025; Filippucci et al. 2024b; Korinek 2023), but focuses specifically on its environmental implications, an aspect whose importance has been acknowledged but, to our knowledge, not yet systematically examined within a consistent analytical framework (Korinek 2025). We offer an early, and what we believe to be the first, cost-benefit assessment of AI's climate impacts. Unlike recent studies, which are often limited to analyzing AI's emissions through a single channel (Stern et al. 2025; International Energy Agency 2025b) and typically overlook a third critical pathway (Kaack et al. 2022), our analysis captures all three relevant emission channels within a unified framework. In addition, we account for AI's spillover effects on adaptation capacity and its broader economic returns. Our quantification remains internally consistent across all policy scenarios, and our findings——on optimal climate policy, the trade-off between AI investment and carbon abatement, and welfare implications——offer directly relevant insights for policymakers navigating climate policy in the age of AI.

2 Model

Based on Barrage and Nordhaus (2024), we apply the proposed framework to build the DICE-AI model. The model adopts a standard optimal growth framework, in which a representative household's intertemporal welfare is defined over an infinite path of per capita consumption. A social planner[6] is posited to maximize this intertemporal welfare objective. The DICE-AI model similarly accommodates a representative household whose instantaneous utility, U_t, depends exclusively on per capita consumption, c_t. Although recent studies have extended the utility function to include non-consumption arguments (Barrage 2020; Drupp and Hänsel 2021; Bastien-Olvera and Moore 2021; Wang et al. 2024a), we adhere to the DICE-2023 specification to maintain focus within the analytical framework outlined in Fig. 1. The utility function adopts the standard constant-relative-risk-aversion (CRRA) form with elasticity η. DICE-AI maximizes the net present value of aggregate population-weighted utility over time:

$$\begin{aligned} \max V &= \sum_{t=1}^{T} U_t(c_t) L_t^{total} R_t \\ &= \sum_{t=1}^{T} \frac{c_t^{1-\eta}}{1-\eta} L_t^{total} (1+\rho)^{-t} \end{aligned} \tag{1}$$

[6]The original DICE model similarly considers a social planner problem, and impose an exogenously-given path of abatement rates to represent the climate externality with ineffective policy interventions. We follow DICE to analyze a social planner problem. However, note that in addition to the climate externality, our DICE-AI model also introduces the externality of AI development on economic growth, emission, and climate adaptation. Thus, future studies may be interested in starting from the decentralized market to compare the equilibrium outcomes with the results of the social planner problem here.

where L_t^{total} denotes total labor input. R_t is the time-specific consumption discount factor and ρ the constant social time preference rate[7].

The original DICE model has only one final production sector. Here we introduce an intermediate AI production sector that combines capital $K_{AI,t}$ and labor $L_{AI,t}$ using standard Cobb-Douglas technology for AI production:

$$y_t^{AI} = A_{AI,t} K_{AI,t}^{\alpha} L_{AI,t}^{1-\alpha} \tag{2}$$

where $A_{AI,t}$ denotes the AI-specific technology level. To restrict our attention to the interplay between AI and climate, we do not delve into the details of AI production process. However, this simplification suffices to accommodate three main perspectives in our framework, as explained below.

First, we introduce how AI affects total economic production. To maintain the closest comparability with DICE, we preserve the Cobb-Douglas production technology so that the final production is given by:

$$Y_t = A_t(y_t^{AI}) \times K_t^{\gamma(y_t^{AI})} L_t^{1-\gamma(y_t^{AI})} \tag{3}$$

where we allow AI output to affect both the total factor productivity (TFP) growth and the factor income share. K_t and L_t are the capital and labor inputs used in final production. These two channels capture, respectively, the innovation effect and the capital-deepening effect of AI development (Aghion et al. 2018; Trammell and Korinek 2023). For the former, we specify:

$$\frac{\dot{A}_t}{A_t} = g_{base,t} + \theta_{TFP} \times (y_t^{AI} - y_t^{AI,base}) \times A_t^{-\beta} \tag{4}$$

where the dot denotes the first-order derivative with respect to time, and $g_{base,t}$ is the exogenously-given TFP growth forecasts from DICE-2023. θ_{TFP} is simply a scaling constant. Given $\beta > 0$, the term $A_t^{-\beta}$ captures the economic intuition that better ideas are increasingly harder to find (Jones 1995; Bloom et al. 2020). Thus, more AI output is required to sustain higher TFP growth. For better calibration, we infer the implicit level of AI output in the DICE-2023 model, denoted by $y_t^{AI,base}$[8]. Thus, AI's net economic impact depends on the difference between the AI output level endogenously determined in equilibrium y_t^{AI} and this exogenously-given level $y_t^{AI,base}$.

Besides, because AI development is expected to facilitate automation, we model that:

$$\gamma(y_t^{AI}) = \gamma_{asymp} - \gamma_{adj} \times e^{-\theta_\gamma \times (y_t^{AI} - y_t^{AI,base})} \tag{5}$$

[7] Unlike previous vintages, the time preference rate in the latest DICE vintage is in effect an exogenously-given declining path in order to reflect reflect both the precautionary effect (Gollier 2014; Newell et al. 2022) and the climate beta effects (Dietz et al. 2018). See Section 3 for details.

[8] We obtain the path of $y_t^{AI,base}$ by fixing the AI investment rate at its initial-year value, which we assume to best reflect the DICE-2023 economy. It would be unfair to claim that DICE-2023 entirely omits AI's economic influence, as its economic forecasts are themselves based on expert assessments that possibly include AI considerations. The introduction of $y_t^{AI,base}$ here is essentially a scaling device; readers primarily interested in the model's structure may safely ignore it. The same applies to the analogous scaling in the factor-share specification below.

such that a growing AI sector asymptotically increases the capital income share by γ_{adj} to γ_{asymp}. The flip side of the coin is the declining labor income share, as manual labor will gradually be replaced by machinery and robotics (Aghion et al. 2018; Acemoglu and Restrepo 2018; Acemoglu 2025).

Second, we conceive of AI as a stock adaptation (e.g.: Felgenhauer and Webster 2014; Millner and Dietz 2015). Following the DICE-2023 model, the damage function measures a proportional loss of final output, but is now given by:

$$D(T_t, K_{AI,t}) = \left[(1 - a_3) + a_3 \left(\frac{K_{AI,0}}{K_{AI,t}}\right)^{a_4}\right] a_1 T_t^{a_2} \tag{6}$$

This implies that as AI capital accumulates, it will asymptotically alleviate a fraction of $a_3 \in (0, 1)$ in climate damage. Without adaptation, climate damage is governed by $a_1 T_t^{a_2}$, as in DICE.

Third, we introduce AI's emission impact. To calculate aggregate greenhouse gas emission, the original DICE model associates emissions with total economic production. By comparison, DICE-AI leverages the concept of capital-embodied carbon intensity (Seto et al. 2016; Tong et al. 2019; Ye et al. 2023), which is different between the final sector and the AI sector. In addition, to capture the immediate application impact, we model that the AI output will lower the carbon intensity of the overall economy without incurring additional abatement costs. Thus, total carbon emissions are:

$$E_t^{Ind} = (1 - \Omega(y_t^{AI})) \times (\sigma_t^K \times K_t + \sigma_t^{K_{AI}} \times K_{AI,t}) \tag{7}$$

where σ_t^i is the capital-embodied carbon intensity in sector i. Because the AI sector consumes more energy and also emits more throughout its life-cycle, one expects $\sigma_t^K < \sigma_t^{K_{AI}}$. $\Omega(y_t^{AI})$ gauges the fraction of reduced emissions. More specifically, we use:

$$(1 - \Omega(y_t^{AI})) = \psi_{asymp} + \psi_{adj} \times e^{-\theta_{sav} \times (y_t^{AI} - y_t^{AI,base})} \tag{8}$$

such that a fraction of ψ_{adj} emissions will be abated when the AI output increases infinitely. θ_{sav} is the speed scale of the immediate application effect. By construction, $\psi_{asymp} + \psi_{adj} = 1$. The economy-wide emission impact is naturally included, once we allow AI to affect economic production.

Last, we explain how capital and labor are allocated or accumulated. For capital, we follow the putty-clay growth model (Atkeson and Kehoe 1999; Baldwin et al. 2020) that capital accumulation is individual and separate between sectors, which gives:

$$K_{t+1} = (1 - \delta)K_t + I_t \tag{9}$$

$$K_{AI,t+1} = (1 - \delta)K_{AI,t} + I_t^{AI} \tag{10}$$

The economic intuition behind is that once economic output is used for investment either in final or AI sectors, it builds up stranded assets, which, combined with capital-embodied carbon intensity, leads to irreversibility effects on emissions (Baldwin et al. 2020; Van der Ploeg and Rezai 2020). For simplicity, we assume a constant ratio of

labor force in AI sector $L_{AI,t} = \nu L_t^{Total}$ and:

$$L_{AI,t} + L_t = L_t^{Total}. \tag{11}$$

In each period, total economic production net of climate damages and abatement costs is allocated between consumption, general investment, and AI investment:

$$Y_t \times (1 - D(T_t, K_{AI,t}) - \Lambda(\mu_t)) = C_t + I_t + I_t^{AI} \tag{12}$$

As in DICE-2023, $\Lambda(\mu_t)$ is the abatement cost depending on the emission abatement rate μ_t. Thus, an amount of $E_t = (1 - \mu_t)E_t^{Ind}$ unabated emissions will flow into the atmosphere, causing the global mean temperature rise:

$$T_t = \Phi\left(E_0, E_1, ..., E_t\right) \tag{13}$$

where $\frac{\partial T_{t+j}}{\partial E_t > 0}$ holds for $\forall t, j \geq 0$. The global mean temperature rise depends on both current-period and all historical periods of carbon emissions.

3 Calibration

Our calibration strategy seeks to maintain the best comparability with the DICE-2023 model, thereby isolating how the introduction of AI alters its climate-economic projections and associated policy implications. For parameters common to both models, we retain the original DICE-2023 values, making adjustments only where necessary to ensure consistency after incorporating an intermediate AI production sector. Parameters related to the AI sector are calibrated through an extensive review of the existing literature, including the AI production function, AI-induced effects on economic growth, the carbon intensity of AI-related capital, AI-induced mitigation, and AI-powered climate adaptation.

3.1 Utility function and discount rate

DICE-2023 adopts a time-varying discount rate, to reflect both the precautionary effect (Gollier 2014; Newell et al. 2022) and the climate beta effects (Dietz et al. 2018). While these refinements are conceptually justified, they also alter intertemporal saving incentives, which is particularly relevant for both AI and mitigation investment. To isolate the specific impact of AI, we therefore adopt a constant discount rate throughout our analysis. Specifically, we follow the comprehensive expert survey by Drupp et al. (2018) and use the mean rate recommended by economists as the benchmark parameter in the welfare function (Table 1). Recognizing that the discount rate remains one of the most debated parameters in climate policy evaluation (Pindyck 2021), we perform sensitivity analyses using three alternative values: the mean rate suggested by philosophers (Nesje et al. 2023), the constant pure rate of time preference from DICE-2016 (Nordhaus 2018), and the rate adopted by Stern (2007). The latter two represent, respectively, relatively conservative and more stringent normative stances toward climate policy.

Table 1: The discount rates used in DICE-AI

	ρ	η	Source
Benchmark	0.011	1.35	Mean value recommended by economists (Drupp et al. 2018)
Alternatives	0.009	1.4	Mean value recommended by philosophers (Nesje et al. 2023)
	0.015	1.45	DICE-2016 (Nordhaus 2018)
	0.001	1	Stern discounting (Stern 2007)

3.2 Economic frontier

3.2.1 AI sector production function

We first calibrate the initial-period values of AI-specific capital $K_{AI,t}$ and labor $L_{AI,t}$ to produce *pseudo* AI output. The AI-sector capital stock evolves according to the perpetual-inventory method with an assumed depreciation rate $\delta = 10\%$. The time-series data of AI investment I_t^{AI} is drawn from Stanford University's AI Index Report Maslej et al. (2025), which reports global corporate AI investment from 2013 to 2024. We adjust the reported figures [9] and express all values in constant 2019 PPP-adjusted US dollars. Under a steady-state approximation, the initial capital stock in 2013 is given by:

$$K_{2013}^{AI} \approx I_{2013}^{AI}/(g' + \delta) \tag{14}$$

with g' denoting the observed growth rate of AI investment between 2013 and 2014. Applying Eq. (10) recursively yields an AI-sector capital stock of approximately USD 0.95 trillion in 2020. For labor input in AI sector L_t^{AI}, we assume for simplicity a fixed share of total labor force. Total labor force L^{Total} is taken from the original DICE model. The sectoral share parameter $v = 0.3\%$ is calibrated using evidence from OECD statistics (Green and Lamby 2023) and the Stanford AI Index Report 2025 (Maslej et al. 2025).

Then, the capital-income share of the AI sector α is calibrated by using the information and communication technology (ICT) sector as a proxy, following the ISIC Rev.4 classification (United Nations 2008). Using national-accounts data for the United States, the EU-15, and China—treated as representative of the global economy—we compute the compensation-of-employees share in total gross value added. Data for the United States and the EU are obtained from the KLEM database (Luiss Lab of Economics and Energy Transition 2025), while data for China come from the National Bureau of Statistics (National Bureau of Statistics of China 2020).

[9] The data from AI index report capture annual corporate finance transactions involving privately held AI companies. They exclude publicly traded firms (e.g., large technology companies), companies' internal expenditures such as R&D or infrastructure investment, as well as government funding. For example, the European Union has launched the InvestAI initiative to mobilize €200 billion in artificial intelligence investment (Bergeaud 2025). SecondTalent (2025) estimate that government funding accounts for around 40% of total AI investment in China , also the U.S. federal budget for AI R&D is approximately USD 3 billion annually (National Science and Technology Council 2024). In addition, publicly listed firms also undertake AI-related spending; for instance, Alphabet's annual R&D expenditure has been around USD 40 billion in recent years (Alphabet Inc. 2025). Taking these omissions into account, we scale the date from Stanford University's AI Index Report by a factor of 1.9 to construct a time series of total AI investment.

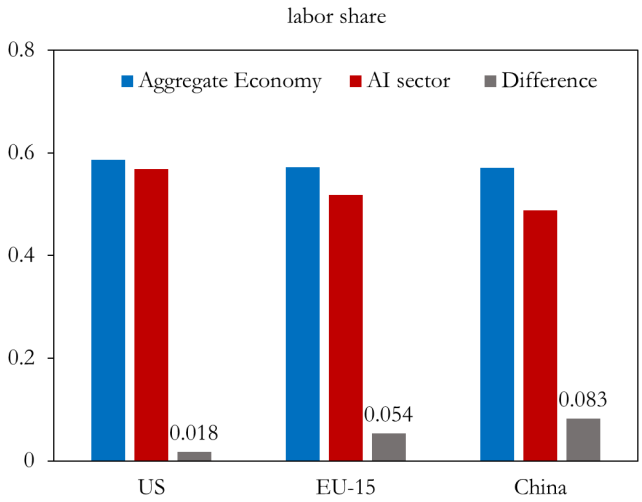


Fig. 2: Labor income share for three representative regions in 2020

Note: Author's calculation based on data from KLEM database (Luiss Lab of Economics and Energy Transition 2025) and data from the National Bureau of Statistics of China (National Bureau of Statistics of China 2020).

As shown in Fig. 2, the AI sector proxied by the ICT sector exhibits a lower labor-income share than the aggregate economy, with the difference ranging from 0.018 to 0.083 across the three regions. This indicates that the AI sector is, on average, more capital-intensive. Considering the economic shares of these regions and the aggregate labor-income share of 0.7 in DICE-2023, we eventually set the AI-sector labor-income share to 0.66, which is 4 p.p. lower than the economy-wide value.

Finally, the technology level of the AI sector, $A_{AI,t}$, is normalized to unity in the initial year and is assumed to grow at the same rate as labor productivity in the final-goods sector.

3.2.2 Final production sector: Mimicking the DICE-2023's economy with DICE-AI

The DICE-AI model incorporates an AI sector that competes with the final-goods sector for capital and labor. Consequently, less capital and labor remain available for final-goods production. To preserve comparability with the total economic output of the original DICE-2023 model, we adjust upwards the total factor productivity (TFP) of the final-goods sector. We therefore recalibrate the final-sector production function so that DICE-AI with a fixed AI-sector investment rate can replicate the economic frontier of DICE-2023 absent climate damages. Recall that in the final output production both the TFP level A_t and the capital income share γ depend on AI output. When calibrating the initial values of capital stock, labor and TFP, both $A_t(y_t^{AI})$ and $\gamma(y_t^{AI})$ are treated as constants, and the dependence on y_t^{AI} can be ignored. The initial capital stock of the final sector is by definition equal to the difference between

the total capital stock in DICE-2023 and the AI-sector capital stock calibrated earlier:

$$K_{2020} = K_{2020}^{total} - K_{2020}^{AI} = 295 - 0.95 = 294.05 \text{ (trillions \$)}$$

Similarly, labor in the final production sector is obtained by subtracting AI-sector employment from total labor in DICE-2023, with the initial level given by:

$$L_{2020} = L_{2020}^{Total} - L_{2020}^{AI} = 7752.9 - 0.0037752.9 = 7729.6 \text{ (millions)}$$

Finally, we recalibrate both the initial TFP level and its exogenous growth rate for the final sector. The initial TFP level is derived directly using the derived initial capital stock and labor for the final sector—obtained from the calculations described above—together with the total output level taken from DICE-2023. However, the TFP growth rate requires additional adjustment, because the economic projections in DICE-2023 are based on expert surveys on long-term growth that include scholars specializing in AI's economic impact (Christensen et al. 2018; Rennert et al. 2021). To account for this, we fix the AI-sector investment rate at its observed 2020 level and fine-tune the TFP path of the final sector so that total economic output in DICE-AI matches that of DICE-2023 exactly in 2100.

The initial value of AI investment is taken from Stanford University's AI Index Report (Maslej et al. 2025) and adjusted according to Footnote 9, yielding $I_{2020}^{AI} = 0.42$ trillion \$. With total output $Y_{2020} = 134.89$ trillion \$ in DICE-2023, this implies a fixed AI-sector investment rate of $\bar{s}_{AI} = 0.42/134.89 = 0.31\%$.

3.2.3 AI and economic growth

Existing studies (Aghion et al. 2018; Trammell and Korinek 2023) suggest two principal channels through which AI reshapes economic growth, by enhancing total factor productivity (TFP) growth and fostering automation in tasks. Quantitative estimates of AI-driven growth in the existing literature are generally conservative, as they rely on historical data that largely treat AI as part of the broader ICT sector. The future impact of AI, however, remains highly uncertain. The rapid recent diffusion of generative AI suggests a plausible prospect in which AI triggers a new industrial revolution. To capture this uncertainty in calibrating the economic effects of AI, we consider two benchmark prospects: a conservative ICT-like prospect and an aggressive industrial-revolution (IR)-like prospect.

We begin with calibrating the parameters for the ICT-like prospect. Because both total factor productivity (TFP) growth and changes in factor income shares affect endogenous AI investment, we calibrate the two effects separately to avoid interference between them.

For AI-driven TFP growth, we first hold the capital income share fixed at the DICE-2023 value of 0.3. Following Bloom et al. (2020), who estimate the idea-elasticity parameter β across several U.S. sectors, we adopt their aggregate-economy estimate $\beta = 3.1$. We then review existing studies on AI-induced macroeconomic productivity gains (Table C4), which report a wide range of estimates reflecting differing methodologies and time horizons. Adopting a conservative stance for the ICT-like

prospect, we calibrate $\theta_{TFP} = 4.98$ such that, under endogenous AI investment in the economic-frontier scenario of DICE-AI, TFP increases by 0.265% over the next decade (to 2030). This value corresponds to half of the central estimate by Acemoglu (2025), as it excludes AI-driven changes in factor income shares and represents a deliberately cautious assessment.

To calibrate AI's impact on capital income share, in a similar vein, we first hold the TFP growth path of the final-goods sector exogenously fixed at $g_{base,t}$, thereby excluding AI-driven TFP growth. Quantitative evidence on AI- and automation-induced shifts in factor shares remains relatively limited. Cazzaniga et al. (2024) report that the capital income share in advanced economies rose by about 5.5 percentage points during the automation period from 1980 to 2014. Minniti et al. (2025) estimate that AI-driven technological change may have reduced the labor share by 0.09–0.31 percentage points from a baseline of 52%. Based on this evidence, we set a moderate asymptotic capital share $\gamma_{asymp} = 0.34$ and choose $\gamma_{adj} = 0.04$ so that the capital share equals 0.3 when $y_t^{AI} = y_t^{AI,base}$. The scale parameter θ_γ is calibrated to 0.283, with DICE-AI in its economic frontier yielding an increase of 0.01 percentage points in the capital income share by the end of the century under endogenous AI investment. We note that all these parameters are subject to considerable uncertainty. γ_{adj} is chosen so that capital income share equals 0.3 when $y_t^{AI} = y_t^{AI,base}$.

For the industrial-revolution (IR) prospect, quantitative evidence that directly estimates the magnitude of AI-driven total factor productivity (TFP) growth or AI-induced shifts in the capital income share remains scarce. We therefore employ a historical-analogue approach, calibrating both effects by drawing on evidence from past industrial revolutions.

Bouscasse et al. (2025) estimate productivity growth in England between 1250 and 1870 and show that the First Industrial Revolution (the Age of Steam, c. 1760–1840) raised productivity growth by a factor of 2.5, from about 2% to 5% per decade. Using the Maddison Database 2010 (Groningen Growth and Development Centre 2010), we conduct a similar analysis for the Second Industrial Revolution (the Technological Revolution, c. 1870–1914) and the Third Industrial Revolution (the Digital Revolution, post-1970). Specifically, we compute the average annual growth rate of world per-capita GDP before and after each revolution. The Second Industrial Revolution increased the annual growth rate by a factor of 2.24 (from 0.54% to 1.20%), and the Third Industrial Revolution raised it by a factor of 2.08 (from 1.20% to 2.50%) (Fig. A1b). Guided by this historical evidence, we calibrate the IR prospect by setting $\beta = 2$ (an assumed value for heuristic calibration), $\gamma_{asymp} = 0.4$, $\gamma_{adj} = 0.1$, and $\theta_\gamma = 0.314$. Under this parameterization, capital deepening alone increases the capital income share by 5 p.p. by 2100, and the AI-driven IR prospect raises the annual per capita GDP growth rate by approximately 2.3 times, consistent with the scale observed in the three previous industrial revolutions.

We further present future economic growth trajectories in the economic frontier (excluding the climate impacts) for the ICT prospect, the IR prospect, and for IR scenarios that include only automation effects or only R&D effects. These outcomes are compared with DICE-2023 and with historical growth during the three industrial revolutions (see Fig. A1). Under the ICT prospect, AI yields modest but non-negligible

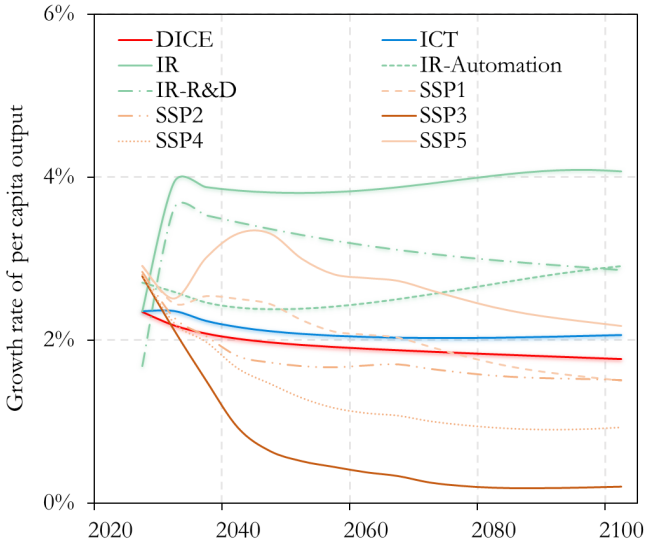


Fig. 3: DICE-AI's growth rate projections v.s. SSP

Note: ICT projects a modest influence on long-run growth from AI, much like earlier information and communications technologies. IR posits a transformative economic impact sufficient to trigger a new industrial revolution. The Shared Socioeconomic Pathways (SSPs), adopted by the IPCC, provide standardized long-term projections of socioeconomic development in the absence of climate policy; data are sourced from the IIASA SSP Scenario Explorer International Institute for Applied Systems Analysis (2025).

economic gains relative to DICE. In per-capita GDP terms, AI raises output by about 4% by mid-century and 14% by the end of the century (Fig.A1a). These magnitudes align with existing estimates in the literature. For example, Cerutti et al. (2025) report that AI-induced productivity gains could increase global GDP by up to 4% over the next decade, and Jones and Tonetti (2025) find that AI and automation produce output gains of around 4% by 2040. In contrast, under the IR prospect, the impact of AI on economic growth is comparable in scale to that of previous industrial revolutions (Fig A1b).

Finally, we compare the economic growth projections of DICE-AI (both IR and ICT prospects) with those of the Shared Socioeconomic Pathways (SSPs) (International Institute for Applied Systems Analysis 2025) used in IPCC AR6. As shown in Fig. 3, under the ICT prospect, the resulting per-capita GDP growth rate lies between the SSP1, SSP2, and SSP5 trajectories, while under the IR prospect it exceeds the growth rates implied by all SSP pathways.

3.3 Emission

3.3.1 Capital-embodied carbon intensity in the AI sector

We derive the initial carbon intensity of AI capital based on the range of estimates for data-center emissions, which are commonly used in the literature as a proxy for AI-sector emissions (Table C5). For the year around 2020, reported global data-center

carbon emissions vary between 38 and 330 $MtCO_2$, depending on system boundaries and the inclusion of embodied emissions. Given the global scope of our analysis and our inclusion of embodied emissions, we set initial-year emissions of the AI sector to 220 $MtCO_2$. The corresponding carbon intensity of AI capital is therefore given by:

$$\sigma_{KAI,2020} = E_{AI,2020}/K_{AI,2020} = 220/0.95 = 0.2316 \text{ (kg/\$)}$$

Next, we specify the rate of decline in the carbon intensity of AI capital. We assume that the AI sector decarbonizes faster than the aggregate economy before 2050, after which both converge to the same rate of decline. This assumption is supported by two lines of evidence.

First, emissions from data centers come largely from electricity consumption. The electricity sector has greater potential for rapid decarbonization than the broader economy, due to the expanding share of low-carbon sources such as solar, wind, and hydropower. According to the IEA, the global carbon intensity of electricity generation has been declining sharply—with a record drop of about 3% in 2024—and is projected to fall by an average of 3.6% per year during 2025–2027 (International Energy Agency 2025a). In contrast, the annual decline in the carbon intensity of the overall economy has averaged only about 1.8% in recent years (2015–2021). Looking ahead, the IEA's World Energy Outlook projects that under current policies, the global economy-wide carbon intensity will decline at an average rate of only about 1% per year between 2024 and 2050 (International Energy Agency 2025d).

Second, improvements in hardware and operational efficiency further reduce the energy intensity of data centers per unit of computation. Masanet et al. (2020) estimate that advances in processor efficiency, reductions in idle power, and gains in storage density and efficiency have lowered the energy intensity of global data centers by an average of 20% per year since 2010, substantially faster than efficiency improvements observed in most other energy-intensive sectors. Consistently, assessments by Lawrence Berkeley National Laboratory highlight that higher server utilization and continued improvements in computing efficiency have been key to moderating data-center energy growth over the past decade (Shehabi et al. 2024).

Building on this combined evidence, we assume a faster decline in carbon intensity for the AI sector than the aggregate economy before 2050, with both converging to the same rate thereafter. Specifically, the decline rate of the AI sector in 2020 is set to be 3.4 times that of the final production sector in DICE-2023. This factor is assumed to decrease gradually over time, falling to 3.0 by 2025, 2.6 by 2030, 2.2 by 2035, 1.8 by 2040, and 1.4 by 2045. From 2050 onward, the decline rates of the AI sector and the aggregate economy are identical.

Moreover, to capture uncertainty in the decline rate of AI-sector carbon intensity, we conduct a sensitivity analysis by first specifying a distribution for this parameter. Specifically, we determine its lower and upper bounds and then assume a normal distribution, with the baseline value set at the distribution mean. For the lower bound, the evidence above suggests that the decline rate of AI-sector carbon intensity is about 1.6 times that of the overall economy (3%/1.8%). For the upper bound, we draw on Masanet et al. (2020), who report an average annual reduction of about 20% in energy use per unit of computation since 2010. According to International Energy Agency

(2025c), the global annul rate of energy-efficiency improvement is around 1.75% since 2010. Because the estimate in Masanet et al. (2020) captures only computing-related efficiency gains, we adjust it downward to 7.83% [10] to account for embodied energy and its efficiency. This implies an upper-bound ratio of 4.5 (7.83%/1.75%) for the decline rate of AI-sector carbon intensity relative to that of the overall economy.

To center the normal distribution at our baseline calibration of 3.4, we calibrate the standard deviation using the more distant bound. Given the remaining uncertainty, we assume that the lower–upper bound range covers 90% of the distribution. Thus,

$$SD_{decline} = (3.4 - 1.6)/1.645 = 1.094 \tag{15}$$

The resulting values at the 2.5th, 25th, 50th, 75th, and 97.5th percentiles are 1.26, 2.66, 3.40, 4.14, and 5.54, respectively. These five values are used in the sensitivity analysis, while the calibrated normal distribution is used for the Monte Carlo simulations.

3.3.2 Capital-embodied carbon intensity in the final sector

Given the time series of AI-sector emissions and the corresponding trajectories of both types of capital in the economic frontier (without climate impacts), the carbon intensity of general capital is computed as::

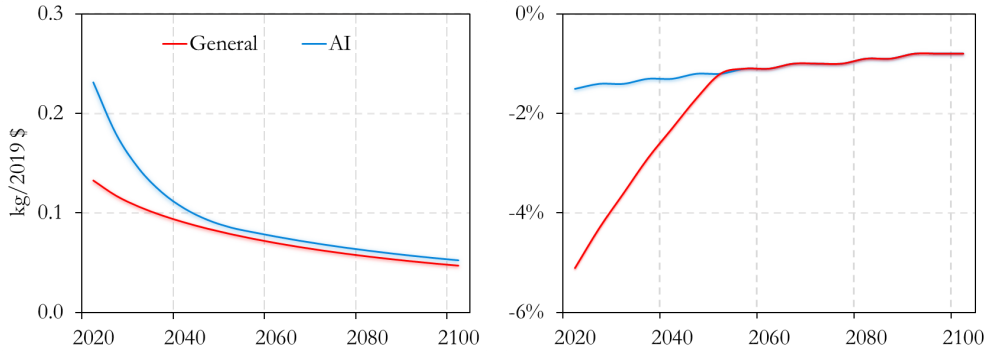
$$\sigma_{K,t} = (E_{total,t} - E_{AI,t})/(K_{total,t} - K_{AI,t}) \tag{16}$$

where $E_{total,t}$ and $K_{total,t}$ are taken from the original DICE-2023 model. Fig. 4 presents the calibrated capital-embodied carbon intensity and its annual growth rate for both general capital and AI capital in our DICE-AI model. We perform this calibration under the economic-frontier scenario to avoid a circular identification problem. In scenarios that include the full climate module (with damages and abatement costs), AI-sector investment—-and hence AI capital—is endogenously determined and varies with the very parameters that govern carbon intensity. Because those parameters are themselves calibrated as functions of K_{AI} such a setting would create a circular dependence and prevent a well-defined calibration. By contrast, in the economic frontier, the path of K_{AI} remains stable regardless of the emissions-related parameters, allowing a consistent and unambiguous calibration.

3.3.3 AI-powered emission conservation

To model the emissions-reduction effect of AI, we introduce a multiplicative scaling factor applied to the aggregate of capital-embodied emissions. Specifically, $\Omega(y_t^{AI})$ captures the share of emissions reduced as AI output rises, such that the factor $1 - \Omega(y_t^{AI})$ represents the fraction of emissions remaining after AI-driven abatement. By construction, when $y_t^{AI} = y_t^{AI,base}$, the factor equals unity, so no abatement occurs. As AI output grows, the factor converges to ψ_{asymp}, the asymptotic lower bound that

[10] According to Table C5 and estimates from IEA (2023, 2025), embodied energy accounts for about two-thirds of total energy consumption (International Energy Agency (2025b); International Energy Agency (2023)). We assume that this component improves at the global average energy-efficiency rate of 1.75%. The combined energy-efficiency improvement rate for data centres is therefore 1.75%×23+20%×13=7.83%



(a) Capital-embodied carbon intensity (b) Annual growth of carbon intensity

Fig. 4: Capital-embodied carbon intensity in DICE-AI

represents AI's maximum mitigation potential. The parameter θ_{sav} governs the speed at which this mitigation effect materialises with increasing AI adoption.

Because direct estimates of ψ_{adj} are not available in the literature, we calibrate it based on a review of related studies (Table C6). We set $\psi_{adj} = 0.1$, which by construction implies $\psi_{asymp} = 0.9$. The adjustment parameter θ_{sav} is then calibrated to 4.315, so that under a business-as-usual (BAU) scenario AI adoption reduces global emissions by approximately 3 $GtCO_2$ in 2035. This 3 $GtCO_2$ reduction lies midway between the estimates reported by Stern et al. (2025) and the (2025) International Energy Agency (2025b). The BAU scenario is used because both references already incorporate existing abatement policies in their quantitative estimates.

Similarly, for the sensitivity analysis of this parameter, we first specify a normal distribution by determining its lower and upper bounds, with the baseline calibration of $\psi_{adj} = 0.1$ set as the mean. Based on the literature reviewed in Table C6, the upper bound is 24% (Stern et al. (2025)) and the lower bound is 4% (International Energy Agency (2025b)). To center the distribution at the baseline value, we use the more distant bound to calibrate the standard deviation. To rule out negative values, we further reset the lower bound to zero and assume that the resulting range covers the 95% confidence interval. The standard deviation is therefore given by:

$$SD_{abate} = (0.1 - 0)/1.96 = 0.05 \tag{17}$$

The resulting values of ψ_{adj} at the 2.5th, 25th, 50th, 75th, and 97.5th percentiles are 0.00, 0.07, 0.10, 0.13, and 0.20, respectively. These five values are used in the sensitivity analysis, while the calibrated normal distribution with mean 0.10 and standard deviation 0.05 is used for the Monte Carlo simulations.

3.4 Damage

3.4.1 Adaptation function

AI adaptation is incorporated directly into the climate damage function. The original DICE-2023 damage function is specified as $D(T_t) = a_1 T_t^{a_2}$, with $a_1 = 0.003467$, and $a_2 = 2$ such that damages are output losses of 3.1% at 3°C warming and 7.0% loss at 4.5°C warming (Barrage and Nordhaus 2024). We extend this specification to include the adaptation effect of accumulated AI capital:

$$D(T_t, K_{AI,t}) = \left[(1 - a_3) + a_3 \left(\frac{K_{AI,0}}{K_{AI,t}}\right)^{a_4}\right] \times a_1 T_t^{a_2} \tag{18}$$

This specification implies that, as AI capital accumulates, it asymptotically alleviates a fraction a_3 of climate damage, leaving a residual fraction $1 - a_3$. To calibrate a_3, we proceed in three steps. We first adopt the sectoral climate damage estimates reported by Tol (2024), ensuring that their aggregate effect is consistent with the DICE-2023 benchmark of a 3.12% loss at 3°C of warming. Second, we assume that an infinitely large stock of AI capital can offset half of the climate damages in selected, adaptation-sensitive sectors, while leaving other sectors unaffected (Forouheshfar et al. 2025). As summarized in Table 2, this assumption results in an aggregate remaining climate damage of 1.81% at 3°C of warming after accounting for AI adaptation, implying that $1 - a_3 = 1.81/3.12$ such that $a_3 = 0.42$.

Table 2: Sectoral climate damages and AI-powered adaptation potentials

	Share	% GDP	Max impact of AI	% GDP
Agriculture	0.085855	-0.26787	0.5	-0.13393
Forestry	0.004259	-0.01329	1	-0.01329
Energy	0.043571	-0.13594	0.5	-0.06797
Water	0.038483	-0.12007	0.5	-0.06003
Tourism	0.033904	-0.10578	1	-0.10578
Other markets	0.242147	-0.7555	0.5	-0.37775
Coastal defence	0.010117	-0.03157	0.5	-0.01578
Dryland	0.023805	-0.07427	1	-0.07427
Wetland	0.062138	-0.19387	1	-0.19387
Ecosystem	0.073789	-0.23022	0.5	-0.11511
Health	0.176982	-0.55218	0.5	-0.27609
Air pollution	0.028585	-0.08919	0.5	-0.04459
Time use	-0.10632	0.331724	1	0.331724
Settlements	0.062327	-0.19446	0.5	-0.09723
Catastrophe	0.077528	-0.24189	0.5	-0.12094
Migration	0.02017	-0.06293	1	-0.06293
Amenity	0.122662	-0.38271	1	-0.38271
Total		-3.12		-1.81056

Last, we assume that by 2050, AI achieves half of its maximum potential adaptation effect, measured relative to the gap between its initial capital level (2020) and its asymptotic (infinite-capital) benchmark. Under the BAU scenario, AI capital increases from 0.95 trillion in 2020 to 51.50 trillion in 2050. Accordingly, $(0.95/51.5)^{a_4} = 0.5$. Thus, $a_4 = \ln(0.5)/\ln(0.95/51.5) = 0.1736$.

Note that when are calibrating the DICE-AI model to mimic the DICE-2023 model, we explicitly incorporate an AI sector with a fixed path of AI-sector investment rates but retain the original DICE damage function without adaptation. This reflects the assumption that climate damages in DICE-2023 are not adjusted to account for AI-driven adaptation effects. In the full DICE-AI model, however, climate damages are modified by Eq. 18, which explicitly accounts for adaptation enabled by AI capital.

Similarly, to conduct the sensitivity analysis for AI-powered adaptation, we first determine the lower and upper bounds of , with the baseline value set at the distribution mean. Our calibration is based on the systematic review by Forouheshfar et al. (2025), which identifies sectors in which AI can enhance resilience to climate change. For the lower-bound case, we exclude sectors that are less closely related to those identified by Forouheshfar et al. (2025) from the set of adaptation-sensitive sectors assumed in the baseline calibration. This yields an aggregate residual climate damage of 2.33% at warming after accounting for AI adaptation, implying that, $1 - a_3 = 2.33/3.12$ such that $a_3 = 0.253$.

For the upper-bound case of AI-driven adaptation, we additionally include sectors that are somewhat related to those identified by Forouheshfar et al. (2025) but were not treated as adaptation-sensitive in the baseline calibration. This yields aggregate residual climate damage of 1.56% at warming after accounting for AI adaptation, implying and thus . $1 - a_3 = 1.56/3.12$ such that $a_3 = 0.5$.

To center the normal distribution at our baseline calibration of $a_3 = 0.42$, we calibrate the standard deviation using the more distant bound. Given that this range is grounded in the literature, we assume that it covers 95% of the distribution. Therefore,

$$SD_{decline} = (0.42 - 0.253)/1.96 = 0.085 \tag{19}$$

The resulting values of a_3 at the 2.5th, 25th, 50th, 75th, and 97.5th percentiles are 0.253, 0.362, 0.420, 0.477, and 0.586, respectively. These five values are used in the sensitivity analysis, while the calibrated normal distribution is used for the Monte Carlo simulations.

3.4.2 Alternative damage estimates for sensitivity analysis

In DICE-2023, the damage function is constructed from three components: a literature-synthesis estimate of global aggregate warming impacts, implying a 1.62% GDP-equivalent loss at 3°C warming; an adjustment for tipping points, adding a further 1% output loss at 3 °C; and a judgment-based allowance of 0.5% to account for omitted impacts and residual uncertainty. Given that the damage function remains one of the most thorniest issues in climate-change economics, we consider alternative damage estimates in sensitivity analyses.

More specifically, we draw on Tol (2024) , which also serves as the basis for our calibration of AI-driven adaptation. The author provides an updated meta-analysis

of the economic impacts of climate change, and estimates seven alternative damage functions using 69 estimates drawn from studies on the total economic impact of climate change. The function parameters are calibrated by minimizing the weighted sum of squared deviations between the model predictions and the primary estimates, assigning equal weight to all estimates within a given study and a total weight of one to each study. We adopt, for sensitivity analysis, the function with the highest likelihood among the seven alternatives as the first damage specification,

$$D(T_t) = 0.01 \times (0.45 \times T_t + 0.082 \times T_t^2) \tag{20}$$

This specification implies GDP losses of around 2.1% under a 3°C increase in global mean surface temperature relative to the preindustrial period, which is lower than the corresponding estimate in DICE, where damages reach 3.12% at 3°C warming. This discrepancy stems primarily from differences in literature search, study selection, weighting schemes, and the treatment of methodological heterogeneity across studies.

In addition, Tol (2024) estimates a fitted global impact function based on studies linking economic growth to temperature levels, which we use as the second alternative damage function in the sensitivity analysis,

$$D(T_t) = 0.002006 \times T_t + 0.000023 \times T_t^2 \tag{21}$$

implying an approximately 0.6% reduction in the annual growth rate of global economic output under 3°C of global warming. The growth effect generates substantially larger cumulative damages than the level effect.

Based on previous calibration Eq. 18, when accounting for AI-driven adaptation effects, Eq. 20 and 21 are modified as follows:

$$D(T_t, K_{AI,t}) = \left[0.58 + 0.42 \times \left(\frac{0.95}{K_{AI,t}}\right)^{0.1736}\right] \times 0.01 \times (0.45 \times T_t + 0.082 \times T_t^2) \tag{22}$$

$$D(T_t, K_{AI,t}) = \left[0.58 + 0.42 \times \left(\frac{0.95}{K_{AI,t}}\right)^{0.1736}\right] \times (0.002006 \times T_t + 0.000023 \times T_t^2) \tag{23}$$

In the sensitivity analysis, we apply Eq. 20 and Eq. 21 to DICE-2023, while Eq. 22 and Eq. 23 are applied to DICE-AI, with the growth-rate effect incorporated into the TFP growth equation.

3.5 Carbon cycle and climate modules

The climate module and its parameters in DICE-AI follow DICE-2023, including the carbon cycle, radiative forcing, and climate dynamics. CO_2 emissions enter through the carbon cycle before affecting radiative forcing, while non-CO_2 greenhouse gases

are linked directly to radiative forcing and short-circuit the atmospheric chemistry.

$$\Delta R^i(t+1) = \xi_i E(t) - \left[\frac{R^i(t)}{\alpha(t)\tau_i}\right], i = 1, ..., 4 \tag{24}$$

$$MAT(t) - MAT(1765) = \sum_{i=1}^{4} R^i(t) \tag{25}$$

$$Cacc(t) = \sum_{v=1765}^{t} E(v) - [MAT(t) - MAT(1765)] \tag{26}$$

Eq. 24 describes the four-reservoir carbon cycle, where $R^i(t)$ denotes the carbon stock in reservoir i and $E(t)$ represents CO_2 emissions. The structural parameter $\alpha(t)$ captures the fraction of cumulative CO_2 emissions remaining in the atmosphere as total emissions increase. Following DICE-2023, the fractions of emissions entering the four reservoirs are $\xi_i = (0.2173, 0.2240, 0.2824, 0.2824)$, with corresponding decay time constants $\tau_i = (1,000,000, 394.4, 36.53, 4.304)$ years. Eq. 25 aggregates the four reservoirs to obtain atmospheric CO_2, $MAT(t)$. Eq. 26 defines accumulated CO_2 in non-atmospheric sinks, $Cacc(t)$.

$$iIRF100(t) = \varsigma_0 + \varsigma_C Cacc(t) + \varsigma_T T_{AT}(t) \tag{27}$$

$$iIRF100(t) = \sum_{i=1}^{4} \alpha(t)\xi_i\tau_i \left[1 - e^{\frac{-100}{\alpha(t)\tau_i}}\right] \tag{28}$$

Eq. 27 computes the 100-year integrated impulse response function, $iIRF100(t)$, where $T_{AT}(t)$denotes global mean surface temperature. The associated parameters are set as follows: the pre-industrial impulse response time is $\varsigma_0 = 32.4$ years; the IRF increases by 0.019 years per GtC of cumulative carbon uptake ($\varsigma_C = 0.019$); and by 4.165 years per kelvin of warming ($\varsigma_T = 4.165$). Eq. 28 implicitly defines the saturation parameter by equating Eq 27 and 28. Note that values of $R, Cacc, E$ are all zero in 1765.

$$F(t) = F_{CO_2 2x} \times \log_2 \left[\frac{MAT(t)}{MAT(1765)}\right] + F_{ABATE}(t) + F_{FX}(t) \tag{29}$$

$$Tbox_1(t+1) = Tbox_1(t)e^{\frac{-5}{d_1}} + teq_1 F(t+1)\left(1 - e^{\frac{-5}{d_1}}\right) \tag{30}$$

$$Tbox_2(t+1) = Tbox_2(t)e^{\frac{-5}{d_2}} + teq_2 F(t+1)\left(1 - e^{\frac{-5}{d_2}}\right) \tag{31}$$

$$T_{AT}(t) = Tbox_1(t) + Tbox_2(t) \tag{32}$$

$$ECS = F_{CO_2 2x} \times (teq_1 + teq_2) = 3^\circ C \tag{33}$$

The remaining climate equations describe radiative forcing and global mean temperature. Greenhouse gas accumulation increases surface temperatures through higher radiative forcing, with the forcing–concentration relationship derived from empirical evidence and climate models. In Eq. 29, $F(t)$ denotes the change in total anthropogenic radiative forcing since 1765 from CO_2 and other GHGs; $F_{EX}(t)$ represents exogenous forcing from non-abatable sources; and $F_{ABATE}(t)$ captures forcing from abatable

non-CO_2 GHGs. Pre-industrial carbon stocks in 1765 are taken as the equilibrium baseline.

Moreover, the climate module in Eqs. 30–32 adopts a two-box temperature model to represent the response to radiative forcing. Global mean surface temperature, $T_{AT}(t)$ is calculated as the sum of two components, $Tbox1$ and $Tbox2$. Parameters d_1 and d_2 denote the time lags (in years) of the two temperature boxes and are set to 236 and 4.07, respectively. Parameters teq_1 and teq_2 represent the corresponding diffusion rates (in $m^2 \cdot K/W$), set to 0.324 and 0.44. Additionally, the equilibrium climate sensitivity is defined in Eq. 33.

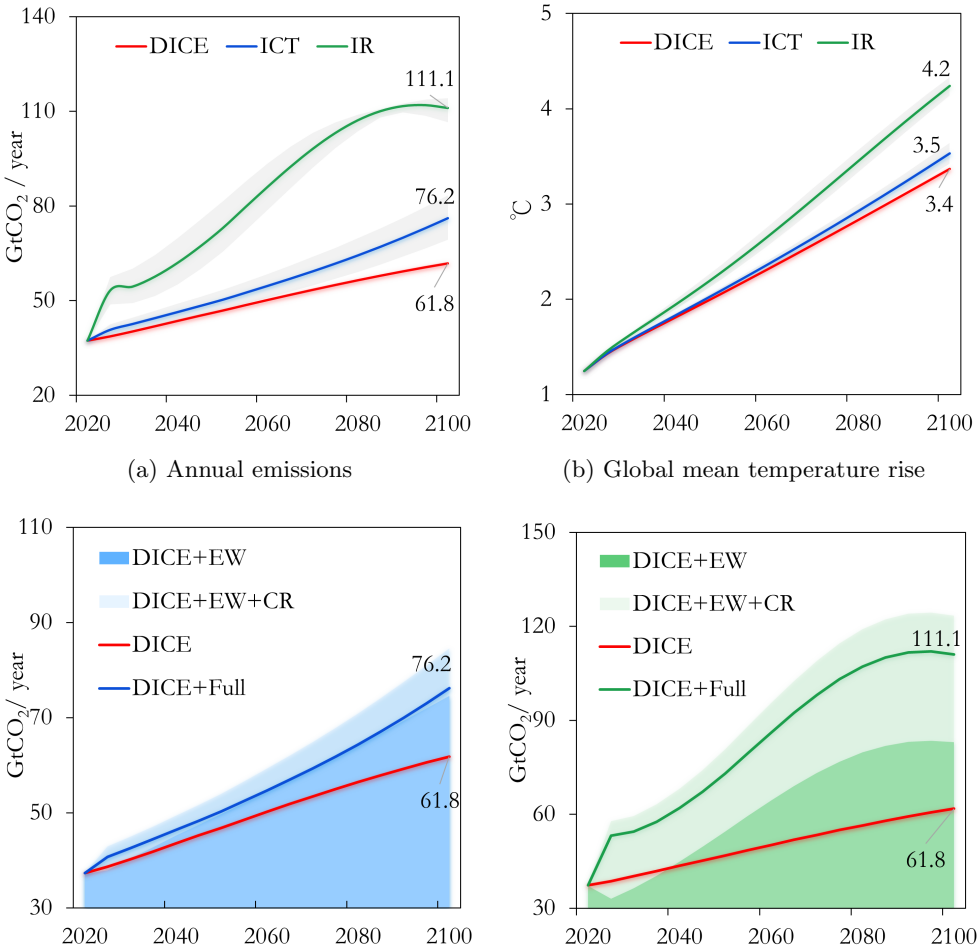
4 Quantitative Results

4.1 Does AI cause more or less emissions?

Figure 5 shows the projected emissions and warming impacts of AI under the two economic prospects by the DICE-AI model, assuming a low abatement path (global average carbon price of \$6/tCO_2 in 2020, rising at 2.5% annually). Relative to the DICE baseline (red line), ICT-like AI yields a higher emission path (blue line), with annual emissions in 2100 rising from 61.8 to 76.2 $GtCO_2$ (Fig. 5a). This raises global warming by an additional 0.1°C (Fig. 5b). In contrast, IR-like AI presents a more substantial challenge. If low abatement persists, 2100 emissions would almost double to 111.1 $GtCO_2$, further elevating the global warming to 4.2°C. Thus, AI will cause more emissions and hence is net polluting, without more stringent climate policies.

We also decompose the AI-associated annual emission changes into distinct categories. For the ICT-like AI (Fig. 5c), the economy-wide (EW) emission impact of AI is substantial (dotted line), increasing by 12.8 $GtCO_2$ to 74.6 $GtCO_2$ in 2100, an increment comparable to its computing-related (CR) impact of 9.9 $GtCO_2$ (the light-blue shaded area). The net effect, also accounting for the immediate applications of AI to reduce GHG emissions, remains at 76.2 $GtCO_2$ (solid line). Under the IR prospect (Fig. 5d), both the EW and CR impacts are amplified in magnitude. In initial periods, the highly profitable AI sector draws investment away from the final sector. This reallocation reduces the capital stock in the final sector, where capital depreciation outpaces new investment, generating a temporary reduction in economy-wide emissions since emissions are associated with capital use. However, this reduction comes at the expense of surging computing-related emissions, because the emissions-intensive AI-capital is rapidly accumulating. By 2100, the EW impact increases annual emissions by 21.2 $GtCO_2$, about half of the increase due to the CR impact (40.4 $GtCO_2$). Together, these increases considerably diminish the relative importance of AI's immediate abatement effects.

Our analysis highlights a critical yet overlooked role of AI's economy-wide emission impact. Increased economic output increases energy use, as energy is an essential factor in production and AI-driven automation spurs the use of energy-using machines, equipment, and robotics. Although the economy-emission nexus is well documented in both Shared Socioeconomic Pathways (SSP) scenarios (Dellink et al. 2017; O'Neill et al. 2017; Koch and Leimbach 2023) and climate economics literature (Nordhaus 2018), and AI's economic potential is recognized (Aghion et al. 2018; Trammell and Korinek



(a) Annual emissions

(b) Global mean temperature rise

(c) Emissions under the ICT-like prospect

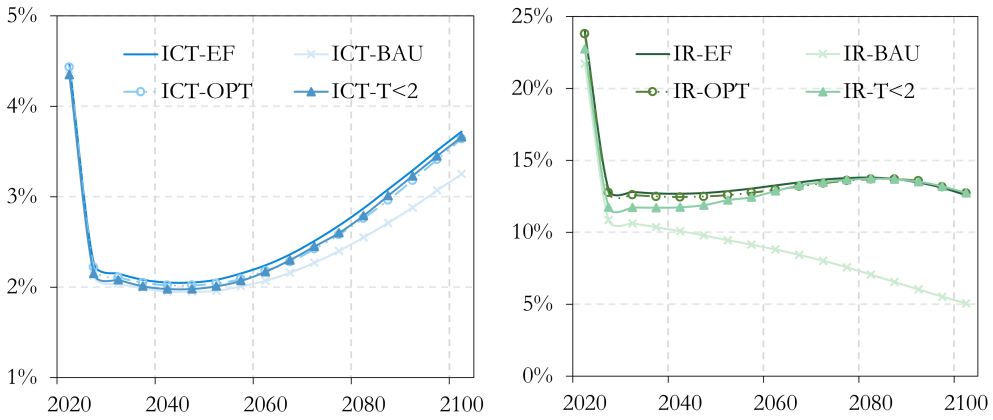
(d) Emissions under the IR-like prospect

Fig. 5: AI and GHG emissions

Note: Annual GHG emissions and global mean temperature rise relative to the preindustrial level are calculated from the DICE-AI model, using the low abatement policy assumed in the DICE-2023 model. EW and CR are short for the economy-wide impact and the computing-related impact, respectively. Their combined effects, plus the abatement from AI's immediate applications, determine the 'Full' impact. ICT projects a modest influence on long-run growth from AI, much like earlier information and communications technologies. IR posits a transformative economic impact, comparable to a new industrial revolution. The shaded areas in panels (a) and (b) indicate the 5th–95th percentile range of outcomes from 2,000 Monte Carlo simulations over three parameters related to AI's emissions and adaptation potential: AI-powered adaptation, the AI carbon-intensity decline rate, and AI immediate application impacts. For each parameter, we first identify the lower and upper bounds from the literature, then assume a normal distribution centered on the baseline value, and finally run the simulations based on these distributions.

2023), the transmission from AI-induced economic growth to emissions remains surprisingly underexplored. Our results show that greater optimism about AI's economic potential implies increased mitigation pressure.

4.2 The interplay between AI and climate policies



(a) ICT-like prospect (b) IR-like prospect

Fig. 6: Optimal AI investment rate

Note: The figure presents the optimal AI investment rate (AI investment as a ratio of final output) from the DICE-AI model. ICT projects a modest influence on long-run growth from AI, much like earlier information and communications technologies. IR posits a transformative economic impact, triggering a new industrial revolution. EF denotes the economic frontier excluding climate impacts, serving as the pure growth benchmark. BAU represents the current business-as-usual low abatement policy as implemented in DICE-2023. OPT employs an optimal carbon price to maximize social welfare. $T < 2$ caps the global mean temperature rise at 2°C above its preindustrial level.

AI development and climate policy interact in two ways. We begin by analyzing the impact of climate policy on AI. Given our prior findings that AI is net polluting, one might expect that GHG mitigation policies hinder AI investment. The results in Figure 6 reveal the opposite.

We simulate the optimal AI investment rate (AI investment as a share of final output) under four scenarios using the DICE-AI model. For the ICT-like prospect (Fig. 6a), the economic frontier (EF) scenario (no climate impact, solid blue line) yields a U-shaped AI investment rate, due to the combined effects of accelerated TFP growth and capital deepening (see Appendix A.2). However, when climate impacts are included under a business-as-usual (BAU) low-abatement policy, the optimal AI investment rate shows a marked drop—by 0.12 pp to 1.96% in 2050, and by a further 0.47 pp to 3.25% in 2100. These estimates already account for AI-powered adaptation; without such adaptation, the decline would be deeper. Notably, when either an optimal carbon tax or a stringent 2°C warming constraint is implemented, these emission-reducing climate policies largely reverse the decline in AI investment observed under BAU, resulting in

AI investment rates of 3.64% by 2050 and 3.66% by 2100, respectively. Although the 2°C warming constraint limits emissions more strictly, which may potentially dampen near-term AI investment, the investment rates in this scenario remain higher than under BAU (e.g., 2.08% v.s. 2.04% in 2030; 1.98% v.s. 1.95% in 2040). A similar pattern is observed under the IR-like prospect (Fig. 6b), where the decline under BAU is more acute relative to EF, and is similarly reversed by mitigation policies.

Thus, we conclude that climate policies are in effect complementary to AI development. The underlying rationale is straightforward. At the BAU low abatement, accelerating global warming inflicts climate damages, undermining the future return on AI capital. Effective climate policies, by curbing damages, preserve the future profitability of AI investment.

Table 3: Social cost of carbon ($/tCO$_2$, 2019$)

Scenario			2025	2030	2050	2100	T_{max}^{21st} (°C)	T_{max} (°C)
DICE		BAU	84	97	166	492	3.4	5.4
		Opt	69	79	132	356	2.6	2.7
		$T < 2$°C	105	122	222	524	2.0	2.0
ICT	BAU	No adaptation	83	97	171	531	3.5	6.1
		Baseline	61	72	126	376	3.5	6.4
	Opt	Baseline	53	61	105	291	2.8	3.0
		Philosopher	55	65	110	301	2.8	3.0
		Stern	118	139	225	463	2.4	2.4
		Nordhaus	40	46	80	238	2.9	3.3
		Alt damage 1	29	33	54	148	3.2	4.2
		Alt damage 2	599	631	849	1796	1.8	2.5
	$T < 2$°C	Baseline	98	117	226	521	2.0	2.0
IR	BAU	No adaptation	118	153	425	4107	4.2	6.9
		Baseline	105	138	396	4239	4.2	6.9
	Opt	Baseline	36	46	105	557	3.3	3.3
		Philosopher	37	46	106	558	3.3	3.3
		Stern	76	98	217	874	2.6	2.6
		Nordhaus	29	36	82	457	3.5	3.5
		Alt damage 1	19	24	50	274	4.5	4.8
		Alt damage 2	313	360	616	2287	2.0	2.0
	$T < 2$°C	Baseline	171	227	677	481	2.0	2.0

Note: ICT projects a modest influence on long-run growth from AI, much like earlier information and communications technologies. IR posits a transformative economic impact, triggering a new industrial revolution. BAU represents the current business-as-usual low abatement policy as implemented in DICE-2023. OPT employs an optimal carbon price to maximize social welfare. $T < 2$°C caps the global mean temperature rise at 2°C above the preindustrial level. The 'No adaptation' scenario precludes AI-powered adaptation from reducing climate damages, as opposed to the Baseline scenario, which assumes that AI development fulfills half of its adaptation potential by 2050. Our baseline simulation adopts the discount rate parameters based on a survey of economists (Drupp et al. 2018). For sensitivity tests, we also consider discounting parameters advocated by philosophers (Nesje et al. 2023), used in the Stern Report (Stern 2007) and in earlier work by Nordhaus (Nordhaus 2018). Additionally, we include two alternative damage estimates from a recent updated meta-analysis of climate damages (Tol 2024). Here, T_{max}^{21st} denotes the highest temperature rise within this century, while T_{max} refers to the maximum temperature rise projected beyond this century.

We next examine how AI development in turn affects climate policies. Table 3 reports the social cost of carbon (SCC) as a yardstick in climate policy (Aldy et al. 2021; Kelleher 2025). Following DICE (Barrage and Nordhaus 2024), it measures the consumption loss due to an additional tonne of carbon emissions. Its magnitude can vary with climate vulnerability, the size of the economic base, and the presence of binding constraints (such as a 2°C warming limit), and other economic distortions (Golosov et al. 2014; Dietz and Venmans 2019; Traeger 2023; Barrage 2020). Under welfare-maximizing conditions, the SCC coincides numerically with the optimal carbon tax, the Pigou tax.

Under BAU low abatement, ICT-like AI can either raise or lower the SCC, depending on whether AI effectively enhances climate adaptation. The SCC is lower than DICE (e.g., 61 v.s. 84 $/tCO$_2$ in 2025, 126 v.s. 166 $/tCO$_2$ in 2050, and 376 v.s. 492 $/tCO$_2$ in 2100). This reduction occurs because AI-powered adaptation outweighs the emission-intensifying impact of AI-induced economic growth under the modest ICT prospect. Without such adaptation, climate damages will be amplified, due to the curvature of the damage function implying increasing marginal damages at higher temperatures, resulting in a higher SCC path (e.g., 83, 171, and 531 in 2025, 2050, and 2100, respectively). Reduced climate vulnerability resulting from AI-powered adaptation also lowers the optimal carbon tax under ICT-like AI. The optimal carbon tax is 105 $/tCO$_2$ in 2050 and 291 $/tCO$_2$ in 2100, more than one-sixth below the corresponding DICE values of 132 and 356 $/tCO$_2$. By comparison, differences are smaller between DICE and ICT-like AI under a 2°C warming constraint, because cost-effective policies are less sensitive to climate vulnerability.

IR-like AI markedly alters both the time profile and the magnitude of the SCC. Substantially larger damages under BAU drive the SCC upward, because the GHG emissions generated by IR-like explosive growth are so extensive that their climate impact overwhelms any adaptive benefits from AI. Compared to DICE, the SCC more than doubles to 425 $/tCO$_2$ in 2050 and soars to 4107 $/tCO$_2$ in 2100. Interestingly, this exponential increase in the SCC under BAU case does not produce a proportional rise in the optimal carbon tax, though the impact remains substantial. Under an optimal climate policy, IR-like AI lowers the SCC in the near term and raises it over the mid- to long term. By 2100, the optimal carbon tax (557 $/tCO$_2$) exceeds the DICE value (356 $/tCO$_2$) by half. When a 2°C warming cap is imposed, the SCC is higher in early decades but lower by 2100, due to the backstop technology in the DICE model. Because IR-like AI stimulates explosive economic growth, it expands the base of GHG emissions, necessitating a higher emission control rate that will activate the backstop sooner. Such a constraint acts as a kink in the damage function, elevating the SCC (Barrage and Nordhaus 2024). If the technology limit is relaxed, the SCC will be lower in the near term and higher in the long term (80, 105, 300, and 566 $/tCO$_2$ in 2025, 2030, 2050, and 2100, respectively), resembling the pattern under the optimal scenario.

The abatement rate confirms our results for the SCC (Table 4). For the ICT-like AI, a stricter abatement path is obtained without considering adaptation, whereas a more lenient pathway results when accounting for adaptation. This generates an optimal temperature rise within this century of 2.8°C that is 0.2°C higher than the DICE

Table 4: Abatement rate and annual investment

Scenario		DICE				ICT				IR			
		2025	2030	2050	2100	2025	2030	2050	2100	2025	2030	2050	2100
Control rate	Opt.-No adapt.	10%	24%	40%	77%	10%	24%	40%	79%	10%	24%	45%	100%
	Opt.	\	\	\	\	10%	23%	34%	69%	10%	21%	37%	100%
	Opt-Alt damage 1	10%	18%	27%	53%	10%	15%	23%	46%	10%	14%	24%	72%
	Opt-Alt damage 2	10%	24%	72%	100%	10%	24%	72%	100%	10%	24%	72%	100%
	$T < 2$°C	10%	24%	55%	98%	10%	24%	55%	99%	10%	24%	72%	100%
Annual investment (Trillion 2019$)	Opt.-No adapt.	0.04	0.37	1.38	11.40	0.04	0.38	1.43	13.74	0.04	0.41	2.91	93.68
	Opt.	\	\	\	\	0.04	0.32	0.99	9.70	0.04	0.30	1.81	94.75
	Opt-Alt damage 1	0.04	0.18	0.53	4.38	0.04	0.12	0.35	3.35	0.04	0.10	0.56	40.36
	Opt-Alt damage 2	0.03	0.32	5.41	15.64	0.04	0.35	6.44	23.74	0.04	0.39	9.72	80.60
	$T < 2$°C	0.04	0.37	3.16	21.56	0.04	0.37	3.38	24.76	0.04	0.40	9.78	93.32
Abate./AI ratio	Opt.-No adapt.	\	\	\	\	0.01	0.10	0.24	0.42	0.002	0.02	0.05	0.23
	Opt	\	\	\	\	0.01	0.08	0.16	0.29	0.002	0.01	0.03	0.22
	Opt-Alt damage 1	\	\	\	\	0.01	0.03	0.05	0.10	0.002	0.00	0.01	0.09
	Opt-Alt damage 2	\	\	\	\	0.01	0.08	0.83	0.85	0.002	0.02	0.18	0.26
	$T < 2$°C	\	\	\	\	0.01	0.10	0.56	0.74	0.002	0.02	0.18	0.22

Note: ICT projects a modest influence on long-run growth from AI, much like earlier information and communications technologies. IR posits a transformative economic impact, triggering a new industrial revolution. BAU represents the current business-as-usual low abatement policy as implemented in DICE-2023. OPT employs an optimal carbon price to maximize social welfare. $T < 2$°C caps the global mean temperature rise at 2°C above the preindustrial level. The 'No adaptation' scenario excludes AI-powered adaptation from reducing climate damages, as opposed to the Baseline scenario, which assumes that AI development fulfills half of its adaptation potential by 2050. Additionally, we include two alternative damage estimates from a recent updated meta-analysis of climate damages (Tol 2024). The 'Abate./AI ratio' measures the amount of carbon mitigation investment per dollar directed to AI investment.

model (Table 3). By comparison, IR-like AI produces a more stringent abatement path from 2060 onward. By 2100, while the DICE model still permits an optimal residual emission level of 23%, IR-like AI requires net-zero emissions. However, despite these efforts, the peak temperature rise is projected to reach 3.3°C, due to a large production base. Under the 2°C warming target, AI development accelerates the timeline for deep decarbonization (see Fig. A3 in 'Extended results'). For example, while DICE model only requires an abatement rate higher than 90% since 2075, ICT-like AI demands a slightly higher abatement rate of 93% starting in the same year. Most strikingly, IR-like AI achieves this since 2060, and a mitigation level consistently above 99% since 2085.

Two remarks are warranted here. First, while AI-powered adaptation has considerable potential to alleviate damages, it may not necessarily justify a more lenient climate policy. Persistent uncertainties around the discount rate, damage estimates, whether AI will materialize as ICT or IR, the impact of AI-powered adaptation, and the interactions among them, can still support more stringent optimal abatement policies or higher optimal carbon taxes than those derived from the DICE model without AI. For instance, adopting the discount rate advocated by Stern (2007) or updating damage estimates based on recent meta-analyses Tol (2024) results in different optimal peak warming levels under the ICT prospect (2.4°C, 4.2°C, and 2.5°C), compared to the resulting 2.6°C from DICE (Table 3). Also, for the IR prospect, although warming levels are higher, both the optimal carbon tax and abatement rates are adjusted upward accordingly, as noted earlier. Second, even if AI development follows an IR-like pathway, it does not paralyze the credibility of the resulting optimal carbon tax in previous studies. However, when AI's economic impact is very promising, it exacerbates the mitigation pressure, particularly under a 2°C warming target, calling for stronger and earlier policy action.

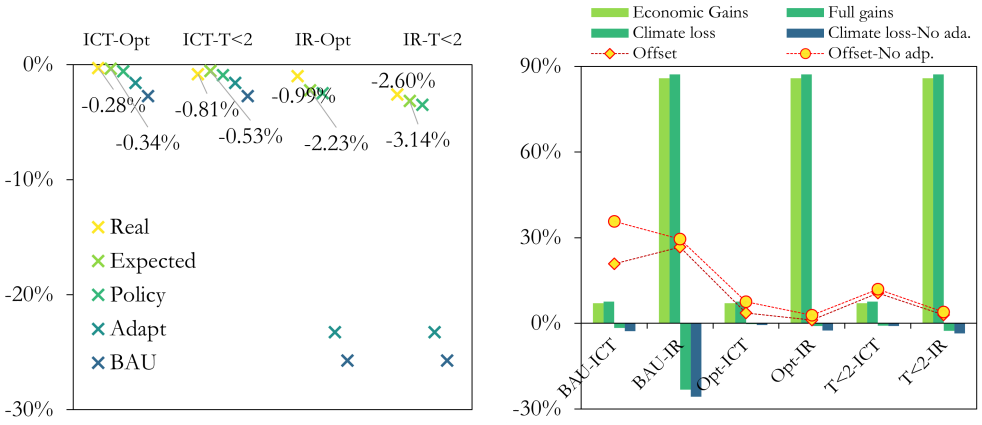
We further examine how climate mitigation investment responds to AI development. We consider the amount of carbon mitigation investment per dollar directed to AI investment. Intuitively, one might expect this ratio to be lower for ICT-like AI than for IR-like AI, because the latter is more polluting with a large emission base. Counterintuitively, Table 4 displays the opposite pattern (e.g., 0.01 v.s. 0.002 in 2025, 0.16 v.s. 0.03 in 2050, and 0.29 v.s. 0.22 in 2100). This is because the ratio more meaningfully reflects which type of investment yields higher marginal returns. Given that IR-like AI heralds greater revenue from AI investment, it is rational for a social planner to invest more heavily toward AI, thereby lowering *the mitigation-investment-per-dollar-AI-investment ratio*. Nevertheless, in absolute terms, annual abatement investment remains higher under IR-like AI, consistent with the larger emission base associated with stronger economic growth. For example, our DICE-AI model projects that ICT-like AI demands an optimal annual abatement investment rising from US$0.04 trillion in 2025 to US$9.70 trillion in 2100, whereas under the IR prospect it increases by an order of magnitude to US$94.75 trillion in 2100. Alternative damage specifications also corroborate this point, with both annual abatement investment and the ratio increasing when a function representing more severe damage estimates is adopted.

We do not vary discount rates in this comparison, because both AI and climate investments are long-term undertakings whose costs are incurred upfront and benefits

accrue in the future. While their maturities can differ, our knowledge is currently limited on the timelines of returns. That said, the discount rate remains critical for intertemporal welfare comparisons, which we address in the following section.

4.3 Welfare analysis of AI development

Section 4.1 shows that AI is net polluting and therefore accelerates global warming. We now proceed to assess the welfare costs associated with AI-induced emissions. Following Barrage (2020), we employ the permanent-consumption-equivalent (PEV) method for this intertemporal welfare comparison. To isolate the specific climate impact of AI, we introduce a method that distinguishes AI-driven warming from the baseline projections of the DICE model (see 'Methods'). Climate-related welfare loss captures both the damages from higher temperatures due to AI pollution and the increased abatement costs. Global warming from non-AI-related emissions, as incorporated in the DICE model, is not attributed to AI-related climate costs. Throughout our analysis, we use the consumption path of the DICE model's optimal scenario as the benchmark.



(a) ICT-like prospect

(b) IR-like prospect

Fig. 7: Climate-related welfare loss under different AI development prospects

Note: ICT projects a modest influence on long-run growth from AI, much like earlier information and communications technologies. IR posits a transformative economic impact, triggering a new industrial revolution. BAU represents the current business-as-usual low abatement policy as implemented in DICE-2023. OPT employs an optimal carbon price to maximize social welfare. T<2 caps the global mean temperature rise at 2°C above its preindustrial level. Using the permanent-equivalent-variation method following Barrage (2020), the figure displays the climate-related welfare loss from AI development, expressed relative to the consumption path of the DICE-2023 optimal scenario. The loss captures both climate damages from AI-induced warming and associated abatement costs (see 'Methods'). 'Policy' excludes AI-powered adaptation, whereas 'AI adapt' assumes the BAU policy. The 'Expected' losses from combining climate policy and AI adaptation are calculated by multiplying their individual residual loss shares, while the 'Real' loss denotes the modeled outcome under their combined implementation.

Our baseline DICE-AI model reveals that under BAU, the welfare loss attributable to polluting AI is substantial, even when AI's adaptation potential is fully utilized (Fig.

7 and Table A1). By aggravating global warming further, GHG emissions from ICT-like and IR-like AI would induce a permanent consumption loss of 2.73% and 25.73%, respectively, if AI-powered adaptation is excluded. When adaptation is enabled, consumption loss remains considerable at 1.59% and 23.24%. These results reflect the compounded effect of AI-driven warming and the convexity of the climate damage function, where damages increase progressively with temperature. This explains why the climate loss for IR-like AI is an order of magnitude greater than that for ICT-like AI.

Nevertheless, well-designed climate policy can mitigate these losses and, when combined with AI-powered adaptation, produce multiplier effects. An optimal carbon tax reduces the permanent consumption loss to 0.58% and 2.47%, respectively. A 2°C warming limit lowers the loss to 0.91% and 3.48%. Under an optimal carbon tax, the expected consumption loss from combining climate policy and AI adaptation—calculated by multiplying their individual residual loss shares—is 0.34% for ICT-like and 2.23% for IR-like AI. However, the modeled outcome under the combined implementation of climate policy and AI adaptation is lower, with realized losses of only 0.28% and 0.99%. These findings indicate that combining AI-powered adaptation with emission abatement policy can generate multiplier effects, offering a promising pathway to significantly reduce welfare losses from AI-induced climate change.

Table A1 in the 'Extended Results' further quantifies how climate-related costs offset the economic gains from AI development, highlighting the critical role of climate policy in safeguarding AI-driven welfare benefits. Although AI adaptation reduces climate damages, residual climate-related losses still offset a notable share of AI economic gains. Under BAU, climate costs due to AI-induced warming offset approximately one-fifth (ICT) or one-quarter (IR) of AI economic gains. In contrast, climate policy preserves most of these gains, reducing the offset to 3.64% (ICT) and 1.14% (IR) under the optimal tax, and to 10.60% and 2.98% under the 2°C warming limit. In addition, the sensitivity analysis yields two notable observations. First, when AI-related economic gains are modest, as ICT-like AI, its climate-related costs based on an alternative damage estimate (Tol 2024) may fully offset or even exceed economic gains. Second, the discount rate exerts dual influence: a lower rate assigns greater weight to future climate damages, but also to future AI economic gains. Thus, both economic gains and climate costs under BAU are amplified in tandem.

5 Sensitivity

In this section, we assess the sensitivity of our results along two complementary dimensions. A central finding of our analysis is that AI, on balance, contributes to higher emissions. To test the robustness of this conclusion, we conduct a thought experiment that asks: how large would AI's abatement potential need to be for it to cease being a net source of emissions? We then examine how variation in the five uncertainty factors affects three key outcomes, including global mean temperature rise, the social cost of carbon, and the ratio of mitigation investment per dollar of AI investment.

5.1 Can AI be non net polluting?

Despite its promising abatement potential, AI is a net source of GHG emissions. The thought experiment (Fig. 8) asks how powerful AI's immediate application impact should be to offset AI emissions from the other two categories (computing-related and economy-wide impacts) under BAU. Reversing the net-polluting verdict proves exceptionally difficult, and likely unrealistic for an IR-like future. This requires ICT-like and IR-like AI to reduce aggregate carbon intensity by around 28% and 90%, respectively, once their abatement potential is fully realized. This is equivalent to global carbon intensity in 2050 falling from today's level in Cambodia to that of Greece under ICT, or from Pakistan's to Sweden's under IR. Notably, our model assumes these reductions occur without extra abatement costs. In reality, for an economy with effective carbon taxes like Sweden, such a comparable decline in intensity took 4 and 26 years historically. These stringent requirements reinforce our finding that AI currently poses a significant climate problem.

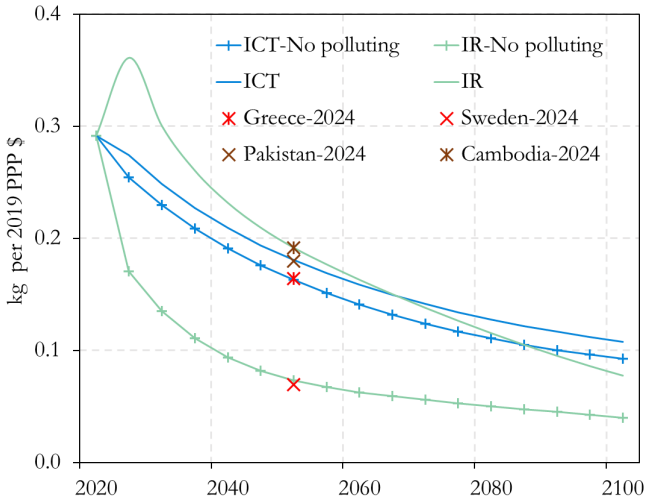


Fig. 8: Production-based carbon intensity under the thought experiment

Note: ICT projects a modest influence on long-run growth from AI, much like earlier information and communications technologies. IR posits a transformative economic impact sufficient to trigger a new industrial revolution. Emissions from AI and general capital are aggregated and then divided by aggregate final output, yielding the standard production-based carbon intensity as used in DICE-2023. In the figure, solid curves depict the time path of this carbon intensity under the BAU low abatement scenario in the DICE-AI model. The solid line with plus markers shows the counterfactual time path required for AI's abatement potential to fully offset emissions from its computing-related and economy-wide impacts. Country-specific carbon intensity data are sourced from the World Bank World Development Indicators and harmonized with the initial global carbon intensity in DICE-2023.

5.2 Identifying critical uncertain sources

We consider five sources of uncertainty in this analysis: the damage-output elasticity, the discount rate, the potential of AI to facilitate adaptation to climate change, the

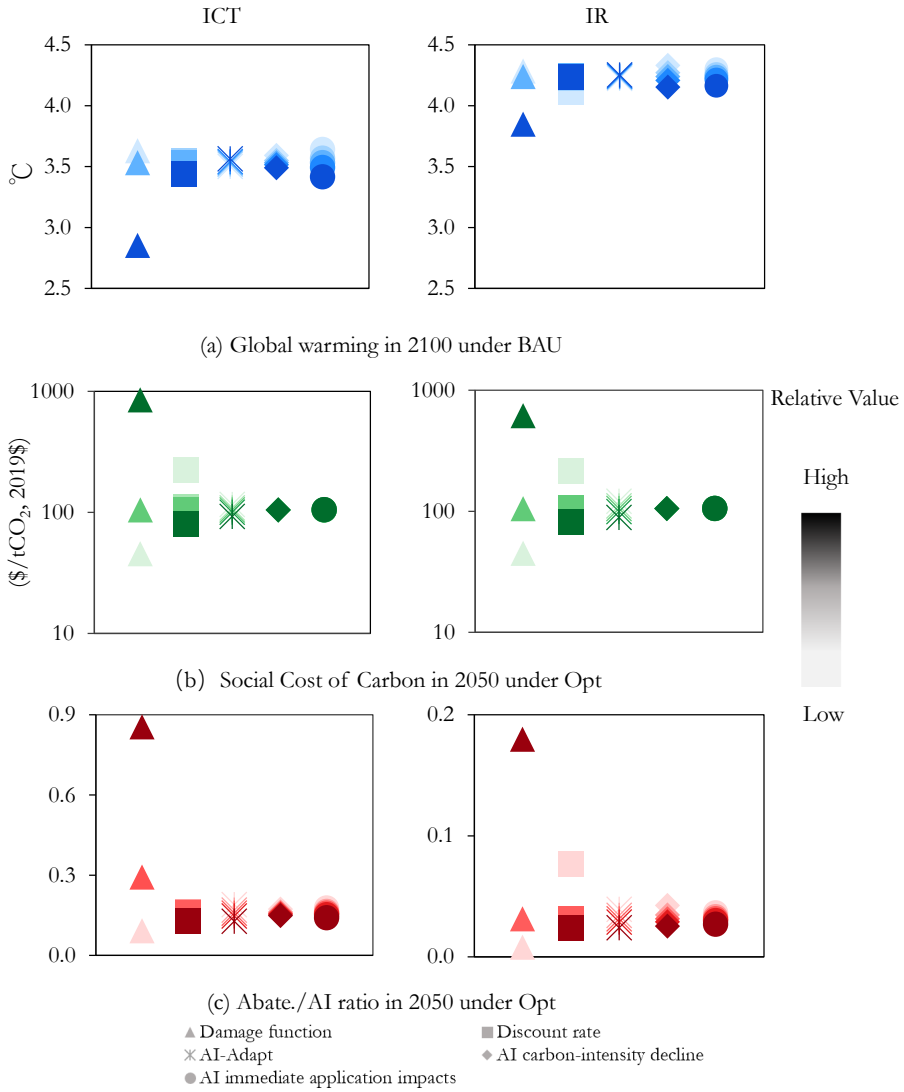


Fig. 9: Main results and their uncertain drivers

Note: ICT projects a modest influence on long-run growth from AI, much like earlier information and communications technologies. IR posits a transformative economic impact sufficient to trigger a new industrial revolution. The darker the mark, the higher the value it represents. For the damage function, we consider three values in the sensitivity analysis: our baseline specification and two alternatives from Tol (2024). For the discount rate, we consider four values: our baseline value (the mean recommended by economists, Drupp et al. (2018)), the mean recommended by philosophers, Nesje et al. (2023), and the values used by Stern (2007) and Nordhaus (2018). For AI-powered adaptation (a_3), the AI carbon-intensity decline rate (captured by the ratio of the AI-sector decline rate to that of the final production sector in DICE-2023), and AI immediate application impacts (ψ_{adj}), we first determine the lower and upper bounds of each parameter based on literature review, then assume a normal distribution with the baseline value as the mean, and finally select the values at the 2.5th, 25th, 50th, 75th, and 97.5th percentiles for the sensitivity analysis. Further details on these parameters are provided in the Calibration section.

rate of decline in carbon intensity specific to the AI sector, and the magnitude of AI's immediate application impacts. The first two are included because they represent the most persistent and widely debated uncertainties in the climate economics literature, and serve as benchmarks for comparison. The remaining three are directly relevant to the cost-benefit framework of this study. Both the decline rate of carbon intensity in AI and the strength of AI's immediate applications influence future GHG emissions and, consequently, warming pathways. Together, they indirectly shape the economic costs of climate change. In contrast, AI's adaptation potential acts as a positive externality, directly reducing climate impacts on the benefit side.

Figure 9 presents simulation results from our DICE-AI model across these five uncertainty dimensions. A key finding is that uncertainty in the damage-output elasticity consistently exerts a dominant influence across all three outcome metrics, under both the ICT-like and IR-like economic scenarios for AI. Perhaps surprisingly, this factor also significantly affects projections of global warming. The underlying mechanism involves a feedback loop: climate damages feed back into the economy and affect the returns to AI investment. Under a persistent low-abatement policy, a higher damage-output elasticity (represented by the dark blue triangle) implies that a rapidly rising emissions trajectory leads to severe future climate damages. These damages, in turn, diminish the value of both AI and conventional capital investment. With reduced capital accumulation and consequently lower emissions, the resulting rise in global mean temperature is moderated. This feedback loop explains why uncertainty in the damage function——a parameter traditionally associated with economic impacts——propagates into a wide range of possible warming outcomes under the low abatement.

In terms of temperature outcomes, our simulations indicate that uncertainty in AI's near-term application impacts dominates variation from the carbon intensity decline rate when AI follows an ICT-like trajectory. However, the pattern reverses under an IR-like scenario, where AI is assumed to be as economically transformative as the Industrial Revolution. The reasoning is that the IR-like case implies exceptionally high returns to AI investment, driving substantial capital accumulation. As a result, the uncertainty surrounding the carbon intensity of AI capital exerts a wider influence on outcomes than that of its application impacts.

Turning to the optimal social cost of carbon, Panel (b) shows that the emission-related externalities of AI play a relatively minor role. Although AI's spillover effects on adaptation matter, particularly in the IR scenario, their overall significance remains modest compared to that of the discount rate and the damage-output elasticity.

Finally, Panel (c) indicates that uncertainties related to AI's computing footprint, near-term applications, and adaptation potential, while considerable, do not fundamentally alter the ratio of mitigation investment per dollar of AI investment. In fact, this metric proves to be quite robust across variations in these three factors.

Taken together, these results suggest that uncertainties tied to AI's emissions and adaptation potential do not fundamentally shift optimal climate policy, as captured by the carbon price. Although they influence projected warming and the investment trade-off between AI and abatement, the ranges of uncertainty they introduce do not surpass those associated with more established drivers in the climate economics literature. Moreover, our findings highlight that the broader development pathway of

AI——whether ICT-like or IR-like——constitutes a more profound source of uncertainty for both future warming trajectories and the balance between AI investment and mitigation efforts.

6 Conclusion

Incorporating AI into integrated assessment models compounds deep structural uncertainties. We address this by evaluating two distinct AI scenarios and conducting sensitivity analyses on core parameters, such as damage functions and the discount rate. These results reveal that the more optimistic the economic prospects of AI development, the greater the resulting emissions, consequently intensifying the mitigation pressure. Even with AI-powered adaptation, AI does not obviate the need for proactive climate policy from the cost-benefit perspective, and may, under many plausible conditions, necessitate its strengthening.

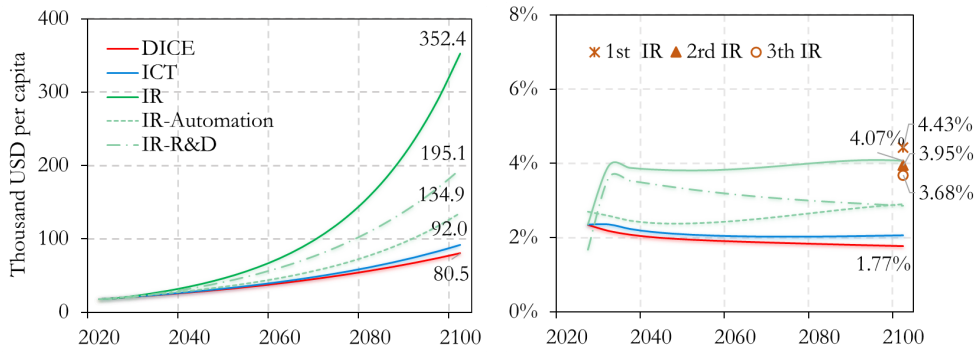
Crucially, our analysis reveals that well-designed climate policy is complementary to AI development. By curbing climate damages, such policy preserves the future economic value generated by AI investments. To fully harness AI's economic benefits, robust climate policy is essential; both an optimal carbon tax or 2°C warming limit can significantly reduce AI's climate-related welfare costs. Furthermore, the primary factor in the trade-off between climate action and AI investment is not AI's own emissions impact, but the relative marginal return on investment in decarbonization versus AI capital.

This study develops an integrated framework and implements it through the DICE-AI model to understand the interactions between AI and climate. This parsimonious, integrated model focuses on macro-level climate effects and policy feedbacks, while inevitably abstracting from the full complexity of AI's real-world impacts. It, however, provides a flexible starting point for systemic analysis. We invite the empirical and modeling communities to build upon this framework to refine and elaborate on the specific channels through which AI will shape—and be shaped by—our climate future.

Acknowledgements. We are grateful to Angus C. Chu, Markus Leibrecht, Le Li, Wenli Xu, Zaifu Yang, Chen Yi, and all participants at the the UM Econ-CityU FOF joint workshop for constructive comments and feedback. Huiying Ye appreciates the funding from National Natural Science Foundation of China (No.72504082). The views expressed are our own and do not reflect the views of the supporting agencies or authors' affiliations.

Appendix A Extended results

A.1 Economic prospects of AI



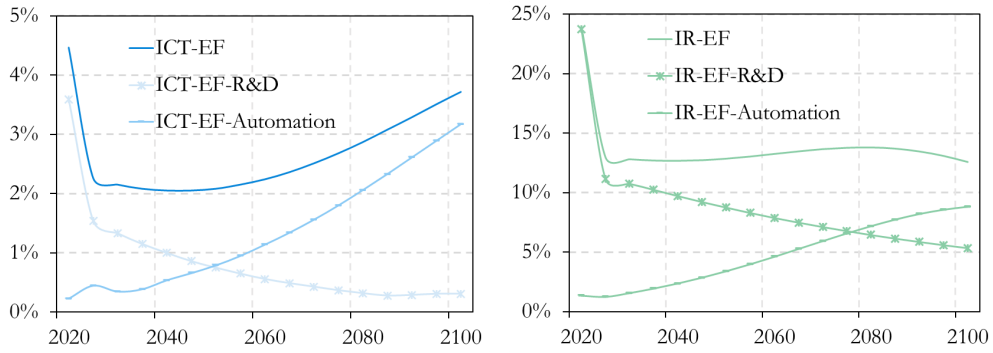
(a) Y/L (b) Growth of Y/L

Fig. A1: Economic prospects under ICT and IR

Note: ICT projects a modest influence on long-run growth from AI, much like earlier information and communications technologies. IR posits a transformative economic impact sufficient to trigger a new industrial revolution. 'Automation' only accounts for AI's impact on increasing capital income share, while 'R&D' merely includes AI's impact on accelerating TFP growth. Three markers corresponding to past industrial revolutions in Panel (b) are obtained by multiplying the respective amplification factors (2.5, 2.24, and 2.08) by the 2100 per capita GDP growth rate in DICE (1.8%).

A.2 AI investment rate

The curve of the optimal AI investment rate resulting from the DICE-AI model is shaped by two distinct forces (Fig. A2). First, AI can accelerate total factor productivity (TFP) growth by enhancing innovation. If AI only raises TFP growth, the optimal investment rate declines over time because the marginal return to R&D diminishes as ideas become harder to find (Bloom et al. 2020), though early-stage incentives remain strong. Second, AI development can automate an increasing fraction of tasks across the economy, gradually raising the capital income share. If AI only drives capital deepening, the optimal investment rate generally increases over time, as the full economic effect of automation unfolds gradually, particularly in the mid- to long-term. Combining these two forces yields an optimal AI investment path that first decreases and later rises in the long run.

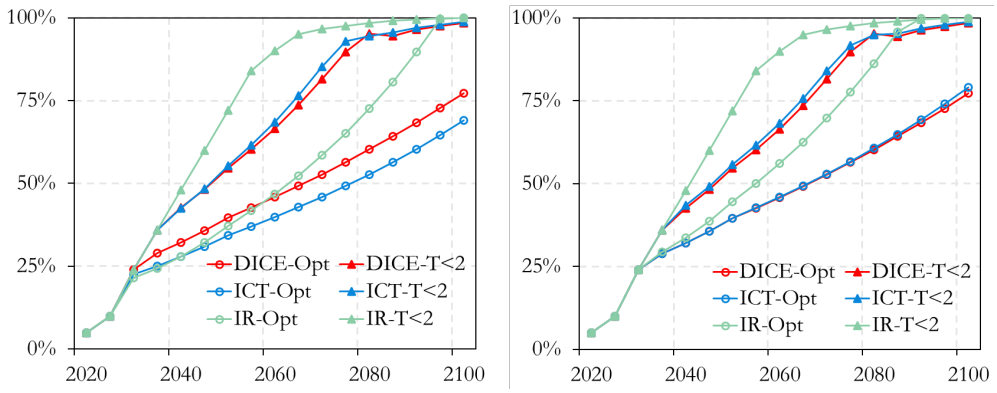


(a) ICT-like prospect (b) IR-like prospect

Fig. A2: AI investment rate in the economic frontier

Note: The figure presents the resulting optimal AI investment rate (AI investment as a ratio of final output) in the economic frontier of the DICE-AI model. ICT projects a modest influence on long-run growth from AI, much like earlier information and communications technologies. IR posits a transformative economic impact sufficient to trigger a new industrial revolution. 'Automation' only accounts for AI's impact on increasing capital income share, while 'R&D' merely includes AI's impact on accelerating TFP growth.

A.3 Abatement rate



(a) With adaptation (b) Without adaptation

Fig. A3: Optimal abatement rate under different economic prospects

Note: ICT projects a modest influence on long-run growth from AI, much like earlier information and communications technologies. IR posits a transformative economic impact sufficient to trigger a new industrial revolution. OPT employs an optimal carbon price to maximize social welfare. T<2 caps the global mean temperature rise at 2°C above the preindustrial level.

A.4 AI-related welfare analysis

Table A1: Welfare analysis of AI under different climate policies

Scenario			AI-related benefits		With AI-powered adaptation		Without AI-powered adaptation	
			Economic gains	Full gains	Climate loss	Offset	Climate loss	Offset
BAU	ICT	Baseline	7.07%	7.62%	1.59%	20.82%	2.73%	35.77%
		Philosopher	8.06%	8.61%	1.86%	21.58%	3.41%	39.55%
		Stern	46.88%	47.27%	14.96%	31.65%	19.46%	41.16%
		Nordhaus	3.67%	4.16%	0.70%	16.73%	1.59%	38.21%
		Alt damage 1	6.98%	7.57%	0.4%	5.29%	1.27%	16.83%
		Alt damage 2	6.87%	14.74%	15.60%	105.86%	26.35%	178.79%
	IR	Baseline	85.92%	87.18%	23.24%	26.66%	25.73%	29.51%
		Philosopher	92.68%	93.99%	25.22%	26.84%	27.88%	29.66%
		Stern	918.49%	922.38%	417.79%	45.29%	458.57%	49.72%
		Nordhaus	48.97%	49.84%	8.98%	18.02%	10.47%	21.00%
		Alt damage 1	86.17%	87.44%	21.92%	25.06%	23.31%	26.66%
		Alt damage 2	89.33%	104.92%	47.69%	45.45%	74.10%	70.62%
Opt	ICT	Baseline	7.07%	7.62%	0.28%	3.64%	0.58%	7.57%
		Philosopher	8.06%	8.61%	0.30%	3.45%	0.89%	10.29%
		Stern	46.88%	47.27%	0.34%	0.71%	0.78%	1.64%
		Nordhaus	3.67%	4.16%	0.20%	4.71%	0.70%	16.94%
		Alt damage 1	6.98%	7.57%	0.19%	2.52%	0.79%	10.48%
		Alt damage 2	6.87%	14.74%	1.17%	7.97%	8.82%	59.81%
	IR	Baseline	85.92%	87.18%	0.99%	1.14%	2.47%	2.83%
		Philosopher	92.68%	93.99%	1.10%	1.17%	2.63%	2.80%
		Stern	918.49%	922.38%	3.03%	0.33%	7.45%	0.81%
		Nordhaus	48.97%	49.84%	0.67%	1.35%	1.73%	3.47%
		Alt damage 1	86.17%	87.44%	0.83%	0.95%	2.33%	2.66%
		Alt damage 2	89.33%	104.92%	4.12%	3.93%	20.31%	19.36%
T< 2°C	ICT	Baseline	7.07%	7.62%	0.81%	10.60%	0.91%	11.97%
		Philosopher	8.06%	8.61%	0.81%	9.35%	1.20%	13.91%
		Stern	46.88%	47.27%	0.53%	1.12%	0.89%	1.89%
		Nordhaus	3.67%	4.16%	0.81%	19.44%	1.14%	27.36%
		Alt damage 1	6.98%	7.57%	1.19%	15.68%	1.55%	20.53%
		Alt damage 2	6.87%	14.74%	1.17%	7.97%	8.82%	59.81%
	IR	Baseline	85.92%	87.18%	2.60%	2.98%	3.48%	3.99%
		Philosopher	92.68%	93.99%	2.78%	2.96%	3.70%	3.94%
		Stern	918.49%	922.38%	32.40%	3.51%	35.20%	3.82%
		Nordhaus	48.97%	49.84%	1.93%	3.87%	2.59%	5.19%
		Alt damage 1	86.17%	87.44%	3.61%	4.13%	4.45%	5.09%
		Alt damage 2	89.33%	104.92%	4.12%	3.93%	20.31%	19.36%

Note: Using permanent-equivalent-variation method following Barrage (2020), the figure displays welfare changes from AI development, expressed relative to the consumption path of the DICE-2023 optimal scenario. 'Full gain' consists of both the AI 'Economic gains' and AI-powered climate adaptation. The climate-related loss captures captures both climate damages from AI-induced warming and associated abatement costs (see 'Methods'). 'Offset' is calculated as a share of 'Full gains'. ICT projects a modest influence on long-run growth from AI, much like earlier information and communications technologies. IR posits a transformative economic impact sufficient to trigger a new industrial revolution. BAU represents the current business-as-usual low abatement policy as implemented in DICE-2023. OPT employs an optimal carbon price to maximize social welfare. $T < 2$°C caps the global mean temperature rise at 2°C above the preindustrial level. The 'No adaptation' scenario precludes AI-powered adaptation from reducing climate damages, as opposed to the Baseline scenario, which assumes that AI development fulfills half of its adaptation potentials by 2050. Our baseline simulation adopts the discount rate parameters based on a survey of economists (Drupp et al. 2018). For sensitivity tests, we also consider discounting parameters advocated by philosophers (Nesje et al. 2023), used in the Stern Report (Stern 2007) and in earlier work by Nordhaus (Nordhaus 2018). Additionally, we include two alternative damage estimates from a recent updated meta-analysis of climate damages (Tol 2024).

Appendix B Literature review

We collect the literature on three perspectives of AI's impact, and examines their implications for climate change and climate policy, specifically through the lenses of economy, energy and climate. This categorization slightly differs from the framework presented in Fig.1, which instead separates economy, emission, and climate. The adjustment is motivated by the observation that energy represents a prominent and widely discussed aspect of AI's influence in both the literature and policy discussions (Masanet et al. 2020; Kaack et al. 2022; International Energy Agency 2025b; Shehabi et al. 2024). Several clarifications can be useful. The 'emission' impact encompasses the 'energy' impact, because AI influence emissions through other channels, such as lifecycle emissions from building AI-related infrastructure and its immediate application impacts. In addition, AI's economic and emission impacts are partially overlapping, since AI-driven economic expansion indirectly raises emissions by enlarging the production base.

Given the breadth of topics intersecting AI and climate, a comprehensive review of all relevant literature is beyond the scope of this study and is hardly possible. Our primary aim is to explore the key interactions between AI and climate change, thereby positioning the present study and clarifying its contributions. For reviews on AI' economic impact, we refer to Aghion et al. (2018) and Trammell and Korinek (2023); for reviews on AI' emission impact, we refer to Kaack et al. (2022); for reviews on AI's use in climate change, we refer to citerolnick2022tackling. The core methodology in this paper builds on integrated assessment modelling, including both aggregate and detailed process IAMs, as reviewed in Weyant (2017),Bosetti et al. (2021) and Dietz (2024).

First, we review the economic impact of AI (Table B2), which is relevant for both economic performance and emissions. This impact operates through two primary channels, productivity growth and capital deepening. By enhancing total factor productivity, AI raises aggregate economic output. This expansion not only permits resources for consumption and investment but also creates a larger base for carbon emissions. At the same time, AI drives capital deepening, whereby capital progressively substitutes for labor in production. While this boosts economic output, it also potentially introduces adverse side effects, including higher emissions and greater inequality.

Table B3 summarizes the literature on AI's energy and climate implications. Existing studies considers both the energy-intensive nature of AI development and its potential to improve energy efficiency. In addition, AI also influences emissions through channels not directly linked to energy use. Consequently, the net emissions impact of AI remains ambiguous and must be evaluated by integrating all these aspects together under different mitigation policy scenarios within a consistent analytical framework. Ultimately, the combined emission and adaptation effects of AI will shape its environmental costs and determine the optimal level of carbon taxation. A formal assessment, however, requires an integrated climate–economy–AI modeling framework.

Table B2: The economic impact of AI and its implications for climate change and climate policy

	Aspect	Details	Discussions
Economy	TFP gains	AI acts as both a labor-augmenting technology (for instance, assisting an inexperienced driver through an automated system), and as a catalyst for innovation, generating new products, patents, and knowledge (Aghion et al. 2018; Trammell and Korinek 2023; Erdil and Besiroglu 2023; Acemoglu 2025). For example, it accelerates R&D (e.g., Nobel Prize in Chemistry for AI use in protein folding (Åqvist 2024)) and fuels firm growth through product innovation (Babina et al. 2024). Notably, both technology workers and the firms that employ them are more exposed to AI (Eloundou et al. 2024; Labaschin et al. 2025).	Despite broad agreement that AI enhances productivity, projections of its economic magnitude vary dramatically across academia (Davidson 2021; Acemoglu 2025; Aghion and Bunel 2024) and major institutions (Chui et al. 2023; Filippucci et al. 2024a; Cerutti et al. 2025). Whether its impact will be moderate or transformative enough to launch a new industrial revolution remains uncertain (e.g., the Baumol effect (Jones and Liu 2024; Jones and Tonetti ????)). Although several AI scenarios have been examined in economic research (Korinek 2023; Trammell and Korinek 2023), they have not yet been integrated into different socioeconomic pathways for climate-related studies (Luers et al. 2024).
		The scale of production fundamentally shapes greenhouse gas emissions (Rennert et al. 2022). Indeed, economic projections serve as key inputs to integrated assessment models (IAMs) (Nordhaus 2018) and Shared Socioeconomic Pathways (SSPs) (Dellink et al. 2017; O'Neill et al. 2017). A larger economic base typically leads to higher carbon emissions.	Economic prosperity could also support emission reductions, provided that advances in general-purpose technologies spur innovation in abatement and channel resources toward low-carbon activities (Hepburn and Bowen 2013; IEA 2025). Given AI's potential to drive future affluence, its net emission impact remains ambiguous, hinging on both the evolving size of the economy and resource allocation alongside climate policy.
		On the welfare, an expanded production base supports greater consumption and investment. Higher consumption improves current well-being, while increased investment in productive capital boosts future consumption potential, enhancing future welfare (Barro and Sala-i Martin 2025; Acemoglu 2008).	If a larger AI-augmented economy raises emissions, it accordingly elevates environmental costs (Korinek 2025), which weigh against above benefits. Yet such trade-offs have rarely been quantified in the literature. As a result, the net welfare impact of AI remains uncertain, which should be assessed with other aspects of AI (Korinek 2025; Jones 2024).
	Capital deepening	From an emissions perspective, energy consumption is closely linked to capital formation (Struckmeyer 1987; Atkeson and Kehoe 1999; Baldwin et al. 2020; Van der Ploeg and Rezai 2020; Campiglio et al. 2022). Capital deepening, driven by increased capital-labor substitutability (Nordhaus 2021) or task automation (Zeira 1998; Acemoglu and Restrepo 2018; Jones and Liu 2024) due to AI, implies a greater reliance on machinery to replace human labor (Trammell and Korinek 2023; Acemoglu 2025). When additional equipment, machinery, or factories are deployed, they typically require more energy to operate, thereby raising emissions.	While several recent studies have identified channels through which AI may raise or lower carbon emissions (Kaack et al. 2022; International Energy Agency 2025b; Stern et al. 2025; Lu and Liao 2025), less attention has been paid to the direct emissions increase from operating more capital (the *intensive* margin of capital deepening). This can bias the assessment of AI's net environmental impact. A recent study (Harding and Moreno-Cruz 2025) evaluates the direct emission impacts of AI adoption, yet its analyses does not incorporate broader general equilibrium effects.
		The welfare effects of AI-driven capital deepening are multifaceted. On one hand, a rising capital share in production enhances economic output (Trammell and Korinek 2023; Acemoglu 2025; Filippucci et al. 2024a) and can thereby support higher consumption. On the other hand, as AI substitutes capital for labor, the labor income share tends to decline in national accounts (Acemoglu and Restrepo 2018, 2022; Grossman and Oberfield 2022). A falling labor share, accompanied by rising capital share, is often linked to widening inequality (Piketty 2014), which may adversely affect overall social welfare.	Capital deepening also affects emissions on the *extensive* margin, when it boosts all polluting economic activities at a larger economic base, other than emissions directly from using more capital (*intensive* margin). These dynamic impacts of AI are not yet captured in current IAMs or climate policy studies (Stern et al. 2025; Luers et al. 2024). Although AI also raises distributional concerns that affect welfare (Korinek and Stiglitz 2021; Korinek and Juelfs 2024; Ren and Wierman 2024), such inequality effects are difficult to analyze within highly aggregated models like DICE (Emmerling et al. 2024). Examining AI's impact on inequality thus remains an important direction for future research.

Table B3: The energy and climate impacts of AI and their implications for climate change and climate policy

	Aspect	Details	Discussions
Energy	Energy-intensive AI	The training, inference, and development of AI systems are computationally intensive, significantly increasing energy demand (De Vries 2023; Kaack et al. 2022; Masanet et al. 2020; Bogmans et al. 2025). This demand is further amplified when considering the full lifecycle of AI infrastructure, including the manufacturing, transportation, and disposal of related hardware (International Telecommunication Union 2025; International Telecommunication Union (ITU) and World Benchmarking Alliance (WBA) 2025). Collectively, these constitute the computing-related energy impacts of AI.	While recent studies have attempted to quantify AI-related energy use, these estimates are subject to substantial uncertainty, due to limited transparency and data availability of AI data center (Masanet et al. 2024), inconsistent measurement methodologies (International Telecommunication Union 2025), geographic variability (Gibney et al. 2022), etc. Moreover, the future carbon intensity of AI remains highly uncertain, shaped by countervailing forces. On one hand, factors such as wider AI adoption, rebound effects that raise energy demand, and the increasing scale of models requiring more training data may elevate emissions (Masanet et al. 2020; Bashir et al. 2024). On the other, improvements in hardware and algorithmic efficiency, together with a growing share of renewable energy in powering AI operations, could reduce the carbon footprint (Masanet et al. 2020; De Vries 2023; International Energy Agency 2025b).
	Energy-saving AI	By redesigning and transforming complex systems (Stern et al. 2025), AI can optimize energy supply, increase the transportation efficiency in electricity networks, improve energy end-use, etc (Gentine et al. 2024; International Energy Agency 2025b). Also, AI can be expected to accelerate battery innovation for energy storage, catalysts in synthetic fuel, etc (International Energy Agency 2025b).	Some recent studies are positive and speculate that the potential of AI to abate emissions will outweigh the additional emissions of energy consumption in data centers (Stern et al. 2025). However, these estimates are subject to significant uncertainties and have not yet included the economy-wide emissions, which are critical for a complete assessment of AI's emission impact (Kaack et al. 2022; Luers et al. 2024).
Climate	Non-energy mitigation	AI also influences emissions that are not directly tied to energy use. For example, it can aid in identifying carbon sinks, innovating carbon capture materials, and updating clinker reduction methods in cement production (Gloege et al. 2022; Asibor et al. 2023; International Energy Agency 2025b). Furthermore, AI can support low-carbon shifts in consumer behavior, such as through smart home systems with learning capabilities or AI-guided planning of more fuel-efficient travel routes (Stern et al. 2025).	Together with its potential to reduce direct energy demand, these channels represent positive environmental impacts of AI and are expected to support progress toward climate targets. Both preference-driven behavior changes (Stern et al. 2022; Besley and Persson 2023) and negative-emission technologies play important roles in deep-decarbonization scenarios. However, current estimates of AI's emission-reduction potential vary widely (Luderer et al. 2018; Wei et al. 2021). Besides, future research could develop IAMs that account for how AI shapes social norms and preferences, thus informing both the pace and policy design in the green transition (Stern et al. 2025; Wang et al. 2024a).
	Climate adaptation	AI can empower next-generation multiscale climate modeling (Eyring et al. 2024), improving the monitoring, forecasting, and warning systems for climate-related events (Gentine et al. 2024). For instance, by integrating physical laws with machine learning, models such as GraphCast and Google's FloodHub enhance the accuracy of weather and flood predictions (Lam et al. 2023; Nearing et al. 2024). It may also foster developments in solar geoengineering (Rolnick et al. 2022).	Even without considering AI's impact (Carleton et al. 2024), quantifying the potential of climate adaptation is inherently difficult. Despite the promising future of AI adoption in climate adaptation (Rolnick et al. 2022; Bibri and Coi 2025), the extent to which it can reduce climate impacts remains uncertain and is not yet backed by empirical evidence. When AI-powered adaptation takes effect, its interaction with AI's emission impacts alters the associated climate costs, thereby shifting the optimal climate policy derived from cost-benefit analysis.

Appendix C Surveys for calibration

Table C4: Survey on AI-driven total factor productivity growth

Sources	AI-driven TFP gains	Scope	Method
Filippucci et al. (2024c)	Annual growth increases by 0.25-0.6 p.p over a 10-year horizon.	OECD	Estimate micro-level gains, map them to sectors, and aggregate economy-wide impacts using a multi-sector general equilibrium model with input-output linkages.
Aghion and Bunel (2024)	Annual growth increases by 0.68 to 1.3 p.p over next decade	Global	Comparative analysis and theoretical modeling
Acemoglu (2025)	TFP gains over the next decade are 0.53% or 0.66%.	Global	Macroeconomic general equilibrium model
Rockall et al. (2025)	Annual growth increases by 1.4% or 1.7%	Global	Structural macro model
Haskel (2025)	Annual growth increases by 0.1 to 0.5 p.p	Global	A General-Purpose Technology Approach
Bergeaud (2025)	A 1 p.p. increase in the IT capital share (within the total capital stock) corresponds to a 6 % rise in labor productivity.	US & EU	Ordinary Least Squares
Briggs and Kodnani (2023)	Labor productivity growth increases by 1.5 p.p. over a decade.	US	Decomposition-based accounting
Baily et al. (2023)	Annual growth increases by 1.50 or 1.96 p.p	US	Estimate approximately

Note: For analyses at the global scale, the existing quantitative evidence is largely derived from data on developed economies. Baily et al. (2023) present future growth trajectories graphically, from which we infer the corresponding annual productivity gains attributable to AI.

Table C5: Literature survey of data-center emission estimates

Sources	Scope	CO_2 emissions	Projection for 2030	Embodied emissions included?
Masanet et al. (2020)	Global (2018)	208 TWh (95 $MtCO_2$)	—	No
Shehabi et al. (2024)	US (2018/2023)	76/176 TWh (27/61 $MtCO_2$)	325–580 TWh (2028)	Partly
International Energy Agency (2025b)	Global (2020)	269 TWh (123 $MtCO_2$)	669–1246 TWh	No
International Energy Agency (2023)	Global (2020)	330 $MtCO_2$	—	Yes
McKinsey & Company (2025)	US (2023)	147 TWh (51 $MtCO_2$)	606 TWh	No
Patel et al. (2024)	Global (2020)	300 TWh (137 $MtCO_2$)	750–2150 TWh	No
Accenture (2024)	Global (2022)	38 Mt CO_2	491–756 TWh	No
Gelvanovska-Garcia et al. (2024)	Global (2022)	500–700 TWh (229–321 $MtCO_2$)	—	Partly
Xiao et al. (2025)	US (2024–2030)	24–44 $MtCO_2$	—	Partly

Note: Electricity consumption is converted to carbon emissions using the carbon intensity of electricity generation for the United States and the global average, as reported by the International Energy Agency (2022). For Patel et al. (2024), numerical values are approximated based on figures in the report, as explicit values are not provided.

Table C6: Literature survey of AI's abatement potentials

Sources	Describe	Channel	Method
Knittel and Stolper (2025)	AI reduces household electricity use by an average of 9 kWh per month.	Causal forests with selective targeting improve the effectiveness of randomized behavior nudges for household energy conservation.	Difference-in-Differences regression
Stern et al. (2025)	AI reduces annual global BAU emissions in covered sectors by 3.2–5.4 $GtCO_2e$ by 2035 (13.7 to 24.1%)	To transform complex systems, accelerate technological discovery & resource efficiency, enable behavioural change, model climate systems & policy interventions, and strengthen adaptation & resilience	Bottom-Up Quantitative Estimation
Hua et al. (2025)	AI can reduce emissions by up to 15%	Forecasting, management and real-time monitoring of carbon emissions	Literature review
International Energy Agency (2025b)	AI could reduce CO_2 emissions by about 1,400 Mt in 2035, excluding potential AI-driven breakthroughs.	To enable diverse optimizations that reduce emissions	A hybrid top-down–bottom-up, data-driven framework
Ding et al. (2024)	In U.S. office buildings, AI adoption could reduce emissions by 8–19% by 2050; combined with energy policies and low-carbon power, reductions could reach 90%	To expand high-efficiency and net-zero building penetration	Bottom-up building energy modeling approach combined with scenario analysis
Wang et al. (2024b)	A 1% increase in AI reduces carbon emissions by 0.0081%.	To improve production efficiency, optimize processes, and support environmental protection and energy transitions	OLS: System Generalized Method of Moments (SYS-GMM) and Dynamic Panel Threshold Models (DPTM)
Li et al. (2023)	In China, AI reduced carbon emissions from 5G mobile networks by 20.90 $\pm$ 0.98 Mt in 2023.	To leverage collaborative deep reinforcement learning and graph neural networks to coordinate 5G cell operations	Data-driven, simulation-based operational carbon accounting approach
Wolf et al. (2022)	Autonomous AI encounters can reduce GHG emissions by up to 80% relative to in-person specialist visits	To reduce travel-associated GHGs through enhanced telemedicine	Real case: bottom-up, process-based carbon footprint analysis with counterfactual scenarios.

Appendix D Model

The framework of the DICE-2023 model is illustrated in Fig. D4, with further technical details available in Barrage and Nordhaus (2024). a global social planner determines consumption, general investment, and abatement investment in each 5-year period, starting in 2020. The planner maximizes social welfare, which depends solely on the time path of consumption.

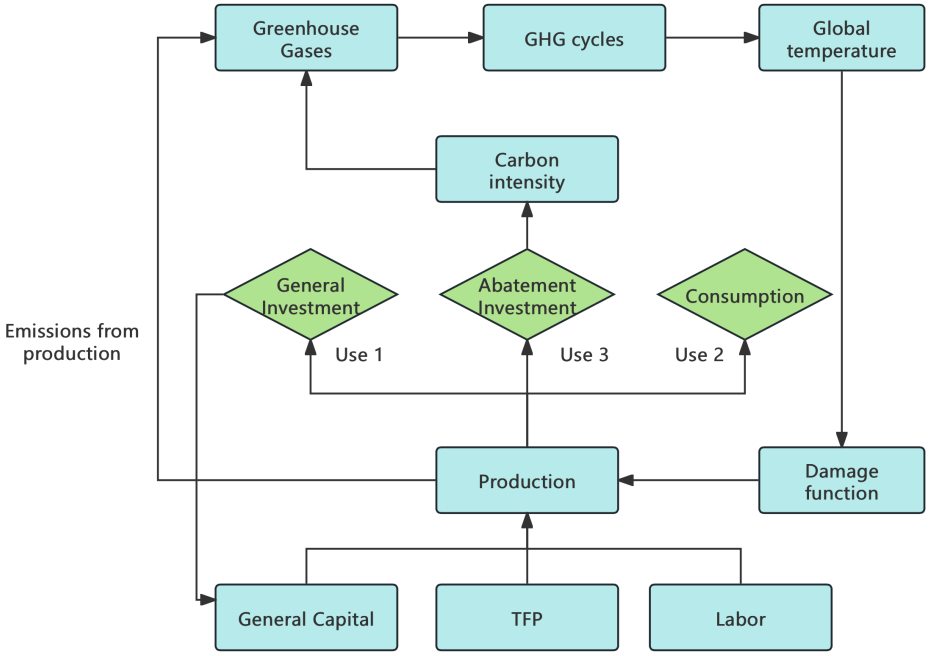


Fig. D4: The framework of DICE-2023

Our extended model, DICE-AI, modifies this structure in two key respects (Fig. D5). First, it shifts from a production-based to a capital-embodied accounting of carbon intensity for emissions calculation (see Appendix 3.3). Second, it integrates the three perspectives of AI outlined in our conceptual framework (Fig. 1) directly into the DICE model structure.

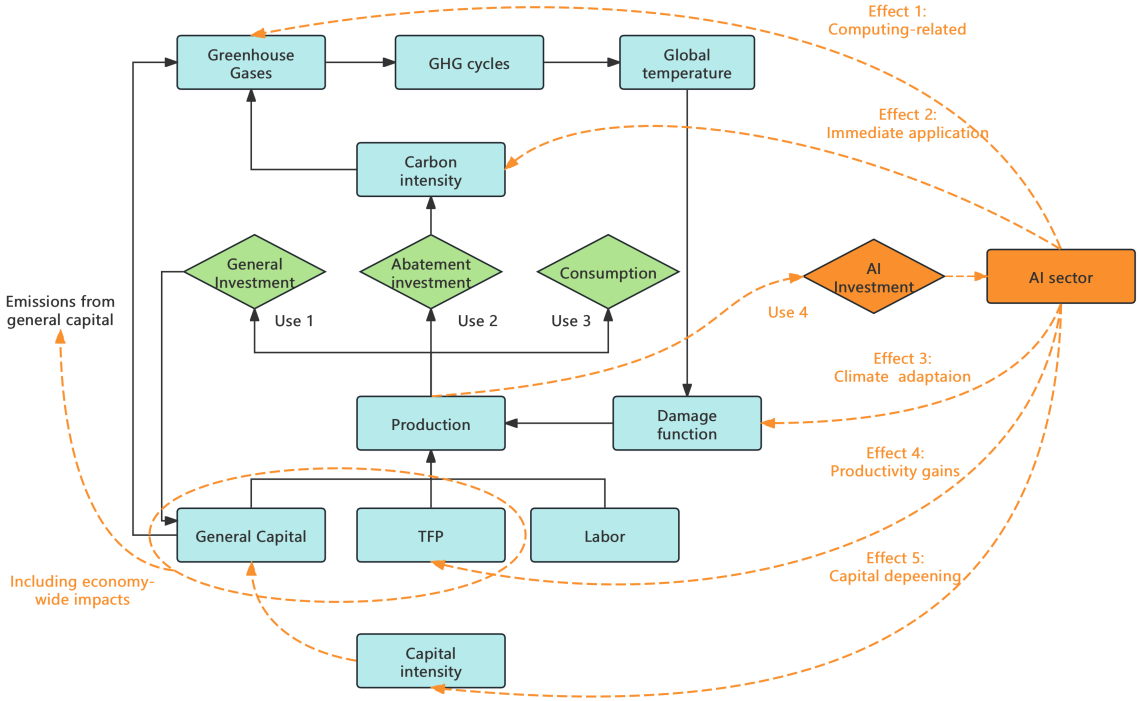


Fig. D5: The framework of DICE-AI

Appendix E Methods for welfare analysis

Our analysis further relies on detailed post-processing of the DICE-AI model outputs to enable welfare comparisons across scenarios. This is accomplished in two stages. First, we employ the Permanent-Equivalent Variation (PEV) method following Ref. Barrage (2020) to compare welfare between any two scenarios with distinct consumption paths, $\{C_t^{Base}\}_{t=0}^{\infty}$ and $\{C_t^*\}_{t=0}^{\infty}$. This method requires adopting a unified definition of the social welfare:

$$W \triangleq \sum_{t=0}^{\infty} \beta^t U(C_t) L_t \tag{E1}$$

It solves for a constant scaling factor φ that equates the welfare of the compared path to a proportionally reduced version of the baseline path:

$$W^* = \sum_{t=0}^{\infty} \beta^t U(C_t^*) L_t = \sum_{t=0}^{\infty} \beta^t U\left((1-\varphi) C_t^{Base}\right) L_t \tag{E2}$$

Here, φ gauges the permanent consumption loss of path $\{C_t^*\}_{t=0}^{\infty}$ relative to $\{C_t^{Base}\}_{t=0}^{\infty}$. The PEV method provides an internally consistent metric for comparing welfare under vastly different assumptions about growth, damages, and policy. While the consumption-equivalent SCC offers a simpler alternative for direct welfare calculation, it is a marginal concept. Its use can introduce significant approximation inaccuracies in aggregate welfare assessment when emission differences between scenarios are large.

Second, we implement a five-step procedure to structure the comparison across different scenarios:

Step 1 Run the DICE-AI model under the optimal carbon price. This represents a world incorporating AI's full economic, emission, and adaptation impacts. The resulting AI-sector investment rates are saved.

Step 2 Run the DICE-AI model with a fixed temperature pathway from standard DICE and the predetermined AI investment rates from Step 1. This constructs an 'ideal' counterfactual world where AI delivers its economic and adaptation benefits without exacerbating climate change. The resulting consumption path is saved.

Step 3 The welfare difference between the consumption path from this ideal world (Step 2) and that from the standard DICE optimal scenario (without AI) defines the maximum potential welfare gain from AI. This gain combines AI's direct economic contribution and its adaptation benefits. The adaptation component can be isolated by simply deactivating the adaptation function within the DICE-AI model.

Step 4 Compare the consumption path from any policy scenario featuring AI's full impact to the ideal-world path from Step 2. The resulting loss in welfare measures the climate-related costs attributable to AI. Under the optimal carbon tax policy scenario, these costs reflect only the climate damages from AI-induced warming. Under the 2°C warming limit scenario, the costs incorporate both damages and the required abatement expenditures.

Step 5 Normalize all computed welfare gains and climate-related costs using the consumption path from the standard DICE optimal scenario as the numeraire, ensuring consistent scaling.

References

Accenture (2024) Powering sustainable AI: Balancing growth with environmental responsibility. Research report, Accenture, URL https://www.accenture.com/us-en/insights/sustainability/powering-sustainable-ai, accessed on: 2026-01-05. Please check the webpage for the exact publication date.

Acemoglu D (2008) Introduction to modern economic growth. Princeton university press

Acemoglu D (2025) The simple macroeconomics of AI. Economic Policy 40(121):13–58

Acemoglu D, Restrepo P (2018) The race between man and machine: Implications of technology for growth, factor shares, and employment. American Economic Review 108(6):1488–1542

Acemoglu D, Restrepo P (2022) Tasks, automation, and the rise in us wage inequality. Econometrica 90(5):1973–2016

Aghion P, Bunel S (2024) AI and growth: where do we stand? Policy Note

Aghion P, Jones B, Jones C (2018) Artificial intelligence and economic growth. In: The Economics of Artificial Intelligence: An Agenda. University of Chicago Press, p 237–282

Agrawal A, McHale J, Oettl A (2024) Artificial intelligence, innovation, and economic growth. Tech. rep., Working Paper

Aldy JE, Kotchen MJ, Stavins RN, et al (2021) Keep climate policy focused on the social cost of carbon. Science 373(6557):850–852

Alphabet Inc. (2025) Form 10-k for the fiscal year ended december 31, 2024. URL https://www.sec.gov/Archives/edgar/data/1652044/000165204425000014/goog-20241231.htm, accessed: 2025-9-1

Åqvist J (2024) Computational protein design and protein structure prediction. Stockholm (Sweden): The Royal Swedish Academy of Sciences

Asibor JO, Clough PT, Nabavi SA, et al (2023) A machine learning approach for country-level deployment of greenhouse gas removal technologies. International Journal of Greenhouse Gas Control 130:103995

Atkeson A, Kehoe PJ (1999) Models of energy use: Putty-putty versus putty-clay. American Economic Review 89(4):1028–1043

Babina T, Fedyk A, He A, et al (2024) Artificial intelligence, firm growth, and product innovation. Journal of Financial Economics 151:103745

Baily MN, Brynjolfsson E, Korinek A (2023) Machines of mind: The case for an AI-powered productivity boom. Tech. rep., Brookings Institution, URL https://www.brookings.edu/articles/machines-of-mind-the-case-for-an-ai-powered-productivity-boom/, published May 10, 2023

Baldwin E, Cai Y, Kuralbayeva K (2020) To build or not to build? capital stocks and climate policy. Journal of Environmental Economics and Management 100:102235

Barrage L (2020) Optimal dynamic carbon taxes in a climate–economy model with distortionary fiscal policy. The Review of Economic Studies 87(1):1–39

Barrage L, Nordhaus W (2024) Policies, projections, and the social cost of carbon: Results from the DICE-2023 model. Proceedings of the National Academy of Sciences 121(13):e2312030121

Barro RJ, Sala-i Martin XI (2025) Economic growth. MIT press

Bashir N, Donti P, Cuff J, et al (2024) The Climate and Sustainability Implications of Generative AI. An MIT Exploration of Generative AI Https://mit-genai.pubpub.org/pub/8ulgrckc

Bastien-Olvera BA, Moore FC (2021) Use and non-use value of nature and the social cost of carbon. Nature Sustainability 4(2):101–108

Bergeaud A (2025) The past, present and future of european productivity, URL https://www.oecd.org/content/dam/oecd/en/about/programmes/global-forum-on-productivity/events/workshops/A_Bergeaud_GFP%20Slides_US-EU%20Productivity.pdf, presentation slides at the OECD Global Forum on Productivity.

Besley T, Persson T (2023) The political economics of green transitions. The Quarterly Journal of Economics 138(3):1863–1906

Bibri SE, Coi O (2025) Artificial intelligence for climate action: Advancing mitigation and adaptation in developing countries. Technical paper, United Nations Framework Convention on Climate Change (UNFCCC) and United Nations Industrial Development Organization (UNIDO), URL https://unfccc.int/ttclear/misc_/StaticFiles/gnwoerk_static/AI4climateaction/f2922b97c4cf431996c468e622127eb5/112f8be560ea447dab5ff2e53ab3f6e4.pdf

Bilal A, Stock JH (2025) A guide to macroeconomics and climate change. Working Paper 33567, National Bureau of Economic Research, https://doi.org/10.3386/w33567, URL http://www.nber.org/papers/w33567

Bloom N, Jones CI, Van Reenen J, et al (2020) Are ideas getting harder to find? American Economic Review 110(4):1104–1144

Bogmans C, Gomez-Gonzalez P, Ganpurev G, et al (2025) Power hungry: How ai will drive energy demand. IMF Working Papers 81(4):2025

Bosetti V, et al (2021) Integrated assessment models for climate change. In: Oxford research encyclopedia of economics and finance. Oxford University Press

Bouscasse P, Nakamura E, Steinsson J (2025) When did growth begin? new estimates of productivity growth in england from 1250 to 1870. Quarterly Journal of Economics 140(2):835–888

Briggs J, Kodnani D (2023) The potentially large effects of artificial intelligence on economic growth. Global Economics Analyst, Goldman Sachs Research, URL https://www.gspublishing.com/content/research/en/reports/2023/03/27/d64e052b-0f6e-45d7-967b-d7be35fabd16.html, published March 26, 2023, 9:05PM EDT

Campiglio E, Dietz S, Venmans F (2022) Optimal climate policy as if the transition matters URL https://eprints.lse.ac.uk/117609/1/working_paper_387.pdf

Carleton T, Duflo E, Jack BK, et al (2024) Chapter 4 - adaptation to climate change. Handbook of the Economics of Climate Change, vol 1. North-Holland, p 143–248, https://doi.org/https://doi.org/10.1016/bs.hesecc.2024.10.001, URL https://www.sciencedirect.com/science/article/pii/S3050729424000011

Cazzaniga M, Jaumotte F, Li L, et al (2024) Gen-AI: Artificial Intelligence and the Future of Work. No. 2024/001 in IMF Staff Discussion Notes, International Monetary Fund, https://doi.org/10.5089/9798400262548.006, URL https://doi.org/10.5089/9798400262548.006

Cerutti MEM, Pascual AIG, Kido Y, et al (2025) Global Impact of AI: Mind the Gap. Working Paper No.2025/076, International Monetary Fund

Christensen P, Gillingham K, Nordhaus WD (2018) Uncertainty in forecasts of long-run economic growth. Proceedings of the National Academy of Sciences 115(21):5409–5414. https://doi.org/10.1073/pnas.1713628115

Chui M, Yee L, Hall B, et al (2023) The state of AI in 2023: Generative AI's breakout year. Tech. rep., McKinsey & Company, URL https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-in-2023-generative-ais-breakout-year

Davidson T (2021) Could advanced AI drive explosive economic growth. Open Philanthropy 25

De Vries A (2023) The growing energy footprint of artificial intelligence. Joule 7(10):2191–2194

Dellink R, Chateau J, Lanzi E, et al (2017) Long-term economic growth projections in the Shared Socioeconomic Pathways. Global Environmental Change 42:200–214

Dietz S (2024) Chapter 1 - introduction to integrated assessment modeling of climate change. Handbook of the Economics of Climate Change, vol 1. North-Holland, p 1–51, https://doi.org/https://doi.org/10.1016/bs.hesecc.2024.10.002, URL https://www.sciencedirect.com/science/article/pii/S3050729424000023

Dietz S, Venmans F (2019) Cumulative carbon emissions and economic policy: in search of general principles. Journal of Environmental Economics and Management 96:108–129

Dietz S, Gollier C, Kessler L (2018) The climate beta. Journal of Environmental Economics and Management 87:258–274

Ding C, Ke J, Levine M, et al (2024) Potential of artificial intelligence in reducing energy and carbon emissions of commercial buildings at scale. Nature Communications 15(1):5916

Drupp MA, Hänsel MC (2021) Relative prices and climate policy: How the scarcity of nonmarket goods drives policy evaluation. American Economic Journal: Economic Policy 13(1):168–201

Drupp MA, Freeman MC, Groom B, et al (2018) Discounting disentangled. American Economic Journal: Economic Policy 10(4):109–134

Eloundou T, Manning S, Mishkin P, et al (2024) GPTs are GPTs: Labor market impact potential of LLMs. Science 384(6702):1306–1308

Emmerling J, Andreoni P, Charalampidis I, et al (2024) A multi-model assessment of inequality and climate change. Nature Climate Change 14(12):1254–1260

Erdil E, Besiroglu T (2023) Explosive growth from AI automation: A review of the arguments. arXiv preprint arXiv:230911690

Eyring V, Gentine P, Camps-Valls G, et al (2024) AI-empowered next-generation multiscale climate modelling for mitigation and adaptation. Nature Geoscience 17(10):963–971

Felgenhauer T, Webster M (2014) Modeling adaptation as a flow and stock decision with mitigation. Climatic Change 122(4):665–679

Fernández-Villaverde J, Gillingham KT, Scheidegger S (2024) Climate change through the lens of macroeconomic modeling. Annual Review of Economics 17

Filippucci F, Gal P, Jona Lasinio CS, et al (2024a) The impact of artificial intelligence on productivity, distribution and growth. Working Paper No.15, OECD publishing, URL https://doi.org/10.1787/8d900037-en

Filippucci F, Gal P, Schief M (2024b) Miracle or myth? assessing the macroeconomic productivity gains from artificial intelligence. Tech. rep., OECD Publishing

Filippucci F, Gal P, Schief M (2024c) Miracle or myth? assessing the macroeconomic productivity gains from artificial intelligence. OECD Artificial Intelligence Papers 29, OECD Publishing, Paris, https://doi.org/10.1787/b524a072-en, URL https://doi.org/10.1787/b524a072-en, oECD Artificial Intelligence Papers, No. 29

Forouheshfar Y, Ayadi R, Moghadas O (2025) Enhancing system resilience to climate change through artificial intelligence: A systematic literature review. Frontiers in Climate 7:1585331

Gelvanovska-Garcia N, Mačiulė V, Rossotto CM (2024) Advancing Cloud and Data Infrastructure Markets: Strategic Directions for Low- and Middle-Income Countries.

Sustainable Infrastructure Series, World Bank, Washington, DC, https://doi.org/10.1596/978-1-4648-2065-6, URL https://doi.org/10.1596/978-1-4648-2065-6, license: CC BY 3.0 IGO

Gentine P, List G, Thompson K, et al (2024) Landscape assessment of AI for climate and nature. URL https://www.climate.columbia.edu/ai-climate-nature-landscape-assessment, commissioned by and in collaboration with the Bezos Earth Fund.

Gibney E, et al (2022) How to shrink ai's ballooning carbon footprint. Nature 607(7920):648–648

Gloege L, Yan M, Zheng T, et al (2022) Improved quantification of ocean carbon uptake by using machine learning to merge global models and pco2 data. Journal of Advances in Modeling Earth Systems 14(2):e2021MS002620

Gohr C, Rodríguez G, Belomestnykh S, et al (2025) Artificial intelligence in sustainable development research. Nature Sustainability 8(8):970–978

Gollier C (2014) Discounting and growth. American Economic Review 104(5):534–537

Golosov M, Hassler J, Krusell P, et al (2014) Optimal taxes on fossil fuel in general equilibrium. Econometrica 82(1):41–88

Green A, Lamby L (2023) The supply, demand and characteristics of the ai workforce across oecd countries. OECD Social, Employment, and Migration Working Papers (287):1–62

Groningen Growth and Development Centre (2010) Maddison database 2010. https://www.rug.nl/ggdc/historicaldevelopment/maddison/releases/maddison-database-2010, university of Groningen

Grossman GM, Oberfield E (2022) The elusive explanation for the declining labor share. Annual Review of Economics 14:93–124

Guerrón-Quintana P, Mikami T, Nosal J (2024) The macroeconomic implications of the gen-ai economy. Available at SSRN 4989979

Harding AR, Moreno-Cruz J (2025) Watts and bots: the energy implications of ai adoption. Environmental Research Letters 20(11):114084

Haskel J (2025) Ai and productivity: A general purpose technology approach, URL https://www.ecb.europa.eu/press/conferences/shared/pdf/20250401_ai/KeyNote_Haskel.pdf, keynote speech presented at the European Central Bank Conference on 'The Transformative Power of AI: Economic Implications and Challenges', Frankfurt, April 3, 2025. Slides available. Joint work within the EUKLEMS-INTANProd project with Filippo Bontadini, Carol Corrado, Cecilia Jona-Lasinio.

Hepburn C, Bowen A (2013) Prosperity with growth: Economic growth, climate change and environmental limits. In: Handbook on energy and climate change. Edward Elgar Publishing, p 617–638

Hua J, Wang R, Hu Y, et al (2025) Artificial intelligence for calculating and predicting building carbon emissions: a review. Environmental Chemistry Letters pp 1–34

IEA (2025) World Energy Investment 2025. Tech. rep., International Energy Agency, URL https://www.iea.org/reports/world-energy-investment-2025

International Energy Agency (2022) Emissions factors 2022. Data product, IEA, Paris, URL https://www.iea.org/data-and-statistics/data-product/emissions-factors-2022, licence: Terms of Use for Non-CC Material

International Energy Agency (2023) Tracking clean energy progress 2023. Tech. rep., IEA, Paris, URL https://www.iea.org/reports/tracking-clean-energy-progress-2023, licence: CC BY 4.0

International Energy Agency (2025a) Electricity 2025. Tech. rep., IEA, Paris, URL https://www.iea.org/reports/electricity-2025, licence: CC BY 4.0

International Energy Agency (2025b) Energy and AI. URL https://www.iea.org/reports/energy-and-ai, licence: CC BY 4.0

International Energy Agency (2025c) Global progress on energy efficiency picks up in 2025. URL https://www.iea.org/news/global-progress-on-energy-efficiency-picks-up-in-2025

International Energy Agency (2025d) World energy outlook 2025 free dataset. IEA Data Product, URL https://www.iea.org/data-and-statistics/data-product/world-energy-outlook-2025-free-dataset, licence: CC BY NC SA 4.0

International Institute for Applied Systems Analysis (2025) Ssp scenario explorer (version 3.2.0). https://data.ece.iiasa.ac.at/ssp/, accessed 2025-09-06

International Telecommunication Union (2025) Measuring what matters: How to assess ai's environmental impact. Report S-GEN-GDA.001-2025, International Telecommunication Union (ITU), Geneva, Switzerland, URL https://www.itu.int/hub/publication/s-gen-gda-001-2025/, green Digital Action

International Telecommunication Union (ITU), World Benchmarking Alliance (WBA) (2025) Greening digital companies 2025: Monitoring emissions and climate commitments. Tech. rep., International Telecommunication Union and World Benchmarking Alliance, Geneva, Switzerland and Amsterdam, The Netherlands, URL https://www.itu.int/en/ITU-D/Environment/Pages/Publications/GDC-25.aspx, 4th Edition

Jones BF, Liu X (2024) A framework for economic growth with capital-embodied technical change. American Economic Review 114(5):1448–1487

Jones CI (1995) R & d-based models of economic growth. Journal of Political Economy 103(4):759–784

Jones CI (2024) The ai dilemma: Growth versus existential risk. American Economic Review: Insights 6(4):575–590

Jones CI, Tonetti C (????) Past automation and future ai: How weak links tame the growth explosion URL https://web.stanford.edu/~chadj/JonesTonetti_Automation.pdf

Jones CI, Tonetti C (2025) Past automation and future A.I.: How weak links tame the growth explosion, URL https://web.stanford.edu/~chadj/JonesTonetti_Automation.pdf, working Paper. Version 0.25. Stanford Graduate School of Business and National Bureau of Economic Research (NBER). December 12, 2025.

Kaack LH, Donti PL, Strubell E, et al (2022) Aligning artificial intelligence with climate change mitigation. Nature Climate Change 12(6):518–527

Kelleher JP (2025) The Social Cost of Carbon: Ethics and the Limits of Climate Change Economics. Oxford University Press

Knittel CR, Stolper S (2025) Using machine learning to target treatment: The case of household energy use. The Economic Journal p ueaf028

Koch J, Leimbach M (2023) SSP economic growth projections: Major changes of key drivers in integrated assessment modelling. Ecological Economics 206:107751

Korinek A (2023) Scenario planning for an A (G) I future. IMF Finance & Development Magazine 60(4):30–33

Korinek A (2025) Economic policy challenges for the age of AI. In: Gourinchas PO, Obstfeld M, Topalova P (eds) Rethinking Economic Policy: Steering Structural Change. MIT Press, Cambridge, MA

Korinek A, Juelfs M (2024) Preparing for the (non-existent?) future of work. In: The Oxford Handbook of AI Governance. Oxford University Press, https://doi.org/10.1093/oxfordhb/9780197579329.013.44, URL https://doi.org/10.1093/oxfordhb/9780197579329.013.44

Korinek A, Stiglitz JE (2021) Artificial intelligence, globalization, and strategies for economic development. Tech. rep., National Bureau of Economic Research

Korinek A, Suh D (2024) Scenarios for the transition to agi. Tech. rep., National Bureau of Economic Research

Labaschin B, Eloundou T, Manning S, et al (2025) Extending "GPTs Are GPTs" to Firms. AEA Papers and Proceedings 115:51–55

Lam R, Sanchez-Gonzalez A, Willson M, et al (2023) Learning skillful medium-range global weather forecasting. Science 382(6677):1416–1421

Li T, Yu L, Ma Y, et al (2023) Carbon emissions of 5g mobile networks in china. Nature Sustainability 6(12):1620–1631

Lu Y, Liao Z (2025) The influence of ai application on carbon emission intensity of industrial enterprises in china. Scientific Reports 15(1):12585

Luderer G, Vrontisi Z, Bertram C, et al (2018) Residual fossil CO_2 emissions in 1.5–2°C pathways. Nature Climate Change 8(7):626–633

Luers A, Koomey J, Masanet E, et al (2024) Will AI accelerate or delay the race to net-zero emissions? Nature 628(8009):718–720

Luiss Lab of Economics and Energy Transition (2025) Euklems & intanprod database. Database portal, URL https://global-intaninvest.luiss.it/, version 2025. Integrated productivity database with intangible investment estimates. Funded by the European Commission Directorate General for Economic and Financial Affairs (DG-ECFIN) and the WIPO-Luiss Business School Partnership.

Masanet E, Shehabi A, Lei N, et al (2020) Recalibrating global data center energy-use estimates. Science 367(6481):984–986

Masanet E, Lei N, Koomey J (2024) To better understand ai's growing energy use, analysts need a data revolution. Joule 8(9):2427–2436

Maslej N, Fattorini L, Perrault R, et al (2025) The AI Index 2025 Annual Report. https://doi.org/10.48550/arXiv.2504.07139, URL https://doi.org/10.48550/arXiv.2504.07139

McKinsey & Company (2025) Scaling bigger, faster, cheaper data centers with smarter designs. McKinsey Insights URL https://www.mckinsey.com/industries/private-capital/our-insights/scaling-bigger-faster-cheaper-data-centers-with-smarter-designs#/, published August 1, 2025

Millner A, Dietz S (2015) Adaptation to climate change and economic growth in developing countries. Environment and Development Economics 20(3):380–406

Minniti A, Prettner K, Venturini F (2025) Ai innovation and the labor share in european regions. European Economic Review p 105043

Moore FC, Drupp MA, Rising J, et al (2024) Synthesis of evidence yields high social cost of carbon due to structural model variation and uncertainties. Proceedings of

the National Academy of Sciences 121(52):e2410733121

National Bureau of Statistics of China (2020) Input–output table of china (2020). https://data.stats.gov.cn/ifnormal.htm?u=/files/html/quickSearch/trcc/2023_1.html&h=740, accessed: 6 Sep 2025

National Science and Technology Council (2024) Federal budget for artificial intelligence research and development, fiscal years 2021–2025. URL https://www.nitrd.gov/ai-rd-investments/, u.S. Office of Science and Technology Policy. Accessed: 2025-12-1

Nearing G, Cohen D, Dube V, et al (2024) Global prediction of extreme floods in ungauged watersheds. Nature 627(8004):559–563

Nesje F, Drupp MA, Freeman MC, et al (2023) Philosophers and economists agree on climate policy paths but for different reasons. Nature Climate Change 13(6):515–522

Newell RG, Pizer WA, Prest BC (2022) A discounting rule for the social cost of carbon. Journal of the Association of Environmental and Resource Economists 9(5):1017–1046

Nordhaus W (2018) Projections and uncertainties about climate change in an era of minimal climate policies. American Economic Journal: Economic Policy 10(3):333–360

Nordhaus WD (2021) Are we approaching an economic singularity? information technology and the future of economic growth. American Economic Journal: Macroeconomics 13(1):299–332

O'Neill BC, Kriegler E, Ebi KL, et al (2017) The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century. Global environmental change 42:169–180

Patel D, Nishball D, Ontiveros JE (2024) Ai datacenter energy dilemma - race for AI datacenter space: Gigawatt dreams and matroyshka brains limited by datacenters not chips. SemiAnalysis, URL https://newsletter.semianalysis.com/p/ai-datacenter-energy-dilemma-race, published March 14, 2024

Piketty T (2014) Capital in the twenty-first century. Harvard University Press

Pindyck RS (2021) What we know and don't know about climate change, and implications for policy. Environmental and Energy Policy and the Economy 2(1):4–43

Van der Ploeg F, Rezai A (2020) Stranded assets in the transition to a carbon-free economy. Annual Review of Resource Economics 12(1):281–298

Ren S, Wierman A (2024) The uneven distribution of AI's environmental impacts. Harvard Business Review

Rennert K, Errickson F, Prest B, et al (2021) The social cost of carbon: Advances in long-term probabilistic projections of population, gdp, emissions, and discount rates. Brookings Papers on Economic Activity 2021(2):223–275

Rennert K, Errickson F, Prest BC, et al (2022) Comprehensive evidence implies a higher social cost of CO_2. Nature 610(7933):687–692

Rockall E, Mendes Tavares M, Pizzinelli C (2025) Ai Adoption and Inequality. IMF Working Papers 2025(068):1. https://doi.org/10.5089/9798229006828.001, URL http://dx.doi.org/10.5089/9798229006828.001

Rolnick D, Donti PL, Kaack LH, et al (2022) Tackling climate change with machine learning. ACM Computing Surveys (CSUR) 55(2):1–96

SecondTalent (2025) Top 50+ chinese ai investment statistics. URL https://www.secondtalent.com/resources/chinese-ai-investment-statistics/, accessed Oct 1, 2025

Seto KC, Davis SJ, Mitchell RB, et al (2016) Carbon lock-in: types, causes, and policy implications. Annual Review of Environment and Resources 41(1):425–452

Shehabi A, Hubbard A, Newkirk A, et al (2024) 2024 united states data center energy usage report URL https://escholarship.org/uc/item/32d6m0d1

Stern N (2007) The economics of climate change: the Stern Review. Cambridge University Press, Cambridge

Stern N, Stiglitz J, Taylor C (2022) The economics of immense risk, urgent action and radical change: towards new approaches to the economics of climate change. Journal of Economic Methodology 29(3):181–216

Stern N, Romani M, Pierfederici R, et al (2025) Green and intelligent: the role of AI in the climate transition. npj Climate Action 4(1):56

Struckmeyer CS (1987) The putty-clay perspective on the capital-energy complementarity debate. Review of Economics and Statistics pp 320–326

Tol RS (2023) Social cost of carbon estimates have increased over time. Nature Climate Change 13(6):532–536

Tol RSJ (2024) A meta-analysis of the total economic impact of climate change. Energy Policy 185:113922. https://doi.org/10.1016/j.enpol.2023.113922

Tong D, Zhang Q, Zheng Y, et al (2019) Committed emissions from existing energy infrastructure jeopardize 1.5 $^{\circ}C$ climate target. Nature 572(7769):373–377

Traeger CP (2023) ACE—Analytic climate economy. American Economic Journal: Economic Policy 15(3):372–406

Trammell P, Korinek A (2023) Economic growth under transformative AI. Tech. rep., National Bureau of Economic Research

United Nations (2008) International Standard Industrial Classification of All Economic Activities (ISIC), Rev.4. United Nations, New York, https://doi.org/10.18356/8722852c-en, URL https://doi.org/10.18356/8722852c-en, revised 4

Wang F, Liao H, Tol RS, et al (2024a) Endogenous preference for nonmarket goods in carbon abatement decisions. Decision Analysis 21(4):235–251

Wang Q, Li Y, Li R (2024b) Ecological footprints, carbon emissions, and energy transitions: the impact of artificial intelligence (ai). Humanities and Social Sciences Communications 11(1):1–18

Wei YM, Kang JN, Liu LC, et al (2021) A proposed global layout of carbon capture and storage in line with a 2 c climate target. Nature Climate Change 11(2):112–118

Weyant J (2017) Some contributions of integrated assessment models of global climate change. Review of Environmental Economics and Policy

Wolf RM, Abramoff MD, Channa R, et al (2022) Potential reduction in healthcare carbon footprint by autonomous artificial intelligence. NPJ digital medicine 5(1):62

Xiao T, Nerini FF, Matthews HD, et al (2025) Environmental impact and net-zero pathways for sustainable artificial intelligence servers in the usa. Nature Sustainability pp 1–13

Ye Q, Krol MS, Shan Y, et al (2023) Allocating capital-associated CO_2 emissions along the full lifespan of capital investments helps diffuse emission responsibility. Nature Communications 14(1):2727

Zeira J (1998) Workers, machines, and economic growth. Quarterly Journal of Economics 113(4):1091–1117