

AI Productivity Model Methodology Note

Overview of Economic Model

We model the impact of AI adoption on UK productivity and GDP growth over a 10-year horizon (2026-2036) using a sector-level task-based growth accounting framework. Three components multiply together at the sector level – worker productivity uplift (μ), AI task exposure (β) and the change in firm adoption (ΔA) – to yield a sector-level total factor productivity (TFP) shock. This is then aggregated to the economy, converted to labour productivity and translated into GDP.

The framework builds on the methodology of Eloundou et al. (2023),¹ Acemoglu (2024)² and Filippucci et al. (2025),³ and is closest to the OECD application in its aggregation method. It diverges in two ways: we use ILO Working Paper 140 (2025) occupation exposure scores,⁴ worker-reported, ISCO-08 coded, and classified into four gradient tiers, rather than the O*NET-based binary scores used by the OECD; and we extend the framework with an explicit depth dimension distinguishing broad horizontal AI adoption from sector-tailored deep adoption, allowing us to quantify the additional economic gain from moving beyond off-the-shelf tools into workflow-integrated AI in the most exposed sectors. This approach puts extra emphasis on assumptions on micro productivity uplift (μ), which we address through scenario analysis and by drawing on a much wider range of literature and experience when it comes to the productivity gains from AI adoption.

Our three scenarios produce annual UK labour productivity contributions of 0.3 to 0.8 percentage points per year, equivalent to cumulative GDP gains of £400 billion to £1 trillion over the decade. These figures sit below the OECD's comparable UK scenarios, which assume expanded future AI capabilities; our estimates use only current capabilities and should be considered conservative relative to the published literature.

¹ Eloundou, T., Manning, S., Mishkin, P., and Rock, D. (2023). "GPTs are GPTs: An early look at the labor market impact potential of large language models." NBER Working Paper No. 32966.

² Acemoglu, D. (2024). "The simple macroeconomics of AI." NBER Working Paper No. 32487. Economic Policy, forthcoming

³ Filippucci, F., Gal, P., Laengle, K., and Schief, M. (2025). "Macroeconomic productivity gains from Artificial Intelligence in G7 economies." OECD Artificial Intelligence Papers, No. 41.

⁴ International Labour Organisation (2025). "Generative AI and jobs: A refined global index of occupational exposure." ILO Working Paper No. 140.

The Task-Based Approach to AI Productivity

The model is built on the task-based framework of Autor, Levy and Murnane (2003)⁵ and Acemoglu and Autor (2011),⁶ in which occupations are decomposed into tasks that can be performed by labour or capital. Eloundou et al. (2023)⁷ applied this to generative AI by scoring occupations by their share of GPT-4-assistable tasks; Acemoglu (2024) formalised the link to aggregate TFP.⁸ We adopt this sector-level specification:

$$\Delta TFP_j = \mu_j \times \beta_j \times \Delta A$$

Where μ_j is the average productivity gain per AI-using worker in sector j , β_j is the employment-weighted exposure score, and ΔA is the change in adoption over the period. Sector-level TFP gains are aggregated using Hulten's theorem (Hulten 1978):⁹

$$\Delta TFP_{economy} = \sum_j (\Delta TFP_j \times s_j)$$

Where s_j is each sector's share of market value added – the same approach used by Filippucci et al. (2025)¹⁰ and Briggs and Kodnani (2023).¹¹

Economy-wide TFP is converted to labour productivity via:

$$\Delta LP = \Delta TFP \times \frac{1}{s_j}$$

We use a labour share of 0.57 (multiplier ≈ 1.75), following Acemoglu (2024),¹² who calibrates this specifically for AI-exposed tasks. This is more appropriate than the conventional economy-wide labour share of 0.67 (multiplier ≈ 1.5), which does not distinguish between task types and represents a long-run average across the whole economy. A lower labour share for AI-exposed work is consistent with evidence that automating technologies tend to

⁵ Autor, D.H., Levy, F., and Murnane, R.J. (2003). "The skill content of recent technological change: An empirical exploration." *Quarterly Journal of Economics*, 118(4): 1279–1333.

⁶ Acemoglu, D., and Autor, D. (2011). "Skills, tasks and technologies: Implications for employment and earnings." *Handbook of Labor Economics*, Volume 4: 1043–1171.

⁷ Eloundou, T., Manning, S., Mishkin, P., and Rock, D. (2023). "GPTs are GPTs: An early look at the labor market impact potential of large language models." NBER Working Paper No. 32966.

⁸ Acemoglu, D. (2024). "The simple macroeconomics of AI." NBER Working Paper No. 32487. *Economic Policy*, forthcoming.

⁹ Hulten, C.R. (1978). "Growth accounting with intermediate inputs." *Review of Economic Studies*, 45(3): 511–518.

¹⁰ Filippucci, F., Gal, P., Laengle, K., and Schief, M. (2025). "Macroeconomic productivity gains from Artificial Intelligence in G7 economies." *OECD Artificial Intelligence Papers*, No. 41.

¹¹ Briggs, J., and Kodnani, D. (2023). "The Potentially Large Effects of Artificial Intelligence on Economic Growth." *Goldman Sachs Economic Research*.

¹² Acemoglu, D. (2024). "The simple macroeconomics of AI." NBER Working Paper No. 32487. *Economic Policy*, forthcoming.

be capital-augmenting in the tasks they reach (Acemoglu and Restrepo 2020¹³; Aghion et al. 2023¹⁴).

Finally, GDP impact is:

$$\Delta GDP = \Delta LP \times GVA_{base}$$

This gives the level shift in GDP at full adoption. Annual flows over the 10-year period are derived by scaling this level shift by the share of full adoption reached in each year, following the S-curve specification described below.

Model Components

Worker productivity uplift (μ)

The productivity uplift parameter μ captures the percentage gain in output per AI-using worker, conditional on the worker using AI on AI-amenable tasks. We set μ separately for two adoption modes.

μ_{broad} captures the productivity gain from off-the-shelf domain-agnostic horizontal AI tools, such as general-purpose large language model assistants applied to writing, summarisation, customer service and basic coding. This applies in all scenarios to the universe of AI-affectable tasks.

μ_{deep} captures the gain from sector-tailored, custom AI deployment, including domain-specific models, integration with existing software and fine-tuning on proprietary data. This applies in deep scenarios for sectors that meet exposure thresholds.

We set μ values sector-by-sector based on available empirical evidence for that sector. We have drawn on over 175 sources from BCG cases and publications, alongside external academic research to inform our assumptions in the model. This includes realised results from randomised controlled trials of AI-assisted work, including Brynjolfsson, Li and Raymond (2023)¹⁵ on customer service productivity, Noy and Zhang (2023)¹⁶ on professional writing, Peng et al (2023)¹⁷ on coding tasks, and Cui et al (2024)¹⁸ on software developer productivity. We supplement these with BCG case evidence on enterprise AI deployment in

¹³ Acemoglu, D., and Restrepo, P. (2020). "Robots and jobs: Evidence from US labor markets." *Journal of Political Economy*, 128(6): 2188–2244.

¹⁴ Aghion, P., Antonin, C., Bunel, S., and Jaravel, X. (2023). "The effects of automation on labor demand: A survey of the recent literature." NBER Working Paper No. 31126.

¹⁵ Brynjolfsson, E., Li, D., and Raymond, L. (2023). "Generative AI at work." NBER Working Paper No. 31161.

¹⁶ Noy, S., and Zhang, W. (2023). "Experimental evidence on the productivity effects of generative artificial intelligence." *Science*, 381(6654): 187–192.

¹⁷ Peng, S., Kalliamvakou, E., Cihon, P., and Demirer, M. (2023). "The impact of AI on developer productivity: Evidence from GitHub Copilot." arXiv preprint 2302.06590.

¹⁸ Cui, Z., Demirer, M., Jaffe, S., Musolff, L., Peng, S., and Salz, T. (2024). "The effects of generative AI on high-skilled work: Evidence from three field experiments with software developers." SSRN Working Paper.

specific industries. The arithmetic mean is taken from the range of evidence accepted for each assumption in the model (N=90). For a single source, where a range of productivity outcomes is given, we have used the upper limit. Productivity gains from the evidence, including time saved, are treated as direct 1:1 TFP gains. This is consistent with the approach taken by Filippucci et al. (2025)¹⁹ and Briggs and Kodnani (2023).²⁰ This reflects the standard assumption in the task-based productivity literature that time released from AI-assisted tasks is reallocated to productive use within the same role.

Where strong sector-specific evidence is unavailable, we apply a baseline of 15% to μ_{broad} , constructed from evidence on general tasks common across the whole economy – scheduling, email management and simple writing tasks – representing an arithmetic mean of the range of evidence available for these cross-economy tasks (range: 2.5-45.9%, N=15). This is more conservative than the flat 30% applied across all sectors by other studies. For μ_{deep} , we apply the same 15% baseline unless there is strong-sector specific evidence of additional gains from deep, workflow-integrated AI – as is the case for ICT, finance, and professional services. Where it does not exist, μ_{deep} is set equal to μ_{broad} , on the basis that without evidence of deep adoption gains we do not assume any uplift beyond broad adoption.

AI task exposure (β)

The β parameter measures the share of a sector's work that AI can affect, weighted by the intensity of AI's impact on each affected task. We construct β from the ILO Working Paper 140 (2025) occupation exposure scores mapped onto UK employment data.

The ILO scores assess each ISCO-08 four-digit occupation against generative AI's capabilities, classifying each occupation into one of four exposure tiers ("gradients"):

- **Gradient 4 (G4):** occupations where AI can perform or substantially assist with the highest share of tasks
- **Gradient 3 (G3):** occupations with substantial AI exposure across a large share of tasks
- **Gradient 2 (G2):** occupations where AI provides meaningful partial assistance
- **Gradient 1 (G1):** occupations largely unaffected by current AI capabilities.

We construct two scenario-specific exposure measures from the gradient classifications to reflect what AI can realistically reach under broad versus deep adoption models.

β_{broad} is the employment-weighted mean ILO score among workers in G3 and G4 occupations, divided by total sector employment. This captures work that off-the-shelf, horizontal AI tools can substantially assist with – the two highest exposure tiers where AI's impact is most consistent and reliable across tasks. G2 workers are excluded from β_{broad}

¹⁹ Filippucci, F., Gal, P., Laengle, K., and Schief, M. (2025). "Macroeconomic productivity gains from Artificial Intelligence in G7 economies." OECD Artificial Intelligence Papers, No. 41.

²⁰ Briggs, J., and Kodnani, D. (2023). "The Potentially Large Effects of Artificial Intelligence on Economic Growth." Goldman Sachs Economic Research.

because, while partially exposed, their tasks exhibit high variability and typically require vertical or custom AI tools to generate meaningful productivity gains. G1 and unexposed workers are excluded from the numerator as AI has minimal impact on their tasks, but they are retained in the denominator (total sector employment) to ensure β reflects AI's reach across the whole workforce rather than just the exposed population.

β_{deep} is the employment-weighted mean ILO score among workers in G2, G3 and G4 occupations, divided by total sector employment. This adds G2 workers (those with moderate, variable AI exposure) on the basis that vertical or custom AI tools can reach tasks that off-the-shelf horizontal tools cannot. As with β_{broad} , the denominator is total sector employment. β_{deep} is always larger than β_{broad} because it includes a wider population of AI-reachable workers in the numerator while holding the denominator constant.

To map ILO scores (at ISCO-08 four-digit level) to UK sectors (ISIC Rev. 4 sections at the level of 19 sectors), we combine the ONS Annual Population Survey for employment by SOC 2020 occupation and sector with the ONS SOC 2020 to ISCO-08 crosswalk, aggregating to the 19-sector ISIC level.

Change in firm adoption (ΔA)

ΔA measures the change in firm adoption over the 10-year period, from 8% in 2026 to approximately 76% by 2036 – a change of 68 percentage points, which is the value used in our TFP formula.

We model adoption as a logistic S-curve of the form:

$$A_t = \frac{L}{1 + \exp^{-k(t-t_0)}}$$

The shape and parameters of this curve are calibrated to the historical trajectory of UK internet adoption.²¹ We chose internet adoption as our analogue because it is the closest historical parallel to enterprise AI: it was software-led, required no significant additional physical infrastructure investment, and diffused primarily through changes in how businesses organised and operated. The steepness parameter $k = 0.399$ is derived from the growth rate of the UK internet adoption curve, and the long-run asymptote $L = 0.908$ reflects internet saturation among UK businesses observed. The resulting curve implies fastest adoption growth around 2031-2032.

The baseline ($A_0 = 0.08$) is drawn from ONS BICS Wave 153, using the share of UK firms reporting data processing via machine learning.²² We use this narrow definition, rather than the broader "any AI use" figure of approximately 35% from the same survey, because it best

²¹ Our World in Data; World Bank, 1990–2024.

²² Office for National Statistics (2026). "Business Insights and Conditions Survey, Wave 153." March 2026.

reflects the kind of operational AI integration that drives the productivity gains in our TFP formula.

We treat the S-curve as a central case rather than a precise forecast. AI may, in reality, diffuse faster or slower than the internet did.

Key Assumptions

Labour share for the labour productivity multiplier

We use a labour share of 0.57 in computing the TFP-to-labour-productivity multiplier ($1/s_L \approx 1.75$). This follows Acemoglu (2024), who calibrates the labour share specifically for AI tasks using recent micro evidence on automation and task displacement.²³

Cumulative impact over the decade

Annual TFP and GDP gains in any given year depend on the cumulative adoption reached by that year. For year t we compute:

$$\Delta TFP_t = \Delta TFP_{full} \times \frac{A_t - A_0}{A_{max} - A_0}$$

Where ΔTFP_{full} is the level shift at full adoption. Cumulative GDP over 2027-2036 is the sum of these year-by-year flows. This approach correctly captures the back-loaded nature of the S-curve: gains are modest in the early years (2027-2029), accelerate sharply through 2031-2033 as adoption reaches its inflection point, and plateau toward 2035-2036. This is more accurate than treating the level shift as accruing in every year, which would overstate the cumulative impact by approximately a factor of two given the S-curve adoption profile.

Data Inputs

The following table summarises the data sources used in the model:

Indicator	Source
AI task exposure scores by ISCO-08 occupation	International Labour Organisation, Working Paper 140 (2025)
UK employment by SOC 2020 occupation and ISIC sector	Office for National Statistics, Annual Population Survey (2024)
SOC 2020 to ISCO-08 crosswalk	Office for National Statistics

²³ Acemoglu, D. (2024). "The simple macroeconomics of AI." NBER Working Paper No. 32487. Economic Policy, forthcoming.

UK firm-level high-intensity AI adoption (baseline)	Office for National Statistics, Business Insights and Conditions Survey, Wave 153 (2026)
Sector-level gross value added (current basic prices)	Office for National Statistics, Blue Book 2025
Historical UK internet adoption	Our World in Data; World Bank World Development Indicators
Worker productivity uplift estimates (μ)	Brynjolfsson, Li and Raymond (2023); Noy and Zhang (2023); Peng et al (2023); Cui et al (2024); BCG case studies
Labour share calibration	Acemoglu (2024); Bergeaud, Clette and Lecat (2016)

Scenario Design

We model three scenarios that vary along two dimensions: the breadth of AI deployment (how many sectors are deeply transforming their operations rather than simply using off-the-shelf tools) and the depth of deployment (the productivity uplift each sector can capture).

Scenario 1 (Broad horizontal AI). All 19 sectors use off-the-shelf AI tools. The sector-level TFP gain is:

$$\Delta TFP_j = \mu_{broad,j} \times \beta_{broad,j} \times \Delta A$$

This captures a world in which businesses adopt AI but without significant investment in sector-tailored applications.

Scenario 2 (Targeted deep AI). Sectors that pass a high exposure threshold, defined as a G2+G3+G4 employment share above 33 percent of the sector workforce, move to a deep adoption mode where:

$$\Delta TFP_j = \mu_{deep,j} \times \beta_{deep,j} \times \Delta A$$

Other sectors retain the same inputs as in the broad scenario. The rationale for the 33 percent threshold is that there is a natural gap in the data between the six sectors that qualify and the rest. The six sectors within this threshold – finance and insurance, ICT, professional and scientific services, public administration, real estate, and electricity, gas and steam – all have significantly higher shares of their workforce in G2+G3+G4 occupations than the next tier of sectors, making the threshold a reflection of the underlying likelihood of and gains from adopting deeper AI rather than an arbitrary cut-off.

Scenario 3 (Broader deep AI). A slightly broader threshold – defined as a G2+G3+G4 employment share above 20% of the total sector workforce – brings additional sectors into this expanded deep scenario. This lower threshold of 20 percent reflects that, below this level, even well-implemented deep adoption is unlikely to reach a sufficient share of the workforce to generate material productivity gains at the aggregate level. The additional sectors brought into deep adoption – manufacturing, wholesale and retail, administration

and support services, arts and recreation, mining and quarrying, and other services – all sit in a second tier of exposure, where meaningful but less concentrated AI assistability exists across the workforce.

What the Model Can and Cannot Tell Us

The model estimates the productivity *potential* of AI adoption – what the UK economy could gain if firms adopt AI at internet speed and workers achieve the productivity gains documented in RCTs. Several important scope conditions apply.

It is not a GDP forecast. The framework estimates a long-run equilibrium shift at full adoption, phased in via an S-curve. It does not model dynamic adjustment costs, price and wage effects, or sectoral reallocation. Realised GDP growth will depend on how smoothly the economy adjusts.

Gains may be backloaded beyond what the S-curve implies. Evidence from previous general-purpose technologies suggests productivity gains often lag adoption due to the time needed for complementary investments in workflows and skills: the J-curve effect (Brynjolfsson, Rock and Syverson 2021).²⁴ The S-curve produces a similar back-loaded pattern in our cumulative numbers but does not capture this explicitly.

It reflects current AI capabilities only. We model AI as a single technology shock. Successive waves of capability improvement – and the possibility that some sectors hit capability ceilings before full adoption – are not captured. This makes our estimates conservative over a longer horizon.

It does not address distribution. The model says nothing about how productivity gains are shared between workers, firms and capital owners, nor about implications for employment, wages or inequality. It also keeps sector weights constant throughout the forecast period, which means significant structural changes to the composition of the UK economy in the period are not accounted for.

These scope conditions apply equally to comparable models in the literature (Filippucci et al. 2025;²⁵ Acemoglu 2024;²⁶ Aghion and Bunel 2024²⁷).

²⁴ Brynjolfsson, E., Rock, D., and Syverson, C. (2021). "The productivity J-curve: How intangibles complement general purpose technologies." *American Economic Journal: Macroeconomics*, 13(1): 333–372.

²⁵ Filippucci, F., Gal, P., Laengle, K., and Schief, M. (2025). "Macroeconomic productivity gains from Artificial Intelligence in G7 economies." *OECD Artificial Intelligence Papers*, No. 41.

²⁶ Acemoglu, D. (2024). "The simple macroeconomics of AI." *NBER Working Paper No. 32487*. *Economic Policy*, forthcoming.

²⁷ Aghion, P., and Bunel, S. (2024). "AI and growth: Where do we stand?" *Communications & Strategies*, 134.